A LONGITUDINAL STUDY OF SCHOOL PRACTICES AND STUDENTS' CHARACTERISTICS THAT INFLUENCE STUDENTS' MATHEMATICS AND READING PERFORMANCE OF ARIZONA CHARTER MIDDLE SCHOOLS

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In 1995, Arizona legislators passed laws specifically to implement charter schools in Arizona. Approving 15 year charters (i.e., contracts), allowing charter schools to cross school district boundaries, and requiring the charter schools to administer the state assessment are three of the many charter school statutes written into law. In 2010, those initial charters are expiring. The variation in school practices that occur between charter schools is great as reported by researchers nationwide. This difference does not stop at the borders of Arizona; some Arizona charter schools are labeled as excelling in performance while others are labeled as underperforming. There is limited research of Arizona charter schools and the variance that exists among them.

There were two purposes for this dissertation. The first purpose was to analyze the influence of school practices and student characteristics on charter middle school students’ mathematics and reading performance at grade 8. The second purpose was to assess those influences over time (i.e., 2007-2009). The assessment used was Arizona’s Instrument to Measure Standards (AIMS) which remained stable during this span of time.

Multiple imputations were performed for missing data. Hierarchical linear cross-classified random effects modeling (HLM/CCREM) was used to assess the data
while taking student mobility into consideration. The results showed that the effect of teacher experience influenced lower achieving students, that teachers teaching out of their area of expertise had a negative effect on mathematics and reading achievement of students, and attending a charter school that was converted from a traditional public school has an advantage in Arizona. An indicator of whether a student was attending a charter school in 2006 (prior to the time period of this study) was added to the model and showed that students scored higher in mathematics and reading if they also attend a charter school in 2006. All factors assessed in this study were accounted for even if they didn’t remain in the model due to fit statistics. These results will contribute to the field of education by providing empirical evidence of the effects of charter school practices on student achievement.
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CHAPTER I

Introduction

Background of the Study

Since 1992, charter schools (publically funded schools that operate according to a contract or “charter”) were adopted into 40 states’ (plus, the District of Columbia) education systems as an alternative to traditional public school. Charter schools were incorporated into educational systems: 1) to give parental choice to an alternative type of public schooling for their child, 2) to create a school with an innovative organizational climate, and 3) to serve a specific population of students (Dawson, 1999; Peterson & Campbell, 2001; RPP International, 2000).

The first charter school law was passed in Minnesota in 1991 which allowed the first charter school in the United States to open its doors the following year. Minnesota set precedence but other states’ legislators were quick to adopt their own charter laws (e.g. California passed their charter law in 1992). By 2009, forty states and the District of Columbia had adopted charter school laws – all unique to their jurisdiction. Each charter law states its own set of rules and laws for the structure of charter schools in their jurisdiction. In 2009, 4600 charter schools were in operation with 1.4 million students enrolled (Center of School Reform 2008; National Alliance of Public Charter Schools, 2008; U.S. Charter Schools, 2008).

The Public Charter Schools Program (CFDA #84.282), initiated by President Bush’s administration and fully supported by President Obama’s administration, offers competitive grants to State Departments of Education to financially fund the
development of charter schools, the initial implementation of those schools, and providing some funding to operate the schools (State Education Reforms, 2005; U.S. Department of Education, 2009). Charter laws as a whole allow charter schools to offer a free education to all and cannot discriminate against any students. Charter schools may focus on a specific student population such as special needs students with learning or physical disabilities.

As reported by RPP International (2000) there are many advantages in charter schools that may not be available in traditional public schools, including smaller class sizes which allow students more individual attention from teachers. More often than in traditional public schools, teaching staff are reported to be part of the charter school governing board and thus have a vested interest in the overall climate of the school and the curriculum used in the classroom (RPP International, 2000). This may foster a supportive environment for the staff members who are united in both mission and goals. This unity could promote creative and innovative approaches to curriculum specific to student population. The addition of charter schools to the education system has also created new teaching opportunities, giving teachers a chance to design unique educational programs (Collins, 1999; Greene et al., 1996; Hadderman, 2002; Hess, Maranto, Milliman, & Grammatico Ferraiolo, 2002; Lubienski, 2001; Mead & Rotherham, 2007).

Disadvantages for charter school staff, as reported in the current research, includes teachers working long hours and having less job security. Charter school enrollments can fluctuate quite a bit from one year to the next which directly affects funding for support staff and teachers. A stand-alone charter does not have the flexibility
to move teachers to another site due to low attendance and, therefore, may be forced to lay off teachers one year and hire double the amount of teaching staff the next year. Oftentimes charter school staff members may have to fulfill multiple roles due to the lack of staff (Collins, 1999; Hess et al., 2002; Lubienski, 2001; Mead & Rotherham, 2007).

Charter schools can only open their doors after an authorizing body of some sort (e.g., education management organization, state board of education, a university, or a private corporation) approves their charter (i.e., contract). Authorizing bodies vary in how much involvement they have in the development process of their school and monitoring the school on a regular basis (Gau, 2006).

Nearly all jurisdictions have a cap on how many charter schools can be approved per year. Arizona is unique in that sense because their cap of 25 charter schools per school year was lifted with Arizona Senate Bill 1302 in 2000 (Arizona Department of Education, 2006; Hassel & Terrell, 2004).

The length of charters (a.k.a. charter school contracts) varies from one jurisdiction to another. Arizona and Washington D.C. hold the longest charters of fifteen years. Arizona’s charter laws require program reviews at five year intervals (Gill, Timpane, Ross & Brewer, 2001; Arizona Education Laws and Regulations, 2008a).

Charter schools vary from one school to the next from type of authorizer and the authorizer’s involvement to the type of curriculum used in the school. The purpose of this dissertation was to investigate the effects of school practices on students’ mathematics and reading achievement of Arizona charter middle school students. For the scope of this study charter school practices are defined by Raudenbush and Willms (1995) in their
study titled, *The Estimation of School Effects* as those which consist of areas that are treatments within a school such as administrative leadership, utilization of resources, grade structure, and the number of students per classroom (i.e., classroom size). It was *not* assumed in this study that school practices have a uniform effect on students; instead, student scores were examined individually across years.

**Evolution of U.S. Charter Schools**

The first charter school law passed in the U.S. was in Minnesota in 1991. This law allowed for up to eight charter schools to be opened. Charter schools, now numbering up to 4600 and serving over one million students in 40 states plus the District of Columbia as of 2009, are said to have freedom from most bureaucracy that may occur in traditional schools (National Alliance of Public Charter Schools, 2008). In most cases, however, charter schools are tied to some state regulations (albeit fewer than traditional schools) and are being held accountable for school achievement to their authorizing agency, their school governing board, the parents, an education management organization, and to public scrutiny (Bulkley, 2001; Gill et al., 2001; Hassel, Terrell, Kain, & Ziebarth, 2007; Manno, Finn, Jr., & Vanourek, 2000; Palmer & Gau, 2003; RPP International, 2000; US Dept of Education, 2004).

Mead and Rotherham (2007) concluded from their research that the “strength” of state charter laws has a direct effect on the success of the school (i.e., in terms of student achievement and management). They judged the quality of charter laws on the following criteria: 1) “high-quality” professional authorizing (i.e., sufficient resources and authority over a significant number of schools), 2) reliance on authorizing as opposed to regulation,
3) public accountability, 4) measures of student performance, 5) no cap on the number of charter schools permitted in a year, 6) equitable funding, and 7) incentives to encourage use of “proven charter school models” in underserved communities (Mead & Rotherham, 2007).

The Center for Education Reform has slightly different criteria for determining strong charter laws. They rank states annually and assign a letter grade to each state and the District of Columbia based on the following criteria for charter laws: 1) multiple authorizers permitted in a state (independent from traditional school boards), 2) number of schools allowed to open (annually or as a state total), 3) operational independence from state and district rules and procedures, and 4) fiscal equity in amount of funds received and identical funding sources as those available to traditional public schools (Center for Education Reform, 2010).

There are 40 states plus the District of Columbia that have charter laws which makes a total of 41 unique charter laws in the nation; therefore, to investigate an impact in any one state, a closer look is required. Arizona is consistently ranked in the top five states in the nation for their charter school laws by the Center of School Reform. As of 2008, Arizona had the highest number of charter schools per capita in the nation and is second, only to California, for the number of charter schools overall (Center for Education Reform, 2008; Hassel & Terrell, 2004).

**Arizona Charter School System**

The issue of adopting a charter law in the state of Arizona was a very politically charged debate in the 1993 Arizona state legislature, starting with the end of a very close
race defeating a voucher system (Dee & Fu, 2004). On the coattails of deliberating the voucher issue, the Arizona congress was called back for a special summer session to discuss charter schools for education reform (Dee & Fu, 2004).

In 1994, the allowance of charter schools passed and the first charter was in operation during the 1995-1996 school year (Dee & Fu, 2004). Arizona was the 10th state in the nation to pass charter school laws and by the second year had the second-highest number of charter schools in operation behind California. According to the Center for Education Reform, Arizona had 348 charter schools and was leading the country in the number of charter schools by February 1999. California had 234 and Michigan reported 175 charters that same year. In 2006-2007, there were 507 charter schools with an enrollment of 92,071 Arizona students. By the 2008-2009 school year, the enrollment rose to 102,380 students (Arizona Department of Education, 2008a; Dawson, 1999; Hassel & Terrell, 2004). (See Appendices C-E for the disaggregate enrollment count of students in charter schools.) In the late 2000s, Arizona was ranked number one in the country with the highest percentage (9%) of market share in a single state (Buddin & Zimmer, 2005; Center for Education Reform, 2006; Dawson, 1999; Hassel & Terrell, 2004; National Alliance for Public Charter Schools, 2008).

Arizona’s charter laws are considered to be the model of charter school legislation by some yet considered too liberal by others. The following are a summary of a few statutes that are considered by some to create a “strong” charter law. An autonomous State Board of Charter Schools was created to oversee the charter schools with the allowance, by law, to grant up to 25 new charters each year (the cap on new charter
schools was lifted by Arizona Senate Bill 1302 in 2000) (Dawson, 1999; Hassel & Terrell, 2004). The law also permitted an unlimited amount of charter schools each year to be granted by local school districts (Dawson, 1999). Local school districts, up until July 1, 2000, were permitted to authorize charter schools outside of their district boundaries. Also as mentioned earlier in the chapter the length of charters (i.e., contract) in Arizona are for a fifteen year term with an evaluation and audit at every five year interval (Arizona Education Laws & Regulations, 2007). There were two reasons why the fifteen year term charter contract passed in Arizona’s legislation. The first was to give investors a chance to see their investments prosper. Private investors are more apt to get involved when a charter school has the time to build a solid foundation over a period of time allowing them to grow in enrollment. Secondly, the long-term contract gives traditional public schools that converted to a charter school because of an “underperforming” status on the adequate yearly progress (AYP) scale a chance to turn around their student performance (Dawson, 1999; Hassel & Terrell, 2004). Within the fifteen year contract the sponsor shall review a charter school at five year intervals to make sure that the school doesn’t breach their charter provisions. At the end of the fifteen year contract, the charter can be renewed for another fifteen years (Arizona Education Laws & Regulations, 2007).

Any public body, private person, or private organization can qualify as a charter school applicant in the state of Arizona according to the Arizona Education Laws and Rules (2007). Authorizers in Arizona are the Arizona State Board for Charter Schools
(ASBCS) or a school district. Arizona’s Education Law and Rules (2006) states the following regarding charter schools:

A. Charter schools may be established pursuant to this article to provide a learning environment that will improve pupil achievement. Charter schools provide additional academic choices for parents and pupils. Charter schools may consist of new schools or all or any portion of an existing school. Charter schools are public schools that serve as alternatives to traditional public schools and charter schools are not subject to the requirements of article XI, section 1, Constitution of Arizona [i.e., 15-161. State control over private schools], or chapter 16 of this title [i.e., School Capital Finance].

B. Charter schools shall comply with all provisions of this article in order to receive state funding as prescribed in section 15-185 [Charter schools; financing; definitions]. (p31)

The applications consist of:

1. Detailed business plan.
2. Description of the charter school’s organizational structure and governing body.
3. Description of their hiring policy.
4. Name of the applicants and requested sponsor (i.e., LEA or the ASBCS).
5. Description of grades being served.
6. Description of school facilities and location of the school.
7. An outline of criteria designed to measure effectiveness of the school (every public school in the state of Arizona is required to administer the Arizona’s Instrument to Measure the Standards (AIMS) and to submit the same electronic data to the Arizona Department of Education).

8. A financial plan for the first three years of operation.

Arizona charter schools are granted waivers from most state and local school board regulations and are funded directly by the state as opposed to a tax effort. This means that charter schools receive base support, capital funding, and money to support bus transportation available for their students as would any school district in the state. Traditional public school teachers have the option of taking a 3-year leave of absence to work in a charter school without losing their seniority in their traditional school, any right of certification, retirement benefit, salary status, or any other benefits offered to teachers of traditional schools. These areas and many more topics regarding charter schools are fully described in the literature review (Arizona Education Laws and Rules, 2006; Dee & Fu, 2003).

Arizona has a history of fifteen years in the charter school business and with the implementation of AIMS, their state assessment, they now have standardized data to compare schools and show growth within schools. The longevity of the charter contracts and the longitudinal data available make Arizona an excellent state to investigate for the makeup of charters and whether school practice affects student achievement. As charter schools mature, researchers are able to study their affects on students. This lends itself to the purpose of this dissertation.
Statement of the Problem

The variations of charter school laws make it nearly impossible to compare achievement scores across the states (Zimmer, et al, 2009). Charter school regulations, for one, vary from one state to the next in reporting requirements, enrollment policies, teacher qualifications, and funding sources (Gill, et al., 2001; Loveless & Jasim, 1998; Mead & Rotherham, 2007). The variation among charter schools is vast, from the type of governing board, to the qualifications of the teachers hired, to the chosen curriculum implemented. The autonomy and flexibility in curriculum and scheduling has resulted in very few charter schools being similar in structure unless they are overseen by the same authorizing agency (Gill et al., 2001; Imberman, 2007). This wearisome realization for researchers occurs when attempting to compare charter schools to traditional public schools within states as well as across states. The prospect warrants very complex analyses.

Over the years there have been many studies conducted on charter schools comparing them to traditional schools within states. Some researchers took precautions to control for the variations among charter schools by matching them to traditional public schools serving similar populations (Bettinger, 2005; Buddin & Zimmer, 2005; Crew & Anderson, 2003; Florida Department of Education, 2005; Gewertz, 2005; Greene, Forster, & Winters, 2003; Gronberg & Jansen, 2001; Hanushek, Kain, Rivkin, & Branch, 2005; Homes, DeSimone, & Rupp, 2003; Horn & Miron, 2000; Lake & Hill, 2005; Miron, 2005; Slovacek, Kunnan, & Kim, 2002; Solmon, Paark, & Garcia., 2001; Wong & Shen, 2002). Although the findings have been mixed overall (and will be described
fully in Chapter II), these studies add to the field of knowledge giving insight to appropriate ways to measure the achievement of charter schools.

In 2004, the National Center for Education Statistics (NCES) commissioned a charter school study that utilized the National Assessment of Educational Progress (NAEP) data from charter schools across the U.S. The NAEP is the only assessment that is administered nationally; therefore, it is often used to study education related issues nationwide. The study focused on two parts, the first compared charter schools to non-charter schools and the second investigated whether charter school practices affect the achievement of attending students. Unfortunately, the second part of the study (which is pertinent to this study) contained small sample sizes. The small sample sizes, paired with the fact that there is so much variability in charter schools, produced many $p$ values that were not statistically significant. The results from Part II can only be suggestive of what can be found in a larger sample and the results of the study overall were mixed (Braun, Jenkins, & Grigg, 2006).

The national study of charter schools by NCES was a necessary component to education research, confirming the variation between states among charter schools (e.g. policy environments, charter school accountability requirements, curriculum, etc.). Due to the variation that occurs across charter schools, the methodology used in the NCES study exemplifies the complex analysis needed to run an empirical investigation of this nature. The NCES study fulfills a necessary void in the current body of knowledge on charter schools, and the mixed results may mean that each state will have to conduct their own study of schools according to their own state charter laws (Brown, Henig,
There are very few empirical studies that compare one charter school to another. Nearly all compare traditional schools to charter schools; albeit, some compare by matching each charter school to a counterpart serving a similar student population in the traditional school system (Braun et al., 2006; Hoxby, Murarka, & Kang, 2009; Solmon et al., 2001). Before one can compare charter schools across states, a study of charter schools within state education systems should occur. Furthermore, before one charter school can be compared to another within states, an assessment of the structure of charter schools themselves should be conducted to determine what constitutes a successful charter school in terms of student achievement and management within that particular state charter law.

Although Arizona has been ranked one of the top five states in the nation for strongest charter school laws by the Center of School Reform (2010), the infrastructure of the charter school system has come into question in the past in terms of not being aggressive enough when closing poorly performing schools and of not enacting a useful database for charter school statistics (Hassel & Terrell, 2004). The support of various organizations has shifted slightly over the years as well. For example, some school districts “sold” their charters for a profit, companies that provided support services have changed, and a national “think tank” has scaled back their direct involvement in the charter school movement in Arizona (Hassel & Terrell, 2004).
For nearly ten years, Arizona charter schools have been administering AIMS. Based solely on the school report cards, it can be seen that one charter school has a higher performance rating than another on the state assessment, but it is unclear exactly why that is the case. Yet, to date there are no empirical studies published that use longitudinal AIMS data to assess the variance in school practices that affect student achievement in mathematics and reading of Arizona charter middle school students.

Purpose of the Study

The objective of this dissertation was to investigate the effects of Arizona charter school practices on students’ mathematics and reading achievement over a period of three years in an effort to set “best practices” as a guide - guidance for structure without losing autonomy - for authorizers and researchers.

Coleman, Campbell, Hobson, McPartland, Mood, Weinfeld et al., (1966) found in their study, *Equality of Education Opportunity*, that student characteristics (i.e., low SES and minority students) show a strong correlation with academic achievement and the quality of school facilities, teacher quality, and teacher experience. These are factors that were addressed in this study, more than 40 years later, to see if they have the same effect on student achievement in the twenty-first century schools (i.e., charter schools) as they did in the 1960s.

Student achievement, school effectiveness, and the interaction of those two elements on school “success” is accounted for through a number of means, not just test scores (e.g., student portfolios, testimonials, etc.); however, exploring all possible modes of success was not feasible for this study. Test scores are commonly used and widely
accepted as a measure of achievement by researchers and the public (Buddin & Zimmer, 2005; Collins, 1999; Imberman, 2007; Zimmer et al, 2009). In addition, Collins found in his study (1999), *Charter schools: An approach for rural education?*, that parents of students attending charter schools are more apt to change schools based on test scores than parents of students attending traditional schools. Thus, for the purpose of this study, reading and mathematics test scores over the time period of 2007-2009 were used as an outcome to assess the longitudinal effects of school practices on charter school students’ achievement entering grade 6 in the 2006-2007 school year and competing grade 8 in 2008-2009.

**Research Questions**

The research questions addressed in this study are:

1. How do school practices, while controlling for student characteristics, affect average mathematics and reading achievement for Grade 8 students at the exit year (i.e., 2009)?

2. What is the average growth rate in mathematics and reading achievement of students at Arizona charter middle schools?

Student characteristics helped to explain variability in the growth rate across students and across schools.

**Significance and Rationale**

According to the National Center of Education Statistics and the RAND Corporation, the “structure” of charter schools affects student achievement more than the
structure of traditional schools affects their students (Braun, et al., 2006; Buddin & Zimmer, 2005). Before a comparison of charter schools to traditional schools on any level can occur, some semblance of structure within charter schools is needed - that is, structure without losing autonomy. “Structure” in this study refers to school practices (e.g., class size, start-up versus conversion school, years of teacher experience) and school context (e.g., economic and social aspects of the community the school serves - reflected by student demographic variables in this study) as defined by Raudenbush and Willms (1995).

Once the impact of school practices, while controlling for student characteristics, has been thoroughly investigated, a determination of the factors that had a positive effect on student achievement (in terms of reading and mathematics) can be given to governing boards as a guideline that may serve to improve achievement among their charter school students. In addition, based on an accurate picture of school practices, researchers will also be able to measure comparable charter schools to traditional public schools and parents may be able to make a more informed decision about charter schools. Furthermore, the hierarchical linear cross-classified random effects model used in this complex analysis can be seen as a template for use in other states.

Limitations

AIMS is administered by the classroom teacher; therefore, teacher effect may be an issue for students. Because this was a quasi-experimental research study using students previously assigned to classrooms, teacher effect on the class as a whole is an issue of internal validity. The reading and mathematics scores may be a reflection of
classroom instruction as well as tutoring, which was not accounted for in this study. Some schools and/or teachers may take longer than a year to show an impact on a student which could underestimate the growth of student achievement, especially in the first few years at the charter school (described in detail in Chapter III) (McMillan & Schumacher, 2001).

Prior reading and mathematics achievement was not accounted for and, although a value-added model was used to measure growth within the charter school system during 2007 through 2009 to try to control for student characteristics, there was the potential for unobserved characteristics to have an impact on the achievement scores of students. The assessment was changed in 2005 and 2010 which limited the years of this longitudinal study to three years.

Maturation of students is also an issue with repeated measures designs because of the natural cognitive development as students advance from grade 6 through grade 8 (Charter School Achievement Consensus Panel, 2006; Hoxby & Murarka, 2008; McMillan & Schumacher, 2001).

Selection issues are problematic when assessing charter schools because parents choose to send their children to a certain school; however, addressing student longitudinal data helps alleviate some of this problem by investigating growth from one year to the next year (Buddin & Zimmer, 2005; Solmon et al., 2001).

Operational Definitions

Academic achievement at exit year (i.e., 2009) – the 2009 Grade 8 mathematics (or reading) AIMS results as measured by a scale score.
Across schools – one school compared to another.

Across students – one student compared to another.

AIMS – the Arizona Instrument to Measure Standards

Charter school – public funded school that has been authorized to open upon review of their contract (i.e., “charter”). This school answers to a governing board, although, may be autonomous from various statutes from the LEA (Gill, et al., 2001).

Growth rate – the gain in mathematics (or reading) results over a three year period, 2007-2009.

Highly Qualified Teachers – The Arizona Department of Education defines highly qualified teachers as those that hold a bachelor’s degree, hold a valid Arizona state certificate (charter school teachers are exempt from this particular requirement), and have a current teaching assignment. In addition, teachers have to possess one of the following six options: 1) pass the AEPA Subject Knowledge Test; 2) hold an advanced degree in the core academic subject area; 3) hold National Board Certification in the core academic subject area; 4) have at least 24 credit hours in the core academic subject area; 5) have earned a minimum of 100 points on the AZ HOUSSE rubric for a core academic subject (e.g., all teaching, coursework, and professional development must be in the core academic subject area); or 6) have documentation that states highly qualified teacher reciprocity (Arizona Department of Education, 2008b).

“Structure” of charter schools – the combination of school practices (e.g. administrative leadership, curriculum) and school context (i.e. “social and economic characteristics of the community” p310) as defined by Raudenbush and Willms (1995).
Teacher Experience – years of service.

Traditional public school – a school tied to the local government (i.e., LEA).
CHAPTER II

Literature Review

Introduction

The charter school concept evolved over time. Some feel that the idea of charter schools developed over time from literature dated as far back as the 1700s. Others feel that the suggestion of charter schools was introduced as an alternative to the voucher system and magnet schools. The following section is a chronological progression of changes in education policy that led to what are now known as charter schools.

Restructuring traditional public schools was a “hot” topic among legislators and educators as early as the first half of the twentieth century, influenced by proposals written in the late 1700’s by Adam Smith and in the 1800’s by John Stuart Mill (Dawson, 1999; Gill et al., 2001; Peterson & Campbell, 2001). The topic continued to be addressed following Friedman’s publication of *Capitalism and Freedom* in the 1962. This publication described government involvement in public schools by subsidizing costs for school programs (Gill et al., 2001). His alternative solution was to give the parents money in the form of a school voucher to allow their children to attend the school of their choice (Dawson, 1999; Peterson & Campbell, 2001).

At the same time the *Equality of Educational Opportunity* report, more commonly known as the Coleman report (1966), spawned changes that affected the structure and climate of schools across the United States. Full of surprises regarding funding and peer influence, this report sparked many changes in policy (Coleman, et al., 1966; Kahlenberg, 2001).
Others believe that charter school systems were a progression from magnet schools, developed in the 1960s (Peterson & Campbell, 2001). Magnet schools are schools that have programs federally funded to offer improved education programs encouraging racial integration in urban schools (Peterson & Campbell, 2001).

Two decades after Friedman introduced the voucher system, Coleman promoted the topic as well as a solution to restructuring the nation’s schools (Kahlberg, 2001; Peterson & Campbell, 2001). Coleman also reported from his work with Catholic high schools that student achievement was more dependent on peers, parental involvement, sense of community, and a shared mission in the schools (Kahlberg, 2001; Peterson & Campbell, 2001). The Brookings Institution conducted a follow-up study on Coleman’s findings and found that the autonomy allotted to private schools allowed for organization that was more effective than in public schools (Peterson & Campbell, 2001).

The focus of the nation’s education community then shifted to voucher systems as a form of education reform (Dawson, 1999). Also in the mid-1980’s, the federal government became actively involved in funding magnet schools and states started experimenting with ways to expand the concept of the magnet school choice system which some say led to what became known as charter schools (Peterson & Campbell, 2001).

By the end of the 1980s, many heated debates over the subject of the separation of church and state led to discussions of another type of school choice as opposed to voucher schools or magnet schools which later became known as charter schools (Dawson, 1999; Dee & Fu, 2004). At that time the term “charter” wasn’t used. The term
“charter” in terms of education was first documented in reference to a contract between school boards and teachers regarding curriculum taught (U.S, Charter Schools, 2008). Later, schools within schools became known as charter schools in the 1980’s (U.S, Charter Schools, 2008). It wasn’t until Ray Budde (1988) published his book titled, *Education by Charter: Restructuring School Districts*, that the phrasing of charter schools caught on and struck a favorable cord for Al Shanker, former president of The American Federation of Teachers and member of President Bush’s Education Policy Advisory Group (Dawson, 1999; U.S, Charter Schools, 2008). Budde (1988), based on recommendations from education reformists, defined the changes that would have to be made in the roles of teachers, principals, the superintendent, the school board, parents, and others in the community. He established that teachers should be given autonomy; decisions about curriculum and other school matters should be made closer to the classroom, and parents should have a choice of schools (Budde, 1988; Dawson, 1999; U.S, Charter Schools, 2008).

Meanwhile discussions on restructuring the current education system and providing choice to parents were the themes of the 1989 Education Summit meeting in Charlottesville, Virginia (Vinovskis, 1999). This meeting was actually the second wave of the great education reform of the 1980’s shortly after *A Nation at Risk: The Imperative for Education Reform*, was reported (Vinovskis, 1999). This meeting focused on restructuring public schools to place more emphasis on student learning, best practices, and the organization and management of public schools (Vinovskis, 1999). After hearing Al Shanker speak on the idea of charter schools (i.e., public schools with autonomy),
Minnesota Senator Reichgott wrote the first bill on charter school law to pass in the nation (Dawson, 1999). In 1992, Minnesota opened the first charter school in the country (Dawson, 1999; Hassel & Terrell, 2004; Peterson & Campbell, 2001; RPP International, 2000).

Charter schools had to reflect specific features of traditional public schools such as non-selective admissions, no tuition, and no religious affiliation (Dee & Fu, 2003). In addition, the charter contracts would expire after a period of time with the opportunity to be renewed, any individual/organization could obtain a charter, and charters would be exempt from some state and federal regulations (Dee & Fu, 2003).

Today, the National Alliance for Public Charter Schools reported that there are 4600 charter schools serving more than 1.4 million students in 40 states plus the District of Columbia. Charter school acceptance seemed to be a way for states to bypass the voucher issue (Dawson, 1999; Dee & Fu, 2004; Hassel & Terrell, 2004).

**Charter School Choice**

The idea of autonomy from the ties that traditional public schools have, aside from meeting health and safety regulations and laws, is meant to allow charter schools more freedom to concentrate on meeting their particular students’ needs. As time passed (nearly 20 years) since the first charters were accepted in 1992, the question still remains: Are charter schools providing a better education than traditional public schools? School districts or authorizers focusing on individual schools rather than entire school systems permit the schools to develop unique programs to service their specific student body. A by-product of this individuality is a large amount of variability among charter schools...
even 20 years later. This continues to make it difficult to compare them to other charter schools or to traditional public schools (Buddin & Zimmer, 2005; Collins, 1999).

Charter schools, for the most part, tend to be smaller than traditional public schools which allows for smaller class size and an opportunity for the school to take a creative and innovative approach to teaching. Charter schools can provide more options for parents and new teaching opportunities just by adding to the sheer numbers of schools available to the populations they serve. Parents’ decisions on which school they choose for their child to attend may not be solely based on academics, but also on proximity of the school, work schedule, after-school care, and extracurricular activities (Collins, 1999).

Dr. Carolyn Hoxby, an education economist from Harvard University, found that when parents make an active choice of which school their child attends, they become more involved in school policy decisions and visit the school more often. This meets one of the National Education Goals, adopted in 2000, which is to acquire greater parent involvement in their children’s education. In some cases charter schools are able to reach dropouts and other at-risk students with classes that may not be offered at the traditional public school. For example, charter schools enhancing their curriculum with technology can offer students the opportunity to be taught with computer-aided instruction as well as the opportunity to use the computers more often than those attending large traditional public schools. This is very attractive to some parents - yet, can we answer the question of whether these schools are more effective in terms of making an impact on student

Although charter schools have been in existence for nearly 20 years, only a handful survive the initial growing pains of the start-up phase (e.g., finding adequate funding and facilities) (Loveless & Jasin, 1998; Ravitch, 2001). Some researchers feel that since so many charter schools are struggling to survive due to lack of funding, low student achievement, or poor management they haven’t had a chance to really imprint their contribution as a whole in our nation’s education system (Ravitch, 2001).

The following charter school factors were reviewed from current research and literature for this dissertation: funding, authorizers, first few years of operation, conversion from traditional school versus start-up charters, teachers (i.e., certification, experience, and advanced degrees), and class size.

Funding

Funding has always been a problem for charter schools (Loveless & Jasin, 1998). Securing available and adequate funding is an ongoing process and is an issue unresolved nationwide. Charter schools in nearly every state do not receive the same percentage of funds that traditional schools receive (Finn, Hassel, & Speakman, 2005; Gill et al., 2001; Imberman, 2007; Loveless & Jasin, 1998; Mead & Rotherham, 2007; RPP International, 2000). Charter schools that have the same per-pupil expenditures may not be able to apply for all of the grants that are available to traditional schools and, as a consequence, a portion of their operating budget, for example, may go toward securing a facility for their students. For instance, charter schools are not eligible for taxpayer-financed bonds so the
U. S. Department of Education and the Office of Innovation and Improvement has set up two ways to help charter schools receive more funds than in years past: 1) a competitive grant program for entities to help charters called the Credit Enhancement for Charter School Facilities (U.S. Department of Education, 2008a); and 2) grants that support per-pupil facilities-aid programs such as the State Charter School Facilities Incentive Grants (U.S. Department of Education, 2008b). Unfortunately, some states may be slower than others at distributing funds to charter schools, thereby affecting their ability to provide for charter school students (U.S. Government Accountability Office, 2005).

*State Supplementation*

Finn, Hassel, and Speakman indicated in the 2005 Fordham report, *Charter School Funding: Inequity’s Next Frontier*, that even if states are making an effort to disperse funds fairly there are differences between traditional and charter schools that will affect spending. For the most part, it is the lack of local funding that causes the problem with adequate funds (Finn et al., 2005; RPP International, 2000). Some states try to compensate for lack of local funding by supplementing the charter schools with additional state funds, but that effort (in most cases) does not match what is missing (Finn et al., 2005). For example, California created a funding package for their charters but it has been reported that it is not updated on a regular basis to match traditional school funding as new adjustments are implemented (Finn et al., 2005).

*District disbursement.* Funds for charter schools, in some states, are distributed through local school districts giving the school district the authority to disperse the funding or hold on to it indefinitely if problems or issues arise (Mead & Rotherham,
2007). Three states have this kind of accounting system in place which can make it difficult for charter schools. For instance, Ohio requires that charter schools report their enrollment every month to the state to receive their monthly funding as opposed to traditional schools that report enrollment once a year (Williams, 2006). The LEAs, as a consequence, quite often hold student records (a.k.a. “flagging”) that may be in question and therefore hold funding until matters are resolved. It has been reported that it can take up to six months to resolve questions while forcing the charter school to go in the red (Williams, 2006; Williams, 2007). Charter schools in Arizona, for the most part, are considered their own school districts and do not have that issue. (A few Arizona charter schools are authorized by traditional school districts and, therefore, may be an exception to this rule) (Arizona Department of Education, 2008c).

Facilities

Some states try to help charters in additional ways other than directly funding them, such as providing them with a list of vacant facilities that are free of charge (Mead & Rotherham, 2007). For example, the Arizona Department of Education publishes a list of vacant unused buildings that are owned by the state or school districts as possibilities to house charter schools. Arizona school districts are also able to sell used school equipment to charter schools prior to disposing of the equipment by other means (Arizona Education Laws & Regulations, 2007). Even with the facilities provided, most charters are under-funded and it affects the students in various ways: 1) the staff are preoccupied trying to acquire funds; 2) facilities may not be of the same quality as
traditional public schools; and 3) school supplies may not be adequate (Arizona Education Laws & Regulations, 2007; Mead & Rotherham, 2007).

Open Enrollment

In addition to what was mentioned above, some states have legislation that permits schools to compete for student enrollment. Charter schools, by their nature, create competition in our education system between traditional versus charter schools and among charters themselves (Hanushek & Rivkin, 2003). Charter schools could possibly result in net financial loss to a school district because students attending the new school (in this scenario – charter school) do not necessarily reduce the sponsoring organization’s (i.e., school district) costs, yet per pupil funding goes with the student (Finn, Manno, & Vanourek, 2001; Hoxby, 2003; Zimmer et al, 2009). In Arizona, charter school patrons, as well as traditional public school students are permitted to cross district boundaries to attend a school of their choice (Arizona Department of Education, 2008c). This open enrollment policy encourages all public schools (i.e., traditional and charter) to attract students to obtain federal funding for capital expenses. Arizona schools within a school district have to give preference to eligible students who reside within their school district boundaries; however, if there is available room at the school they are permitted to accept students from all over the state (Arizona Department of Education, 2008c).

Creating competition is an indirect way of acquiring funds; though in the past, charters have been criticized for “creaming the crop” of students from a district or area and taking all of the money from the districts. Research studies on both of these topics report mixed results overall (Cobb & Glass, 2003; Dee & Fu, 2003; Hess et al., 2001;
RPP International, 2000). It was found that the overall populations served at a charter school are fairly representative of the population of the original school district (Cobb & Glass, 2003; Dee & Fu, 2003; Garcia, 2008; Gifford, Phillips, & Ogle, 2000; Hess et al., 2001; RPP International, 2000; Zimmer et al, 2009). For instance, charter schools are so plentiful in Arizona and, with the open enrollment policy, charter schools tend to be representative of the population in that school location (Hassel & Terrell, 2004). Yet Cobb and Glass (2003) found that there were a higher percentage of white and black students in Phoenix area charter schools than there were of Hispanic students as represented in the state (See Appendix C, D, and E). Solmon et al. (2001) found in their study, *Does Charter School Attendance Improve Test Scores?*, that when comparing Arizona charter school students to traditional public school students that the majority of the population for charter school students were white, English speaking, and special education students (less likely to be gifted students).

In some states, such as Michigan and Arizona, once they were given the “go-ahead” by state legislation, the charter schools took off in the terms of quantity and quality. Superintendents of the first charter schools were anxious and excited to implement long awaited changes that they believed needed to be made (Hoxby, 2003). Politicians claimed that the competition created by charter schools would be healthy for our education system. As it turned out, this did occur. Early on it was found that schools reacted quickly and positively to the threat of competition. In most states, the per pupil revenue follows the student, thereby removing the existing funds from school districts. Rather than depleting the districts of their funds, the traditional public schools were
forced to make some changes to their education programs in order to “fight” to keep the parents of their students happy with their schools. As the years progressed, the research showed mixed results regarding how prevalent the competition was and still is (other than bringing to the public awareness that there are options for parents as opposed to prior years) (Hess et al., 2001). Even at that, the charters seem to have spawned greater enrollment each year (Collins, 1999; Finn et al., 2001; Fiske & Ladd, 2000; Holmes, DeSimone, & Rupp, 2003; Hoxby, 2003; Teske, Schneider, Buckley, & Clark, 2001).

Other Funding Avenues

The Arizona Department of Education (2008c) also provides charter schools with transportation and technical assistance as they do for traditional schools. At the same time, it is mandated by the Arizona State Board of Education that all public school students have to teach the adopted content standards and participate in statewide assessments (Arizona Department of Education, 2008c). The Arizona Department of Education, Business and Finance division, also provides support to Arizona charter schools for analysis of average daily membership counts, anomalies, and/or significant variations in data (on a monthly basis); to consult on issues of budget versus cash flow needs; to provide supportive funding letters to their banks if an unexpected interruption to equalization payments occurs; to provide assistance in preparation for their annual budgets (yet charter schools do not have access to debt services) (Allen & Marcucio, 2005; Arizona Department of Education, 2008c).

Even with this legislation in place, Arizona charter schools still only receive 6% of the total revenue even though their student enrollment is 7.4% of the total enrollment
(Finn et al., 2005). The state tries to compensate for that loss but the final total still comes up short. Traditional schools in Arizona receive compensation for teacher salaries, capital overlay revenue, and “soft capital” revenue which widens the gap in finances between traditional public schools and charter schools (Finn et al., 2005). While charter schools are permitted to accept grants and gifts as a supplement to their state funding this still does not make up for the discrepancy in funds in Arizona between traditional public schools and charter schools (Finn et al., 2005). Arizona was marked by the Finn, Hassel, and Speakman in the Fordham Institute report (2005) as a state that reported a “large” (i.e. 15-24.9 variance) discrepancy between district and charter funding (these numbers are based on 2002-2003 records). Arizona was reported to have a 20.4% variance between district and charter funding. Even though a large percent of charter students are eligible for the free or reduced lunch program, a comparable amount are Title 1 schools, and charter schools serve nearly the same percentage of high schools students as traditional students, Arizona charter schools still receive approximately $1800 less per pupil revenue than traditional schools statewide (based on 2002-2003 school financial reports) (Allen & Marcucio, 2005; Arizona Education Laws & Regulations, 2007; Finn et al., 2005).

In November 2006, the Arizona Superintendent of Public Instruction, Tom Horne, lobbied for additional funding of 15% for Arizona charter schools which would equal the funding of traditional public schools but hit resistance by some legislators who argued that part of the incentive to pass the law for charter schools was that they were more
economically efficient than the traditional education system (Arizona Department of Education, personal communication, September 3, 2009).

Authorizers

Charter schools gained autonomy, but at what price? The price is to be held accountable to authorizers, state departments of education, educators, parents, students, and the media - far more than traditional public schools (Gill et al., 2001; Imberman, 2007). Accountability for charter schools is made up of fiscal successes and academic achievement. The fiscal success is looked at with more scrutiny. The accountability for these issues falls on the authorizers, governing boards, and ultimately, the charter school (Petrilli & Finn, Jr., 2006; Vergari, 2001).

Authorizers range from State Boards of Education to private organizations and universities ranging from 1 to 99 schools (Gau, 2006; Hassel & Herdman, 2000). It was found in the U.S. Department of Education (2004) study of public charter schools that there are significant differences between the type of authorizer and the reasons they sponsor start-up charter schools.

In more detail, different types of authorizers are a) school districts, b) state boards or departments of education, c) other existing public entities (cities, counties, and bureaus that serve multiple school districts, colleges and universities), and d) as in Arizona and Washington, D.C., new public boards were created for the purpose of authorizing charters (Hassel & Herdman, 2000). The researchers found in a U.S. Department of Education (2004) study that typically school districts are very involved in their traditional schools but not as involved in their charter schools, even when they are authorizers. They found
that charters are an extra burden on districts and place implicit or explicit conditions on charter schools, thus discouraging new charter schools to open. State Boards and Departments of Education across the nation are not completely sold on the idea of charters. Across the states, state authorizers were found to create new charters more often than LEAs and universities for the following reasons: improving public school systems, creating competition, creating alternatives for students and parents, and increasing program availability (U.S. Department of Education, 2004).

Sandra Vergari (2001) found in her research that authorizers play three key roles: 1) review charter school applications, 2) monitor for any violations to the laws and regulations under their contract, and 3) determine whether to renew contracts. She adds that authorizers have a complex task of determining the balance between accountability and autonomy within a political forum. Hill et al. (2001) found that authorizers fall into four categories: 1) *ambivalent* approvers, minimal overseers; 2) *reluctant* approvers, rigorous, compliance-oriented overseers; 3) *willing* approvers, overseers that balance performance and compliance; and 4) *eager* approvers, inattentive overseers.

In Johnson and Landman’s (2000) study titled, *Sometimes Bureaucracy has its Charms: The Working Condition of Teachers in Deregulated Schools*, they researched the difference between school-based management schools (SBM), in-district charter schools (sometimes known as pilot schools), and charter schools in Boston, Massachusetts in the late 1990’s. They stated the difference between the three distinctions is that SBM schools are empowered by the district and union to make certain decisions about their programs, budgets, and staffing, but continue to operate under the rules of both the district and
union. The in-district schools are still sponsored by the district but, freed from most bureaucratic and union constraints, can hire their own staff and establish their own working conditions. The teachers working in in-district schools continue to retain limited protections and rights guaranteed by the sponsoring district and union (e.g. their seniority stays on-track when moving to an in-district school). Whereas, charter schools are freed from oversight by local district officials and can hire their own staff, allocate their own budget, and adopt their own curricula. Their research results were that the SBM schools are better with policy (i.e. better work hours, avenues for grievances, and less pressure to perform for job security), while in-district charter and full-blown charter schools were better when it came to “best practices.” The number of work days varied from the standard 188 days in SBM schools to 187 days for in-district charter and 210 days for charter school teachers. Teachers of SBM schools expressed that it was nice to work with others that had the same goals and mission mind-set (Johnson, & Landman, 2000).

Authorizers vary on their policies for the accountability of their charter schools (Hassel & Herdman, 2000). It was reported in the 2000 The State of Charter Schools report, by RPP International, that 81% of all charter schools will turn in an annual report to their governing boards, authorizers, and parents of their students. Charters may have an advantage with flexibility in their instructional practices and management issues, but they have to account to various stakeholders for their financial responsibilities, student attendance, student achievement, and school outcomes (Collins, 1999; Gill et al., 2001; RPP International, 2000).
LEAs in many states are able to authorize charter schools. In some cases, this can create a conflict of interest financially with both entities, competing for the student clientele and the prestige of their traditional public schools. School districts don’t have the same control over a charter school within their district as they do with the traditional public school. So, in a sense, the charter schools may be seen as loose cannons. It is as if the LEAs are given this directive: “You’re responsible for the charter school but not able to have any say in decisions made or actions taken that can affect the school.” In some cases, the charters may have converted from a traditional public school within that school district. In those cases, LEAs are typically able to help with acquiring skilled personnel for staffing (Gau, 2006). State education agencies (SEAs) that are authorizers of charter schools are also known to be a strong support when trying to hire skilled personnel (Gau, 2006). On the other hand, the state holds the charter schools to a stricter guide for accountability with an emphasis on renewal (Gau, 2006). Whereas universities known to authorize charter school boards have fared moderately when it comes to data-driven decision-making, decisions about skilled personnel, providing adequate resources for the schools, and pursuing parental and community input (Gau, 2006; Mead & Rotherham, 2007).

For-profit educational management organizations (EMO) are sometimes questioned as to whether they focus more on the economies of scale (i.e., on the organization as a whole) as opposed to school-level decisions. The research shows that schools under the charge of an EMO tend to be larger than average charter schools and the EMO tends to take control of school-level decisions (Brown, Henig,
Lacireno-Paquet, & Holyoke, 2004). If the school staff has a strong sense of accountability and organizational skills along with a talented teaching staff, then perhaps they will fare well under that type of contract. There are mixed results from the current field as to whether students attending an EMO charter school versus a non-EMO school show higher achievement (Brown et al., 2004; Bulkley, 2005; U.S. Department of Education, 2004). The tendency in the Horn & Miron (2000) study was for students with a higher SES to score higher on achievement tests regardless of whether the authorizer was an EMO or a LEA. Typically in EMO contracts with charter schools, there is an “exit” clause which is a way for the school to leave the EMO-school relationship without penalty (Brown et al., 2004). What has been found is that it is important to look at all stakeholders involved in a charter school and the role that they play in school-level decision making (Brown et al., 2004; Bulkley, 2005; U.S. Department of Education, 2004).

Rebecca Gau wrote in *Trends in Charter School Authorizers* (2006) that she found nonprofit organizations and independent charter board organizations seem to be the most reliable and supportive for their charter schools in the following areas: using data driven decision-making, fostering productive working relationships, supporting the acquisition of skilled personnel, providing adequate resources and autonomy, and encouraging community and parental input. The research is showing, oddly enough, that authorizers with more schools tend to be more engaged in their schools than authorizers that only have a few schools. Mead and Rotherham (2007) found very similar attributes of quality charter school authorizers. In addition to these qualities, the most productive
authorizers are those that are proactive in providing technical assistance and charter advocacy (Palmer & Gau, 2003).

The National Association of Charter School Authorizers (NACSA) describes authorizers as the cornerstone of the infrastructure needed for quality charter schools and can be powerful catalysts for charter development. The NACSA provides resources and technical assistance to authorizers. Whether the charter school survives the growing pains of opening a new school or not could be dependent on the relationship between authorizer and school. Lisa Keegan, former Arizona State Superintendent of Public Instruction, said that the best monitoring program is “a strenuous application process.” Vergari (2001) states carefully examining the governance plans of a new charter before giving the “go ahead” is essential because of the responsibility they will have to the school for all of the operations, including outsourcing of needs. The author states that some authorizers literally pitch in and help their schools while others try to stay clear beyond overseeing activities. This is a political and moral choice of the authorizer – if they help and it fails they may look worse to the populace than if they say they instructed the school on how to attend to problems but the school failed to do so. The charter schools that are frequently monitored by governing boards and authorizers are apt to find problems early and implement interventions to fix the problems (Fiske & Ladd, 2000; Hill et al, 2001; Vergari, 2001).

Finding skilled personnel, acquiring adequate funding, and acquiring parental involvement have been found to be the three most challenging obstacles for schools (Gau, 2006; Loveless & Jasin, 1998). Palmer and Gau (2003) were two of the first researchers
to take a critical look at authorizers. Charter schools were, and still are, breaking new ground in public education by actually holding schools accountable for specific performance results even to the point of closing some schools. Authorizers play a crucial role in charter schools (especially at the start of the charter) in that deciding the fate of a charter schools falls largely on the authorizers at the onset and during review; yet, they had never been scrutinized or evaluated up until the early 2000’s.

Some states are better at reinforcing the accountability piece than others. Two states, for instance, have been publicly criticized. One state was criticized for the lack of “man-power” to possibly oversee the sheer number of charter schools that have been authorized. The other for having no clear authority to evaluate, intervene in, or sanction the state’s original 59 community (a.k.a. charter) school sponsors due to a loop hole in the current law (Hassel & Terrell, 2004; Mead & Rotherham, 2007; Ryan, 2006; Vergari, 2001).

Initially authorizers took a “hands-off” approach to becoming involved in school-level decisions. This way of conducting business to fortify the “autonomy” of the charters paired with the lack of manpower to monitor the charter schools led to problems. In 1994, Arizona had three authorizers for the state: the Arizona School Board of Education, the Arizona State Board for Charter Schools (ASBCS), and individual school districts. Arizona was the first to create a stand-alone entity (i.e., ASBCS) to head up charter schools. In 2003, the Arizona State Board of Education turned over their charters to the ASBCS, leaving the ASBCS and the LEAs as the only authorizers in the state of Arizona. As the forerunner, it seems the ASBCS went through its share of growing pains.
Early on in Arizona, for example, there were a number of charters that were corrupt and financially mismanaged by charter operators. As of July 1, 2000, the Arizona Department of Education prohibits local school districts to authorize charter schools outside of their school district. This may be, in part, because the incentive to oversee them is even lower if the charter school is located outside of the school district geographic boundaries (Arizona Department of Education, 2006; Hassel & Terrell, 2004; Hill et al, 2001).

After narrowing down the number of authorizers, the Arizona State Board for Charter Schools has strengthened its accountability system and created ways for schools to receive funding for transportation and facilities. They have improved in response to state audits and their commitment to authorizing; although they are operating with limited funding and staff. The ASBCS is “comprised of the Superintendent of Public Instruction or designee, six members of the general public (one of whom shall reside on an Indian reservation), two members of the business community, one charter school operator, one charter school teacher, and three non-voting advisory members of the legislature” (Arizona State board for Charter Schools, 2007). Arizona charter schools are expected to fulfill the accountability responsibilities in academics, finances, and general school responsibilities that all public schools follow (see Appendix A).

The research shows that independent charter school boards, entities set up with the sole purpose of authorizing charter schools, tend to have more control over budgetary decisions, issue more charters throughout the year than other authorizing bodies, and are more apt to penalize charters as a means to deal with problems that may arise. Independent charter boards rarely impose additional requirements on charter schools.
Colorado jumped on board in 2002 creating the Colorado Charter Schools Institute. Florida developed the Florida Commission on Schools of excellence as an alternative authorizer in 2006 (Hassel, Ziebarth, & Steiner, 2005).

The political barriers for funding charter schools that has been documented by various states could be detrimental to any school (Loveless & Jasin, 1998). This obstacle causes authorizers to search out funds, shifting their responsibilities from what should be spent on the academic achievement of the students. These barriers can vary from inequalities in funding to the refusal of city zoning commissions granting variances on property for charter schools. In addition, there have been an overwhelming amount of claims by charter schools that the lack of startup funds and/or inadequate operating funds has been the most difficult challenge of the political bureaucracy to overcome. Long standing charter schools have sifted through the tough terrain and barged through the barriers but still may not be considered successful if their authorizers are not following through with the responsibility of overseeing their charter school’s progress (RPP International, 2000; Ravitch, 2001; Smarick, 2008; Williams, 2007).

First Few Years

Charter schools that have survived their first few years of organization learned to deal with these barriers and develop relationships of trust with those that hold it accountable. It takes time to overcome the political barriers and develop relationships of trust between a charter school and parents, teachers, philanthropists, school districts, and, in some cases, authorizers (Gifford et al., 2000; Hill et al, 2001; Loveless & Jasin, 1998; Zimmer et al, 2009). A charter school is very much a community of educators/adults
working together with one mission in mind regarding the administration of the school, the roles each individual plays in the daily operations, and the outcomes they would like their students to achieve. This is not unlike what Coleman reported from his observations of Catholic schools in the 1980’s in terms of “social capital” (Kahlenberg, 2001). Research has shown that it takes schools 2 to 3 years to learn to develop relationships and develop a reliable internal accountability system (Booker, Gill, Zimmer, & Sass, 2009; Collins, 1999; Gifford et al., 2000; Gill et al., 2001; Hanushek et al., 2005; Hill et al, 2001; Zimmer et al, 2009).

In addition to developing relationships with stakeholders, a recently released study by Lavertu and Witte (2009) titled, *The Impact of Milwaukee Charter Schools on Student Achievement*, reported negative results of student achievement often reported for charter schools in their first few years of operation were reversed as the school matured. Gronberg and Jansen (2001) also found that as the Texas charter schools matured the students’ scores leveled off. Booker et al (2007) found the same results for charter schools in their initial phase. Similarly, Bifulco and Ladd (2006) found similar results in North Carolina in their study titled, *The Impacts of Charter Schools on Student Achievement: Evidence from North Carolina*.

Because of these discrepancies accounted for in the first few years of operation for a charter school only Arizona charter schools that have been in operation beyond their third year were included in this study.
Conversion versus Start-Up

As part of the accountability system from the No Child Left Behind Act (NCLB), 2003, President Bush gave school districts the option of turning their underperforming schools over to the state department or converting them to charter schools. Buddin and Zimmer (2005) reported that traditional public schools typically converted to charters for the autonomy of instructional practices, to reduce the bureaucracy from the LEAs and/or to free them from mandated curriculum requirements (Buddin & Zimmer, 2005). Private schools converted mainly for the purposes of attaining state funding (RPP International, 2000).

Advantages of conversion schools over start-up charter schools are that they usually can use the same facility and don’t have the worry about hiring a teaching staff from scratch (Buddin & Zimmer, 2005; Imberman, 2007). Lavertu and Witte (2009) found that the sheer numbers of the charter schools that have operated for a number of years and those that were converted from traditional public schools drive the positive charter school results. Some of the disadvantages for conversion schools were reported by Hill, Lake, Celio, et al. (2001) in their study titled, A Study of Charter School Accountability. The points they listed were that conversion schools tend to have a difficult time ensuring that they will be treated as a charter school as opposed to their traditional public school counterpart within the district (Hill et al, 2001).

Startup charter schools tend to have smaller numbers of students which make it easier to oversee during the earlier years; whereas the converted schools are more likely to have a larger student body to contend with while making the transition to charter
(Imberman, 2007). Imberman (2007) states that the autonomy of a start-up charter school may have other advantages that a “underperforming” traditional school may not have control over such as lengthening the school day or year to allow more instruction time for their students, controlling their budget, and allowing their staff to become creative with the curriculum. The latter is in the hope that it would engage those students that just weren’t adapting to the traditional methods of teaching (Buddin & Zimmer, 2005; Imberman, 2007; RPP International, 2000; Ziebarth & Wohlstetter, 2005).

Whether a charter school was a start-up school or conversion school was a factor in this study. Looking at the difference between conversion schools and start-up schools (after the first few initial years of operation) can give us insight on how managing a new school from the start-up affects student achievement as oppose to autonomy from school district curriculum in conversion schools. Conversion schools may only have autonomy when it comes to curriculum while abiding by minor regulations (i.e., keeping the same school hours of operation) (Imberman, 2007).

*Teachers*

Hiring quality personnel is a challenge for most charter schools. In fact it is listed as one of the top challenges that charter schools face (RPP International, 2000). Compensation, pension systems, and teacher unions often play a negative role in acquiring quality teachers for charter schools. For example, states that do not allow charter schools to participate in the pension programs hinder the hiring of experienced teachers that would be penalized for leaving the school districts for a charter school. On the other hand, states that are required (or eligible) to participate in pension programs
(e.g., Arizona) are tied to allotting a portion of their overall budget to the pension funds and, as a consequence, restricting compensation increases (Dawson, 1999; Gronberg, & Jansen, 2001; Hill et al., 2001; Mead & Rotherham, 2007).

In a study completed for the U.S. Department of Education (2004) titled, *Evaluation of the Public Charter Schools Program*, it was found that there was a significant difference in the number of fully certified teachers and those with an emergency certificate among charter schools versus traditional schools. It was also reported in the study that approximately 61% of the charter schools (representative of five states and 259 charter schools) are in states that have a waiver on teacher contracts and tenure requirements, 56% of the charter schools studied received state policy waivers for hiring/firing requirements, 56% for teacher salary/pay schedules, and 53% for teacher certification requirements (U.S. Department of Education, 2004). As a result charter schools, having more flexibility in hiring than traditional schools, are more apt to hire teachers that may not be state certified and may have less experience.

The No Child Left Behind (NCLB) Act of 2001 stipulates that there is a need for highly qualified teachers in Title I schools; therefore, Title I schools receive financial assistance from the federal government provided to LEAs and schools with high percentages of children from lower socio-economic status (SES) families to help ensure that all children meet challenging state academic standards. Some states required charter school teachers to be certified (e.g., California, Florida, Michigan).

In Arizona, only teachers in traditional public schools are required to be certified; charter school teachers are exempt from that ruling. It is written in the Arizona Education
Laws and Rules (2007-2008) that certified teachers that leave traditional public schools to teach at a charter school for a time will not lose any right of certification, retirement, salary status, or any other benefits stipulated by the governing board of the school district (or charter school) upon returning to the traditional schools. The Arizona Department of Education, defines “highly qualified teachers” as teachers who hold a bachelor’s degree, hold a valid Arizona state certificate (charter school teachers are exempt from this particular requirement), and has a current teaching assignment. In addition, teachers have to possess one of the following six options: 1) pass the AEPA Subject Knowledge Test; 2) hold an advanced degree in the core academic subject area; 3) hold National Board Certification in the core academic subject area; 4) have at least 24 credit hours in the core academic subject area; 5) have earned a minimum of 100 points on the AZ HOUSSE rubric for a core academic subject (e.g., all teaching, coursework, and professional development must be in the core academic subject area); or 6) have documentation that states highly qualified teacher reciprocity (Arizona Department of Education, 2008b). In order to supply schools with teachers and give teachers time to accomplish these tasks, the Arizona Department of Education is issuing emergency certificates to qualified applicants upon school districts’ requests (Arizona State Board for Charter Schools, 2007). Positive correlations between student achievement in mathematics or science and teachers certified in those specific subject areas are reported from longitudinal research studies that controlled for students’ socioeconomic status (Darling-Hammond, Berry, & Thoreson, 2001). Furthermore, the positive affect was found on student achievement regardless of the status of their certification as long as they were teaching in their specific
content area (Darling-Hammond et al., 2001). It was concluded that because of the similar qualifications accomplished by teachers possessing a standard certificate and those that had acquired an emergency certificate the students were showing a positive effect with both groups of teachers; whereas, teachers teaching out-of-field, regardless of certification, had a negative effect on student achievement (Darling-Hammond et al., 2001; Goldhaber & Brewer, 2000).

Seven charter schools were compared to surrounding traditional schools serving a very similar population, in a case study titled, *K-8 Charter Schools: Closing the Achievement Gap* to assess achievement scores of their students. It was found that the charter school students were more successful (in terms of their student achievement) because of the autonomy in the curriculum. They were able to incorporate creative modes of teaching which required highly qualified teachers to be able to keep up with the demands of the curriculum and be successful with it in the classroom. Hiring highly qualified teachers was one of the seven shared qualities of these schools and was felt to contribute to their success rate (U.S. Department of Education, 2007).

In addition to the literature addressing teachers teaching out-of-field, current research has found that the number of years of experience a teacher has will not necessarily make an impact on their students’ achievement if they are teaching out-of-field (Ferguson, & Ladd, 1996). In fact, inexperienced teachers often have fresh ideas for approaching teaching and an enthusiasm that may come across to the students in the classroom. On the other hand, experienced teachers are able to handle most classroom situations efficiently and are apt to be more effective with classroom management;
therefore, new teachers to the field may need a mentoring program and/or some additional training until they feel confident with their students. In addition, current research shows that teachers with advanced degrees (i.e., Master’s Degree in Education) are more affective on student achievement than those teachers who only hold bachelor’s degrees (Ferguson, & Ladd, 1996).

Class Size

Aside from teacher qualifications, class size is an important factor to take into consideration for the effects on student achievement; however, it is riddled with measurement error in terms of independence of variables because so many school level factors can affect the students (e.g., class size of prior years, teachers teaching strategies regardless of class size, whether the student is pulled out of their classroom for specialized classes) (Blatchford, 2003; Ehrenberg, Brewer, Gamoran, & Willms, 2001). As a result, the literature has been mixed in regards to class size reduction and its effects on student achievement (Hanushek, 2003; Krueger, 2003). The Institute of Education Class Size Study (2003) and the Tennessee Student Teacher Achievement Ratio (a.k.a. Project STAR) (1999) program showed a causal relationship between small classroom size (i.e., < 20) and student achievement (Boyd-Zaharias, 1999; Egelson, Harman, & Achilles, 1996; Hanushek, 2003). The Lasting Benefits Study was commissioned to further investigate the STAR results and to continue to follow the students’ progress from their primary school years through their secondary school years. Their results showed lasting effects through grade eight (Egelson et al., 1996). This finding was pertinent to this dissertation.
Not all of the research corresponds with the Project STAR and Lasting Benefit study results; for instance, the Indiana’s Prime Time study in 1984 resulted in positive differences from small classroom sizes in areas of classroom management, teacher instruction, and teacher satisfaction, but the results were mixed when it came to academic achievement (Finn, 1998). The Perry Preschool Project results, although the internal validity was questioned in certain research circles, were that after three years of leaving a small classroom environment there were no lasting effects found. Aside from the actual one-on-one time a teacher may be able to spend with his/her students, class size may not affect student achievement if the teacher does not use an effective or appropriate teaching strategy for the amount of students in the class (Blatchford, 2003; Blatchford, Bassett, Goldstein, & Martin, 2003; Boyd-Zaharis, 1999; Finn, 1998; Indiana Department of Education, 2008; McRobbie, Finn, & Harman, 1998)

Given the fact that class size data may be difficult to obtain and the common misconception that students per teacher ratio can be substituted for class size, many researchers opt for the latter of the two to use in their studies. The students per teacher ratio is typically smaller in charter schools than in public schools; however, the more established charter schools may have a ratio that is much higher than the 16:1 ratio, which was reported to result in positive outcomes in the RPP International (2000) study titled, The State of Charter Schools. If the ratio is higher the student/teacher relationship may show mixed results (Achilles, 1999; Ferguson & Ladd, 1996; Hanushek, 1999; Mosteller, 1999; RPP International, 2000).
The mixed outcomes of current research studies may be a result of underestimation of the actual class size which is misrepresented in the students per teacher ratio. When calculating the ratio of student/teacher, all teachers in the building are taken into consideration (Achilles, 2002; Ehrenberg et al., 2001). For example, reading specialists or school counselors who were former teachers but may not be assigned to a particular classroom are included in the formula thus overestimating the number of full time teachers actually assigned to a classroom within a school (Achilles, 2002; Gill et al., 2001). Therefore, the students to teacher ratio reported in research studies may not represent the actual count of full-time teachers assigned to a class (Achilles, 2002; Blatchford, 2003; Egelson, Harman & Achilles, 1996; Ehrenberg et al., 2001; Glass, Cahren, Smith, & Filby, 1982).

For the purposes of this dissertation class size was obtained from school administrator information on a survey in the form of “How many students in one classroom for grades 6, 7, and 8?” (See Appendix G).

There are very few researchers that investigate long-term effects of small classroom size aside from the Lasting Benefits Study (Finn, Gerber, & Boyd-Zaharias, 2005). Ehrenberg et al. (2001) argue in a report they wrote titled, *Class Size and Student Achievement*, that if the reduction in class room size would have had an effect on student achievement we would see evidence of that in the results in the Long Term Trend study by the National Center for Education Statistics using the NAEP to test nine- thirteen-, and seventeen-year olds. The Long Term Trend study (a.k.a. NAEP) has
been administered since 1969 and is the only nationally assessment administered in every state and U.S. territory (Ehrenberg et al., 2001).

Nonetheless, class size is an important factor to take into consideration and therefore needs to be addressed using a multilevel statistical analysis to properly assess this predictor at both the student level and school level (Ehrenberg et al., 2001). If the Project STAR and Lasting Benefit study results found that small class room sizes at kindergarten had carryover effects up until grade eight then there may be a difference in achievement scores between charter school students that attend smaller classroom sizes as part of their structure and those that attend larger classrooms.

Summary

Based on the research described in this chapter, the following school practices of Arizona charter middle schools were considered for this study: the number of students per classroom for each school, the average number of years of teacher experience per school, the type of charter (i.e., conversion from a traditional public school versus startup), the percent of certified teachers per school, percent of highly qualified teachers per school (criteria for this designation is defined in the Operational Definition section), average number of teachers teaching out-of-field per school, and percent of teachers with higher education degrees beyond Bachelor’s degree per school. The type of authorizer was not used as a factor in this study due to the fact that there are only two types of authorizers in Arizona: the Arizona State Board for Charter Schools and individual LEAs (only a few charter schools included in this study were authorized by LEAs).
These factors were used to investigate the school practices of Arizona charter schools and its effect on its students’ mathematics and reading achievement as described in the next chapter. This study was conducted in an effort to help fill a gap of data needed to set “best practices” as a guide for authorizers.
CHAPTER III
Methodology

Purpose

There are a number of charter schools in Arizona that are deemed “highly performing” as defined by Arizona’s adequate yearly progress (AYP). There are also many charter schools in Arizona that are tagged as “underperforming.” The purpose of this study was to assess how school practices of charter middle schools, controlling for their students’ characteristics, affects student mathematic and reading achievement. Grade 8 students’ achievement was assessed across students and across schools for 2009 as well as their growth from 2007 to 2009. During this time period the Arizona Standards for mathematics and reading along with AIMS remained stable (there was a change in 2005 and in 2010). This study was conducted to give researchers and authorizers insight as to which school practices had a positive effect on student achievement in order to gain the most from the autonomy in curriculum choices that charter schools are allotted.

For this study, “school practices” is used as a descriptor for areas that are treatments within a school (e.g., administrative leadership, utilization of resources, grade structure, and classroom size). This was defined by Raudenbush and Willms (1995) in their study, The Estimation of School Effects. Raudenbush and Willms defined the variation between two conceptually different types of school effects, one that defines the “difference between a child’s actual performance attending one school compared to the performance of that student attending another school” (p. 309), and the second type of school effect (those investigated in this study) is the compilation of school
practices (e.g., class size) and school context (i.e. “social and economic characteristics of the community” [p. 310]) effects. While school practices were the main focus of this study (e.g., class size, teacher experience, etc.), the demographic data for individual students (e.g., English language learners, students with disabilities, etc.) were taken into account for school context.

Student achievement is acknowledged to encompass more than test scores (e.g., student portfolios). Test scores, however, are commonly used as the best gauge to measure academic achievement by researchers and the public (Buddin & Zimmer, 2005; Collins, 1999; Imberman, 2007; Zimmer et al., 2009). The overall achievement of charter school students was not feasible to investigate in this study so mathematics and reading scores of middle school students were used as the measurement outcome. From this point on, the word “achievement” will refer to test scores (either mathematics or reading unless otherwise specified).

**Research Questions**

The following research questions guided the study:

1) How do school practices, while controlling for student characteristics, affect average mathematics and reading achievement for Grade 8 students at the exit year (i.e., 2009)?

2) What is the average growth rate in mathematics and reading achievement of students at Arizona charter middle schools?
Student characteristics helped to explain variability in the growth rate across students and across schools.

*Rationale*

All Arizona charter schools are mandated by Arizona State Board of Education to align their curriculum with the state standards and to administer the state assessment (i.e., AIMS). Some charter schools are labeled “highly performing” while others are labeled “underperforming” on the state’s AYP scale, yet there is no evidence as to which effects from school practices played a role in the differences between charter schools. There is an incredible amount of variation among charter schools and until we assess the structure across theses schools we will continue to wonder what causes one school to succeed and the next to fail. Furthermore, before researchers are able to report whether Arizona charter schools are making a difference in student achievement as opposed to traditional public schools, a look at the variability within the charter system and the factors that may affect students’ achievement at one charter school compared to the next should occur (Buddin & Zimmer, 2005; Charter School Achievement Consensus Panel, 2006; Hassel & Terrell, 2004).

There are no longitudinal studies currently on record that have investigated these aspects of charter schools using the state assessment in Arizona. Results from this longitudinal study show how school practices and student characteristics affect charter school students over a period of time. This dissertation was a necessary component in investigating Arizona charter schools and taking researchers one step further in education research. Findings from this study can help guide charter school authorizers to the school
practices that have a positive effect on student achievement. Also, based on the results from this study researchers will be able to measure comparable differences between charter schools and traditional public schools. Authorizers will be able to use this study to aide in their charter schools and parents will be able to make more informed decisions about which school to choose. In addition, the design and analysis used in this study can be used as a template for other researchers to use.

Sample

All Arizona schools (including charter schools) are required to sign a Declaration of Curricular and Instructional Alignment to the Arizona Academic Standards annually assuring that their curriculum aligns with the state standards in every content area. In addition, every Arizona public school (including charter schools) is required by state law to use AIMS assessment for every content area the State Board of Education requires (Arizona Department of Education, 2006). Although some Arizona charter schools are explicitly for students with learning disabilities, a large number of charter schools in operation across the state are available to the general student population and thus sets the stage for good sample sizes (Hassel & Terrell, 2004).

During the period of 2005-2009 AIMS was not altered; thereby creating a trend-line that can permit a longitudinal study. In addition, during the time period 2007-2009 teacher data (apropos to this study) was collected from schools in the same manner. Therefore, the reading and mathematics achievement scores from Arizona elementary and junior high school students (i.e., grades 6 – 8) in the charter school system from 2007-2009 were used for this study. The focus of this analysis was on
students’ mathematics and reading growth during the years 2007-2009 and at the last year achievement assessed (i.e. 2009) in which the students were in grade eight.

The Arizona Department of Education extracted data for students attending charter schools in Grades 6-8 for the years 2007-2009 recorded by a unique identifier for each student in Arizona Student Accountability Information System (SAIS). There were approximately 4825 Grade 8 students in charter schools in 2009 that have achievement scores in both subject areas. In 2007, there were 101 schools that had greater than 20 students in their grade 6 classes; in 2008, there were 95 schools that had greater than 20 students in their grade 7 classes; and in 2009, there were 101 schools that had greater than 20 students in their Grade 8 classes.

A sufficient sample size is required to ensure unbiased estimates of the effects. In addition, for hierarchical linear models (the method used in this study and described in detail under research design) it is very important to have a large amount of data at the higher levels for the greatest impact (O’Connell & McCoach, 2008; Raudenbush & Bryk, 2002; Stapleton & Thomas, 2008). The sample size reported in this study was sufficient to determine a hypothesized effect with unbiased estimates of the effects based on a study reported by Stapleton and Thomas (2008). This study was to measure student growth (i.e., a student who is proficient in English and is without any known learning disability) in mathematics and reading achievement in a three year period; therefore, English language learner and students with learning disability indicators were added as students’ covariates.
Instrument

The Arizona Instrument to Measure Standards (AIMS) was used to measure students’ achievement. AIMS data and school/teacher data is housed in a data warehouse (i.e., SAIS). In 2005, the cut scores to determine whether a student was meeting the state mathematics standard (i.e., falls far below, approaching, meets, or exceeds the standards, see Appendix F for a detailed description of the performance levels) were established and did not changed during the years 2007-2009. AIMS is a dual purpose assessment made up of items that are criterion referenced and those that are norm referenced; as well as items that are a combination of criterion and norm referenced. Table 1 and Table 2 show the total number of items and Cronbach’s $r$ (a measure of internal consistency that items on the assessment are measuring the construct or content area) for AIMS Reading and Mathematics assessments for years 2007, 2008, and 2009 (CTB/McGraw-Hill, 2007; CTB/McGraw-Hill, 2008; CTB/McGraw-Hill, 2009).
Table 1

*Reading AIMS: Number of Items and Cronbach’s r*

<table>
<thead>
<tr>
<th>Year</th>
<th>Grade</th>
<th>Items</th>
<th>Cronbach’s r</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>CRT</td>
<td>NRT</td>
</tr>
<tr>
<td>2007</td>
<td>6</td>
<td>54</td>
<td>25</td>
</tr>
<tr>
<td>2008</td>
<td>7</td>
<td>54</td>
<td>25</td>
</tr>
<tr>
<td>2009</td>
<td>8</td>
<td>39</td>
<td>15</td>
</tr>
</tbody>
</table>

*Note.* Total includes < 10 field test items. Criterion-referenced test (CRT) and norm-referenced test (NRT) are reported separately.

Table 2

*Mathematics AIMS: Number of Items and Cronbach’s r*

<table>
<thead>
<tr>
<th>Year</th>
<th>Grade</th>
<th>Items</th>
<th>Cronbach’s r</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>CRT</td>
<td>NRT</td>
</tr>
<tr>
<td>2007</td>
<td>6</td>
<td>68</td>
<td>25</td>
</tr>
<tr>
<td>2008</td>
<td>7</td>
<td>68</td>
<td>25</td>
</tr>
<tr>
<td>2009</td>
<td>8</td>
<td>53</td>
<td>13</td>
</tr>
</tbody>
</table>

*Note.* Total includes < 10 field test items. Criterion-referenced test (CRT) and norm-referenced test (NRT) are reported separately.

The majority of the data for this study was obtained from Arizona Department of Education SAIS. A telephone/email survey was sent to 266 charter middle schools (i.e., the schools that housed Grades 6 - 8 during the 2007-2009 school years) to collect the remainder of the data that was not available from the state department (See Appendix G).
Test Administration Procedures

AIMS is administered every spring (within a two week test window) to Arizona students in grades 3 through grade 8 plus grade 10. The assessment is administered in a controlled environment by the classroom teachers during the same month, April, each year.

Factors of Study

As reviewed in Chapter II, authorizers can play a role in school practices (as defined by this study); however, currently in Arizona there are only two allowable authorizers for charter schools, the Arizona State Charter School Board and local school districts. Out of approximately 266 grade 8 schools, only one school district authorized one charter school (Arizona Department of Education website, 2008); therefore the level of authorizer was not assessed because little to no variability among authorizers exists in Arizona charter school system.

Current research has shown that if the school is fairly new it may take a few years to establish the curriculum and make an impact on student achievement. Therefore, only Arizona charter schools that have been in operation since 2003 were used in this study (Collins, 1999; Gifford et al., 2000; Hanushek et al., 2005; Hill et al, 2001; Miron, 2005).

The following school practices (based on the research described in Chapter II) of Arizona charter middle schools were considered for this study: class size, teacher experience (measured by years of services), type of charter (i.e., conversion from a traditional public school versus startup), percent of certified teachers per school, percent of highly qualified teachers per school (criteria for this designation is defined in the
Operational Definition section), average number of teachers teaching out-of-field per school, and percent of teachers with higher education degrees beyond Bachelor’s degree per school.

In addition, characteristics of students who attended Arizona charter schools in 2007-2009 that were taken into consideration are as follows: English Language Learner (ELL) determination, eligibility for the free or reduced lunch program, 2006 charter school enrollment, race, gender, and special education status. These factors were added to the study to clearly define the student and how the school practices affect certain students; for example, how were English language learners’ reading performance influenced by new teachers rather than experienced teachers.

The current research also shows that student achievement is negatively affected (initially) by switching schools or entering/leaving current school systems (e.g., switching from charter school to traditional public school). After 2-3 years, their achievement scores seem to come back up (Booker, Gilpatric, Gronberg, & Jansen, 2007; Solmon et al., 2001; Lavertu & Witte, 2009). Booker et al. (2007) found this to be the case when they conducted research on the impact of charter school attendance on student performance as they move in or out of a charter school. They found that it takes a student that moves into the charter school system two - three years to recover his/her prior student performance levels. Solmon et al. (2001) found that the first year of charter school had an adverse effect and then went up from there. Lavertu & Witte (2009) found that switching schools, regardless of whether they were leaving a charter school, entering the charter school system for the first time, or switching between traditional public
schools, had a strong, negative effect on student performance. Therefore, 2006 data for each student was included to establish whether they attended a charter school in Grade 5 and thus had time to adjust to the new school system. The data for this longitudinal analysis is for the academic years 2007-2009 which encompasses students’ achievement growth in Grade 6 through Grade 8 (Booker et al., 2007).

Research Design

Student achievement at 2009 (Grade 8) was assessed while controlling for student demographic variables that were available from the state. In addition to looking at the grade 8 achievement, growth was examined over time for each student. This longitudinal study (or value-added procedure) was used to measure year-to-year growth over a three academic year period (i.e., 2007, 2008, and 2009). The 2007 (Grade 6) test scores served as a baseline achievement measure.

Hanushek, Kain, and Rivkin (2004) wrote in their research report that value-added measures of school achievement and other student outcomes is the preferred measure for school quality. Many researchers report that year-to-year scores are more directly influenced by school quality rather than influenced by student and family background (Bifulco & Ladd, 2006; Booker et al., 2007; Charter School Achievement Consensus Panel, 2006; Greene et al., 2003; Miron, 2005; Rothstein, 2004; Solmon et al., 2001; Zimmer & Buddin, 2007). Therefore, value-added measures (i.e., reading and mathematics assessment scores for three consecutive years) were used to determine student growth as a reflection the effects of school practices’ while controlling for unobserved background characteristics of students that were available to the researcher.
This procedure adjusted for the unmeasured background effects that may affect students’ achievement on an ongoing basis (Buddin & Zimmer, 2005; Greene et al., 2003; Zimmer & Buddin, 2007).

**Analysis Procedure**

Hierarchical linear cross-classified random effects modeling (HLM/CCREM) was the analysis used for this study. Hierarchical linear modeling (HLM) was referred to as the analysis used and cross-classified random effects model (CCREM) was the type of HLM procedure used to sufficiently assess these data. In the following paragraphs HLM is described fully in terms of how it differs from regression and the advantages of using this analysis. CCREM is then introduced and explained as a special type of HLM procedure necessary to analyze these data.

HLM is similar to regression, in that researchers add factors to the model to try to explain as much of the variability in the outcome as possible. The unexplained variability remains in the error term. However, one regression model can only explain a certain amount of variability before you reach the point of spurious results. Often research questions, such as the research question for this study, are more intricate requiring a closer look at the student, classroom, and school at the same time (i.e., a nested design); thus, a more complex model is required. In this case, each student is nested in their school which allowed the examination of how the school factors may have influenced student achievement. (Buddin & Zimmer, 2005; Dedrick, et al., 2009; Gray, Goldstein, & Thomas, 2001; Holt, 2008; Ma, Ma, & Bradley, 2008; Meyers, 2004; O’Connell & McCoach, 2008; Raudenbush & Bryk, 2002; Wesolowsky, 1976).
HLM is an analysis that runs multiple regression models at different levels of hierarchy simultaneously. Sometimes referred to as multilevel modeling, HLM captures and explains as much variability as possible at all levels. This enables a researcher to see a “snapshot in time” of many different levels to answer one research question as opposed to only getting a look at the classroom level or just a look at the aggregated school level.

Aggregating data to a higher level is a common solution to satisfy the independence assumption of regression models; as a consequence, a significant amount of data and valuable student information is lost (Bifulco, 2002; Raudenbush & Bryk, 2002). HLM naturally accommodates the independence assumption because the error term (which will entail excluded variables) from each level is independent from every variable and independent of error terms from all other levels (Bifulco, 2002; Charter School Achievement Consensus Panel, 2006; Ma et al., 2008; Meyers, 2004; O’Connell & McCoach, 2008; Raudenbush & Bryk, 2002).

HLM allows more specific questions about the topic to be investigated because of the flexibility of the covariance structure and the additional error terms at each level. Additionally, HLM’s efficiency allows a researcher to simultaneously test the effects of variables within a level (e.g., within a classroom comparing one student to the next) and test the effects of variables across multiple levels (e.g., how a student performs who has a teacher teaching out-of-field compared to those that have teachers teaching in their specialty content area). HLM also offers the flexibility of investigating cross-level interaction effects, such as the interaction of teachers teaching out-of-field and a student entering the charter school system in Grade 6 on mathematics achievement.
This allows researchers to ask more specific research questions (Hox, 2002; Raudenbush & Bryk, 2002). Another example is assessing achievement scores across time of students with disabilities attending charter schools that were started from scratch compared to those attending converted charter schools.

In addition, unlike traditional repeated measures designs, hierarchical longitudinal models do not require balanced designs (i.e., equal number of units per individual) as long as the missing data points are random (Buddin & Zimmer, 2005; Dedrick, et al., 2009; Gray et al., 2001; Holt, 2008; Ma et al., 2008; Meyers, 2004; O’Connell & McCoach, 2008; Raudenbush & Bryk, 2002). Further, they do not require time-structured data points (i.e., equal increments between units); even though the time points in this study were approximately one year apart (Holt, 2008).

HLM measures the homogeneity of a cluster utilizing a procedure called intraclass correlation (ICC). If the ICC is 0, then there is no dependency occurring within a cluster or unit. If the ICC is greater than approximately .2, then the cluster is sharing information and factors may have to be added at that level to account for the dependency (Spybrook, 2008; Stapleton & Thomas, 2008). When the ICC is overlooked, the possible homogeneity may cause smaller variance estimates erroneously thereby increasing the chances of a Type I error (reporting statistical significance in error) (O’Connell & McCoach, 2008; Raudenbush & Bryk, 2002). Intra-unit class correlation (IUCC) is a version of ICC that is used for HLM/CCREM. (CCREM is explained in detail later in this chapter.)
Therefore, HLM is the appropriate statistical procedure for nested data in order to account for the variance within any particular level (e.g., within students) and between levels (e.g., between students and schools) (Bifulco, 2002; Buddin & Zimmer, 2005; Dedrick, et al., 2009; Gray et al., 2001; Holt, 2008; Ma et al., 2008; Meyers, 2004; O’Connell & McCoach, 2008; Raudenbush & Bryk, 2002).

This study used test scores describing reading and mathematics achievement as outcomes, students’ data describing students’ characteristics, and schools’ data describing schools’ practices. Ideally this would mean a level one measure each year for each student attending the same school all three years, students’ characteristics would be level two data, and schools’ practices would be level three data. This would have been true if students attended only one school during grades 6 through 8; however this was not the case. Many students attended two different schools and sometimes three schools during the three year period. It is very likely that all of the schools students attend affect their achievement differently, in addition to the impact on the student from the transition. These effects should be taken into account. Thus a cross-classified structure existed between students and schools in this study (i.e., student data are nested within the cross-classification of the schools they attended for Grade 6, Grade 7, and Grade 8) (Beretvas, 2088; Goldstein, 1995; Hox, 2002; Rasbash & Browne, 2008; Raudenbush, 1993; Raudenbush & Bryk, 2000). For example, see data represented schematically in Table 3. Figure 1 is another representation of data that is not purely hierarchical.
Table 3

Measurement Occasions of Students within the Cross-Classification of the Schools

Attended for Grade 6, Grade 7, and Grade 8

<table>
<thead>
<tr>
<th>Participants</th>
<th>School1</th>
<th>School2</th>
<th>School3</th>
<th>…</th>
<th>Schoolk</th>
</tr>
</thead>
<tbody>
<tr>
<td>Student1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Student2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Student3</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
<td>…</td>
</tr>
<tr>
<td>Studentj</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Note. $i_1$ represents time point 2007; $i_2$ represents time point 2008; $i_3$ represents time point 2009.

Figure 1. Schematic diagram for nested structure displayed in Table 3. $i =$ time units, $J =$ students, $k =$ schools.

HLM cross-classified random effects models (CCREM) are not very common in educational research and can quickly become very complex (Meyers & Beretvas, 2006).
Raudenbush completed a CCREM study in 1993 when revisiting a study he and Garner ran in 1991 regarding the effects of neighborhood students feeding into area schools. When it became apparent that this study was not purely hierarchical in that more than one neighborhood fed any one school, they used a cross-classification model for the neighborhoods to school factor in order to be able to generalize from the sample to the population of neighborhoods and schools (Raudenbush & Bryk, 2002). Goldstein used CCREM on studies in 1995 and 1997 (the latter with Sammons) to study the achievement effects of a middle school on student achievement in a secondary school in order to generalize to a population of middle schools and high schools (Meyers, 2004; Raudenbush & Bryk, 2002).

A simple HLM design is not sufficient when a “unit may be classified in more than one dimension” (Goldstein, 1995, p. 113; May & Supovitz, 2006; Rasbash & Browne, 2001; Rasbash & Browne, 2008; Snijders & Bosker, 1999). A number of research possibilities are available when CCREM is appropriately designated. For example, one could estimate the variance in outcomes that lie across schools, across students, and between time periods (that are within school by student cells). A second possibility is to look at which random school factors affected student achievement over time if a student changed schools within the time period of the study (Meyers & Beretvas, 2006; Raudenbush & Bryk, 2002).

If cross classification is ignored there is a possibility of obtaining bias estimates of standard errors, and overestimation/underestimation of second and third level variances can also occur as shown by Meyers (2004). Meyers ran simultaneous studies
regarding student achievement during the transition from elementary school to secondary school and found that many students came from different middle schools (i.e., junior high schools) but attended the same high school. He set up two studies comparing the results of a Monte Carlo simulation applying CCREM to one analysis, the next analysis ignoring CCREM by excluding cases, and the third analysis by aggregating the middle school predictor.

Meyers found that, although HLM effect estimates were similar to CCREM on the student level, the standard errors at the school level were underestimated and created a bias result for the level two predictor. In addition, HLM underestimated the level one variance and overestimated the variance on level two (Meyers, 2004; Meyers & Beretvas, 2006).

Excluding cases that do not fit the purely hierarchical model can create loss of information and lack of generalizability. Such a procedure can lead to spurious results (Beretvas, 2008; Meyers, 2004; Meyers & Beretvas, 2006). In a repeated-measures HLM study (such as this dissertation) if a student is crossing contextual boundaries fundamental to the study then the data is no longer truly nested; therefore, the model will only apply to the students that remain in the purely hierarchical setting (i.e. attend the same school for the period 2007 – 2009) (Raudenbush & Bryk, 2002). For example, students changing charter schools when a researcher is trying to conduct a longitudinal study of school practices that affect student achievement.

Mobility is an issue in Arizona public schools. Many students changed schools within the duration of data collection. In Lavertu and Witte’s (2009) research titled The
Impact of Milwaukee Charter Schools on Student Achievement, they found that switching schools had a statistically significant negative impact on student achievement in reading. Garcia, McIlroy, & Barber (2008) found the same findings in their study titled Starting Behind: A Comparative Analysis of the Academic Standing of Students Entering Charter Schools. They found that test scores in both reading and mathematics went down for the students that changed schools. Booker et al. (2007) found similar results in Texas charter schools. Solmon et al. (2001) found the same results in Arizona.

Hanushek et al. (2004) reported that not only does student mobility (especially during the school year) reduce achievement gains in some cases, but the effects of new students added to a class are felt by everyone in the classroom - especially if that student is at a different level than the other students. They also reported that if the school quality is the same in the new school, then students tend to recover to pre-move achievement growth rates. In addition, Hanushek et al. reported that “extraneous disruptions that directly affect achievement and that accompany a move do not have effects that persist past the academic year of a move” (p. 1729). Bifulco and Ladd (2006) found similar results in North Carolina charter schools. Solmon et al., (2001) found Arizona students recover the second year as well.

The limitations from excluding cases or ignoring the cross-classification are too great. Thus cross-classification of persons by social settings was essential for this study because of the mobility issue.

Raudenbush & Bryk (2002) found that part of the variation in growth curves of students who have different teachers every year is associated with differences in teacher
effectiveness rather than attributed to individual student differences; thus taking the issue of different teachers every year into account helps reduce the instability in student outcomes (Raudenbush & Bryk, 2002). The ideal option would be to account for this factor with appropriate predictors. To account for the student by teacher (i.e., school/teacher) variance, a random interaction effect was initially added to cover the deflection in the growth curve. This random interaction effect captures the residual effects that lie beyond the predicted effects (i.e., predicted effects from the grand mean and the two random main effects). The interaction was later dropped from the model with the supposition that the within cell variance and the interaction variance are confounded. Quite often in studies such as this one the observations per cell size for the interaction effects are too small to capture this residual effect (Beretvas, 2008; Raudenbush & Bryk, 2002).

Prior to building the model that defined the research question and tested the hypothesis, descriptive statistics (e.g., mean, kurtosis, and skewness) and univariate frequency distributions were run on each variable to identify any outlying observations which would have warranted transformations (Goldstein, 1995; Raudenbush & Bryk, 2002). Next, bivariate relationships were examined for any nonlinear relationships and to identify any discrepant cases (Raudenbush & Bryk, 2002). In addition, the Mahalanobis distance test was used to display non-normal behavior and outliers (O’Donnell & McCoach, 2008; Raudenbush & Bryk, 2002). The HLM/CCREM model used to analyze the research question is as follows:
**HLM/CCREM Model**

Level 1 (TIME).

\[ y_{ijk} = \pi_{0jk} + \pi_{1jk}(time - time_{2009})_{ijk} + (\pi_{2jk})W_{1ijk} + (\pi_{3jk})W_{2ijk} + \ldots \]

\[ \quad + (\pi_{pjk})W_{pijk} + e_{ijk} \]

\[ = \pi_{0jk} + \pi_{1jk}(time - time_{2009})_{ijk} + \sum_{p=2}^{P} (\pi_{pjk})W_{pijk} + e_{ijk} \]

\[ e_{ijk} \sim N(0, \sigma^2) \]

\[ i = \text{years 2007, 2008, 2009} \]

\[ j = 1, 2, \ldots, J \] an index for students

\[ k = 1, 2, \ldots, K \] an index for schools

\[ p = 0, \ldots, P \] an index for level one coefficients

*Where:*

\( y_{ijk} \) is the achievement at time \( i \) for student \( j \) in school \( k \) given the time-varying school practices.

\((time_{2009} - time)_{ijk}\) is time change for student \( j \) centered at the end time 2009 (i.e., \( time_{2009} \)).

\( \pi_{0jk} \) is the mean achievement at exit time (i.e., 2009) for student \( j \) in school \( k \) adjusting for the time-varying school practices.

\( \pi_{1jk} \) is the annual achievement growth rate for student \( j \) from the specific combination of schools \( k_{2007}, k_{2008}, \text{and} k_{2009} \).
\( \pi_{pjk} \) \((p = 0, \ldots, P)\) are the effects of time-varying predictors \( W_{pjk} \) for student \( j \) from the specific combination of schools \( k_{2007}, k_{2008}, \text{and} \ k_{2009} \).

\( W_{pjk} \) are the level one time varying school practices for student \( j \) from the specific combination of schools \( k_{2007}, k_{2008}, \text{and} \ k_{2009} \).

\( e_{ijk} \) is the random within-subject residual assumed normally distributed with a mean of 0 and a variance of \( \sigma^2 \).

The focus of this study was to investigate the degree to which school practices of charter schools affect student achievement, \( \pi_{0jk} \), at the end of the three years (i.e., 2009) as well as the growth rate, \( \pi_{1jk} \), over the years 2007 – 2009. Some of the school level predictors vary over time and therefore, were included in level one of the model (e.g., average years of teacher experience, percent of highly qualified teachers in a school, percent of certified teachers in a school). In hierarchical linear modeling the level one intercept (i.e., \( \pi_{0jk} \), the predicted student achievement in 2009), the level one slope (i.e., \( \pi_{1jk} \), the annual student achievement growth rate), and any covariates (\( \pi_{pjk} \)) become outcomes for level two. In order to facilitate ease of interpretation of the level two outcomes, the level one model was centered on the time period of interest for this study (i.e., a Grade 8 student in 2009) (Dedrick et al., 2009; Enders & Tofighi, 2007; Holt, 2008). This allowed for a logical interpretation of the intercept (\( \pi_{0jk} \)) after the effects of charter schools have taken place (time – time\(_{2009}\)). Centering on the end period (i.e., 2009) did not influence the estimation of the growth rate because each data point was taken one year apart; nor did it affect the estimation of the within person variance or the residual variance in the rate of change (Holt, 2008). Focusing on the final time point did
increase the estimation of the variance of the level two intercept and growth rate across students because the variance between a student’s test score at the first year to the last year is different from the variance of the student’s test scores the second year to the last year (Holt, 2008). This choice in centering was to aid in lucid interpretations of the intercept and level two coefficients relevant to the study (Dedrick et al., 2009; Enders & Tofighi, 2007; Holt, 2008; Raudenbush & Bryk, 2002).

One of the findings that Lavertu and Witte (2009) reported in *The Impact of Milwaukee Charter Schools on Student Achievement* was a positive relationship between attending a charter school (i.e., a charter school that has been in operation for greater than three years) and performance on mathematics achievement tests in the initial years of attendance, but this relationship was not statistically significant after the initial years of attendance. (This was not the case with reading achievement scores.) Solmon et al. (2001) found the opposite results when studying Arizona charter school students. They found that achievement scores dropped for the first year students entering the charter school system but increased with noticeable growth rate in the consecutive years, even for those students that returned to the traditional school system. This may have some bearing on the level of growth shown from 2007 to 2009 for students that started to attend a charter school in 2007. So a dichotomous variable was added to the student level to address whether the student attended a charter school in 2006 (i.e., 1 = attended a charter school in 2006; 0 = attended a traditional public school in 2006). The level two model is as follows:
Level 2 Model (STUDENT and SCHOOL).

\[ \pi_{pjk} = \theta_{p00} + (\gamma_{p1} + b_{p1k})X_{1j} + (\gamma_{p2} + b_{p2k})X_{2j} + \ldots + (\gamma_{pQ} + b_{pQk})X_{Qj} + (\delta_{p1} + c_{p1j})Y_{1k} + (\delta_{p2} + c_{p2j})Y_{2k} + \ldots + (\delta_{pR} + c_{pRj})Y_{Rk} + \lambda_{p1jk}Z_{1jk} + b_{p0k} + c_{pj0} + d_{p0jk} \]

\[ = \theta_{p00} + \sum_{q=1}^{Q} (\gamma_{pq} + b_{pqk})X_{qj} + \sum_{r=1}^{R} (\delta_{pr} + c_{prj})Y_{rk} + \sum_{s=1}^{S} \lambda_{psjk}Z_{sk} + b_{p0k} + c_{pj0} + d_{p0jk} \]

\[ b_{p0k} \sim N(0, \tau_{p00k}) \]
\[ c_{pj0} \sim N(0, \tau_{pcj0}) \]

\[ j = 1, 2, \ldots, J \text{ an index for students.} \]
\[ k = 1, 2, \ldots, K \text{ an index for schools} \]
\[ q = 1, 2, \ldots, Q_p \text{ an index for student’s characteristics} \]
\[ r = 1, 2, 3, \ldots, R_p \text{ an index for school practices} \]
\[ s = 1, 2, 3, \ldots, S_p \text{ an index for the student characteristics and school practices’ interactions. } S_p \leq R_p \times Q_p \]

*Where:*

\[ \theta_{p00} \text{ is the predicted average students’ achievement at year 2009, } \pi_{pjk}, \text{ across all students and across all schools;} \]
\[ \gamma_{pq} \text{ is the } q \text{ fixed effect of student characteristics’ predictor, } X_{qj}; \]
\[ b_{pqk} \text{ is the } q \text{ random effect associated with the student characteristics’ predictor, } X_{qj}. \text{ It varies randomly across schools } k = 1, 2, \ldots, K; \]
\( \delta_{pr} \) is the \( r \) fixed effect of school practices’ predictor, \( Y_{rk} \);

\( c_{pjpr} \) is the \( r \) random effect associated with the school practices’ predictor, \( Y_{rk} \); It varies randomly across students \( j = 1, 2, \ldots, J \);

\( \lambda_{psjk} \) is the \( s \) fixed effects of the cell-specific predictor, \( Z_{sjk} \), which is the interaction term created as the products of student characteristics’ predictor, \( X_{qj} \) and school practices’ predictor, \( Y_{rk} \); and

\( b_{p0k}, c_{pj0}, \) and \( d_{p0jk} \) are residual student, school/teacher, and their interaction random effects, respectively, on \( \pi_{pjk} \), after taking into account \( X_{qj}, Y_{rk}, \) and \( Z_{sjk} \). We assume that \( b_{p0k} \sim N(0, \tau_{pb00k}), c_{pj0} \sim N(0, \tau_{pc0j0}), d_{pjk} \sim N(0, \tau_{pd0jk}) \) and the effects are independent of each other;

The vector containing elements, \( b_{pqk} \), is assumed multivariate normal with a mean of zero and a full covariance matrix \( \tau \), and the vector containing elements, \( c_{pjrs} \), is assumed multivariate normal with a mean of zero and a full covariance matrix \( \Delta \).

Teacher and/or school residual effects on student growth are perceived as deflections (i.e., teaching strategies, learning styles, etc.). These deflections may not be captured in the model and can be either positive or negative for each student’s specific growth curve (Raudenbush & Bryk, 2002). These error terms represent deflection associated with the students, school/teacher effect, and their interaction.

Since level one is established as time, model building began at level two (cross-classified of students by schools/teachers). The potential predictors of level two have been established by the literature; however, saturating the model from the start (i.e.,
inserting all predictors of interest at once instead of adding one at a time) would confound the variance component estimates (McCoach & Black, 2008). Over-fitting a model will cause confusion when trying to interpret results. The advantage to building a model one predictor at a time is that it gives the researcher a chance to examine the relationship between the first level (i.e. time) and each predictor at the student and school/teacher level (i.e., level two). The model should be parsimonious yet complex enough to explain the research questions (Ma et al., 2008; McCoach & Black, 2008; Raudenbush & Bryk, 2002, Stockburger, 1998).

Once the baseline model was established with level one time-varying predictors and prior to model building, each predictor was tested for its significance. This test was to determine, with 95% confidence (alpha level of .05), that the differences seen in the variable were significantly different from zero and not to measurement error. Once a statistical difference was established for each predictor then they were treated as random effects in the model across students and across schools. If, however, the variance of the random effects was not found to be significantly different from zero, then the predictors were treated as a fixed effect as the model was built.

In addition, hypothesis testing (H₀: δ_{pjk} = 0) took place to see if interactions among level two predictors affect the outcome (e.g., Does the interaction between the type of charter [i.e., conversion versus startup] with average years of teacher experience affect student achievement?). The random interaction effect associated with cells, d_{0jk}, was removed when the combination of level two predictors were not significant. It is quite possible with the complexity of the study that there were too few observations in
each cell (i.e., each student was observed once a year) making disentangling the
student-by-school variance from the within-cell variance impractical (Raudenbush &
Bryk, 2002). When the interactions are not statistically significant, then the primary focus
of the study is on modeling the random error of the main effects - across students and
across schools (Ma et al., 2008; Raudenbush & Bryk, 2002).

**HLM Assumptions**

The first assumption is that the within-person residuals (i.e., effects not accounted
for by the time element), $e_{ijk}$, are normally distributed and independent with a mean of 0
for each time point and equal variances across time, $e_{ijk} \sim N(0, \sigma^2)$ (Bifulco, 2002;
Raudenbush & Bryk, 2002). Each time point was taken approximately the same day of
the month (within a few weeks) each year. Normal probability plot for level one residuals
confirmed the validity of the normality assumption.

The second assumption is that the level one predictors are independent of the
error term, $e_{ijk}$. A random pattern in a scatter plot of each predictor against level one
residuals indicated that these predictors are independent of the residuals, $e_{ijk}$ (Bifulco,
2002; Raudenbush & Bryk, 2002).

The third assumption is that the distribution of level two residuals (i.e., students
and schools) effects, $b_{p0k}$ and $c_{p0}$ are assumed multivariate normal across students and
schools with variances of $\tau_{p00}$ and $\tau_{pc00}$, respectively, and that their covariances $\tau_{10}$ and
$\tau_{20}$ are $\sim iid \ N(0, \Sigma)$ (i.e., residuals are independent) (Bifulco, 2002; Raudenbush &
Bryk, 2002). The level two variances, $\Sigma$, capture the variation across students and the
variance across schools. This assumption was checked by running a Mahalanobis
distance measure for each case. The Mahalanobis distance test displays non-normal behavior and any outliers in the data.

The fourth assumption is that the student and school level (i.e., level two) predictors (e.g., students with learning disabilities, students classified as English language learners, and charter schools started from scratch) are independent of error effects, $b_{p0k}$ and $c_{p0j}$ (Bifulco, 2002; Raudenbush & Bryk, 2002). The covariances of level two predictors and the error terms are equal to zero. This assumption was checked by plotting the level two predictors and the residual effects to look for randomness of residuals. The variation was random and therefore the predictors are considered independent of the error effects.

The fifth assumption is that the level one residual error term, $e_{ijk}$, is independent of level two residuals, $b_{pjk}$ and $c_{pj0}$ (Bifulco, 2002; Raudenbush & Bryk, 2002).

**HLM Power**

The statistical power of the design was determined to see what the probability of rejecting the null hypotheses (i.e., no differences between schools, etc.) is when it is false and to make sure that effects were measureable with low chance of creating a Type II error (retaining a null hypothesis in error) (O’Connell, & McCoach, 2008; Spybrook, 2008). Factors that affect power in a positive manner are: 1) increases in the number of time points, 2) increases in the sample size of level two persons or units, 3) increases in effect size; 4) decreases in the variance across persons or units; and 5) decreases in the “within” variance, $\sigma^2$ (Dedrick, et al., 2009; Raudenbush & Liu, 2001).
Level one is “time” with three data points over a period of three years. Each data point was taken within the same testing window each year (i.e., ten-day to two week time period). Raudenbush & Bryk (2002) state that when measuring growth over time, the overall sample size can have a greater effect in increasing power than the frequency of data points or the duration between data points. However, data points that are held constant over a period of time with a longer duration between data points (e.g., one year duration as opposed to every six months) will tend to have greater reliability (Raudenbush & Bryk, 2002). The sample size at level two of this study is 6214 students from 261 schools as reported by the HLM software package.

With an increase in IUCC, the power for the model effects will decrease. The higher the sample size, the more power the model will have to determine if statistical significance is applicable. The sample size for this study was sufficient to compensate for any design effect that may cause the IUCC to increase in size (Spybrook, 2008; Stapleton & Thomas, 2008).

**Partitioning the Variability in the Outcome**

The outcome variability can be partitioned into three parts using the IUCCs: the first, between achievement scores for students in a particular year; the second, between achievement scores over time for a student, $j$, who attended different charter schools, and the third, achievement over time of different students who attended the same charter school. This is very similar to intraclass correlations for the conventional HLM analyses (Beretvas, 2008; Meyers, 2004).
The level one and level two models demonstrate the partitioning of variability in students’ mathematics or reading achievement scores into components within time, $\sigma^2$, across students, $b_{00k}$, and across schools, $c_{0j0}$. The IUCC apropos to this study are the variability due to time,

$$
\rho_{\pi_{jk}, \pi_{jk}} = \frac{\sigma^2}{\tau_{b00k} + \tau_{c0j0} + \sigma^2};
$$

the variability that is across students,

$$
\rho_{\pi_{jk}, \pi_{jk}} = \frac{\tau_{b00k}}{\tau_{b00k} + \tau_{c0j0} + \sigma^2};
$$

and the variability that is across schools,

$$
\rho_{\pi_{jk}, \pi_{jk}} = \frac{\tau_{c0j0}}{\tau_{b00k} + \tau_{c0j0} + \sigma^2}.
$$

The measure of reliability or precision of each parameter (i.e., mathematics achievement at exit year, the annual growth rate, and the effect of teacher experience) is an estimate of the individual parameter true mean. The reliability of student effects can be distinguished for annual scale scores (i.e., time units) of those who attended a particular school (Raudenbush & Bryk, 2002) is as follows:

$$
\text{Reliability } [\langle \hat{b}_{00k} + \hat{d}_{0jk} \rangle | c_{0j0}] = \frac{\tau_{b00k} + \tau_{d0jk}}{\tau_{b00k} + \tau_{d0jk} + \sigma^2/n_{jk}}.
$$

The reliability of the school/teacher effects can be distinguished for annual achievement scores (i.e., time units) for one individual student (Raudenbush & Bryk, 2002) is as follows:
Fit Statistics

To determine the best model fit (i.e., whether the deviance of the latest model is significantly different from the deviance of the previous model), a chi-square hypothesis test is most commonly used; however, it has been reported that with large sample sizes most null hypotheses will be rejected even if there are no other indications of differences in the data and, in fact, counterintuitive to the research (Raftery, 1995). Thus, the chi-square test of hypothesis may permit predictors to be added to the model that, in fact, may not add to the explanatory power of the model actually producing a less parsimonious model than necessary. In addition, hypotheses tests just indicate whether the null hypothesis is tenable against an alternative hypothesis not indicating anything beyond the “reject” or “fail to reject” – in this scenario, not clarifying which model is closest to mimicking reality (McCoach & Black, 2008).

The Bayesian Information Criterion (BIC) has been reported to correctly fit the best models (i.e., parsimonious model) in comparison studies by Meyers and Beretvas (2006) and Murphy and Beretvas (2010). BIC is used with full maximum likelihood (FIML) estimations that are based on fixed and random effects and were used for this CCREM study to compare models (McCoach & Black, 2008). Raftery’s (1995) grades of evidence corresponding to values of the Bayes Factor was used to determine whether one model was a stronger fit than other models.

\[
\text{Reliability } \left[ (\hat{c}_{0j0} + \hat{d}_{0jk}) | b_{00k} \right] = \frac{\tau_{c0j0} + \tau_{d0jk}}{\tau_{c0j0} + \tau_{d0jk} + \sigma^2 / n_{jk}}.
\]
In summary, very few education researchers use HLM/CCREM as a method of analysis but in order to answer the research questions from this study this complex analysis was necessary. The following chapter fully describes the data preparation process and the analyses in stages, first as an unconditional model, next a baseline model which includes a time element and time-varying predictors, and lastly, the full model using mathematics achievement scores as the outcome. The second half of Chapter IV consists of a separate set of analyses (and models) that were run using the reading achievement scores as the outcome. All predictors were accounted for, described, and results reported (whether they remained in the full model or not).
CHAPTER IV

Results

Introduction

For two decades the subject of charter schools has been somewhat controversial in terms of how charter schools were defined (e.g., having autonomy from school districts while not discriminating against any students) and whether they were effective (Collins, 1999; Hess et al., 2002; Mead & Rotherham, 2007; Lubienski, 2001). Many studies have been conducted over the last fifteen years with mixed reviews as to whether attending students benefit academically from attending charter schools (Allen & Marcucio, 2005; Braun, 2006; Braun et al., 2006; Buddin & Zimmer, 2005; Dawson, 1999; Finn, Loveless & Jasin, 1998; Manno, Vanourek, 2001; Mead and Rotherham, 2007; Ravitch, 2001). One of the reasons for the mixed results from previous studies is the variation between charter schools. The difference of charter schools between states can vary greatly because of their individual charter laws and the difference between charter schools within a state can vary considerably because of their individual charters (i.e., contracts), thereby making it difficult to infer any results to the population (i.e., charter schools across the nation). It has been recommended by some researchers that perhaps one solution to reducing variation would be to conduct studies on charter schools within one state (Brown et al., 2004; Carpenter, 2005; Charter School Achievement Consensus Panel, 2006).
The purpose of this study was to investigate the school practices that effect student mathematic and reading achievement of Arizona charter middle school students to provide a best practices guide for researchers and authorizers. School practices are defined as treatments within a school such as administrative leadership, utilization of resources, grade structure, classroom size, and curriculum (Raudenbush and Willms, 1995).

The research questions addressed in this study are:

1. How do school practices, while controlling for student characteristics, affect average mathematics and reading achievement for Grade 8 students at the exit year (i.e., 2009)?

2. What is the average growth rate in mathematics and reading achievement of students at Arizona charter middle schools?

Student characteristics helped to explain variability in the growth rate across students and across schools. Currently there are no studies on record that have investigated these aspects of charter schools using the state assessment in Arizona.

While there is an inherent nesting of the data (e.g., time points for students in charter schools) there is also crossing of the data occurring between students and schools because of student mobility. To accommodate such data, cross-classified random effects model (CCREM), as a special type of hierarchical linear modeling (HLM), was used to conduct robust results. CCREM allows the cross random effects to appear on the same level (e.g., level two is students and schools). In this scenario, schools would be columns of a matrix, students would be rows, and time points (which represent level one) would
be nested in the cells for each student/school combination (Beretvas, 2008; Raudenbush, 1993; Raudenbush & Bryk, 2002; Raudenbush, Bryk, Cheong, & Congdon, 2004). All hypotheses were tested using a .05 alpha level which is widely used in education research. This allowed the researcher to be at least 95% confident that the effects seen on achievement scores are due to school practices as well as students’ characteristics and not some other factors such as sampling error. Each variable was added to the model one at a time to see if it was a tenable predictor. If the coefficient estimate for a predictor was statistically significant at the .05 alpha level then it was retained in the model. Each predictor was run as random if the variance of the predictor was significantly different from zero. If the variance was not significantly different from zero, then the predictor treated in the model as having a fixed effect as long as the coefficient estimate was statistically significant. Each model (during the building process) was checked for Bayesian Information Criterion (BIC). This process is to create the simplest model that has the most explanatory power; thus producing a parsimonious model (Stockburger, 1998). This chapter contains descriptive analyses of the data, information about the multiple imputations that were conducted for missing data, a description of the random sample, and two sets of results from the HLM/CCREM studies using mathematics and reading scale scores as outcomes.

Table 4 describes the predictors used in the study.
Table 4

Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1 (time varying)</td>
<td>(includes all years)</td>
</tr>
<tr>
<td>MATH</td>
<td>AIMS mathematics scale score.</td>
</tr>
<tr>
<td>READ</td>
<td>AIMS reading scale score.</td>
</tr>
<tr>
<td>HQ</td>
<td>Percent of teachers highly qualified per school(^{a,b})</td>
</tr>
<tr>
<td>EXPER</td>
<td>Average number of years of teachers’ service per school(^{a,c})</td>
</tr>
<tr>
<td>HGHERED</td>
<td>Percent of teachers that have higher than a Bachelor’s degree(^a)</td>
</tr>
<tr>
<td>CERT</td>
<td>Percent of teachers with teacher certification per school(^{b,c})</td>
</tr>
</tbody>
</table>

*(table 4 continues)*
Table 4 (continued)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Student Predictors</strong></td>
<td></td>
</tr>
<tr>
<td>HISP</td>
<td>Percent of Hispanic students</td>
</tr>
<tr>
<td>N_AMER</td>
<td>Percent of Native American students</td>
</tr>
<tr>
<td>BLCK</td>
<td>Percent of Black students</td>
</tr>
<tr>
<td>ASIAN</td>
<td>Percent of Asian students</td>
</tr>
<tr>
<td>FEMALE</td>
<td>Gender, Male = 0</td>
</tr>
<tr>
<td>SD</td>
<td>Percent of students with disability, No disability = 0</td>
</tr>
<tr>
<td>ELL</td>
<td>Percent of English language learners, English proficient = 0</td>
</tr>
<tr>
<td>FRL</td>
<td>Percent of students eligible for the National School Lunch Program, Not eligible = 0</td>
</tr>
<tr>
<td>CHRTR06</td>
<td>Percent of students attended a charter school in 2006, Did not attend = 0</td>
</tr>
</tbody>
</table>

(table 4 continues)
Table 4 (continued)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>School Predictors</strong></td>
<td></td>
</tr>
<tr>
<td>OUTFLD</td>
<td>Percent of teachers teach out-of-field, No = 0</td>
</tr>
<tr>
<td>CONV</td>
<td>Percent of Schools were converted from traditional public school, No = 0</td>
</tr>
<tr>
<td>CLASS</td>
<td>Average number of students in one classroom per school⁸</td>
</tr>
</tbody>
</table>

*Note.* Level one, n = 14304; Level two student predictors, n = 6214; Level two school predictor, n = 261.

⁸Time-varying predictor. ⁹Centered on the median. ⁵Grand mean centered.

---

**Data Screening and Assumptions**

**Descriptive Analysis**

As was stated in Chapter III, the majority of the data for this study was obtained from the Arizona Department of Education SAIS. The Arizona Department of Education extracted data for 10,043 students attending charter schools in Grades 6-8 for the years 2007-2009. A telephone/email survey was used to collect the remainder of the charter school data for grades 6 -8 that was not available from the state department (See Appendix G). The survey was sent to all active charter schools (i.e., 266 in total as reported by the Arizona Department of Education) to collect the rest of the data but only 153 answered the short telephone or email survey. This left 113 schools missing data from the survey. Forty six schools were also missing school data that was supposed to be
turned into SAIS (i.e., average years of teacher experience, etc.). See Table 5 for the total number of students missing school data by year.

Table 5

Number of Students Missing School Data

<table>
<thead>
<tr>
<th>Years</th>
<th>Missing Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>2007</td>
<td>2283</td>
</tr>
<tr>
<td>2008</td>
<td>2212</td>
</tr>
<tr>
<td>2009</td>
<td>2462</td>
</tr>
</tbody>
</table>

*Note: The sample sizes vary across years because of student mobility and schools attrition.*

The proportion of the population was tested for the subpopulations (e.g., White, ELL, etc.) of participating students using Fisher z transformation statistics ($H_0: P = a$) to determine if the sample data (excluding the missing) was representative of the Arizona charter middle school population. This test was used to determine if the missing data was too large and thus requiring multiple imputation to create a full data set (See Table 6) (Hinkle, Wiersma, & Jurs, 1998).
Table 6

Proportion of Population of Participating Students for each Variable, H0: \( P = a \)

<table>
<thead>
<tr>
<th>Variables</th>
<th>( p )</th>
<th>( S_p )</th>
<th>z-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Sample Proportion)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>2007 (( N = 3565 ))</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>.6283</td>
<td>.0083</td>
<td>6.206*</td>
</tr>
<tr>
<td>HISP</td>
<td>.235</td>
<td>.0075</td>
<td>-5.730*</td>
</tr>
<tr>
<td>BLCK</td>
<td>.056</td>
<td>.0042</td>
<td>-2.844*</td>
</tr>
<tr>
<td>N_AMER</td>
<td>.047</td>
<td>.0035</td>
<td>0.571</td>
</tr>
<tr>
<td>ASIAN</td>
<td>.0337</td>
<td>.0030</td>
<td>0.373</td>
</tr>
<tr>
<td>Male</td>
<td>.500</td>
<td>.0084</td>
<td>-0.717</td>
</tr>
<tr>
<td>FEMALE</td>
<td>.500</td>
<td>.0084</td>
<td>0.717</td>
</tr>
<tr>
<td>SD</td>
<td>.126</td>
<td>.0053</td>
<td>2.060*</td>
</tr>
<tr>
<td>ELL</td>
<td>.035</td>
<td>.0039</td>
<td>-5.455*</td>
</tr>
<tr>
<td>FRL</td>
<td>.282</td>
<td>.0079</td>
<td>-6.076*</td>
</tr>
<tr>
<td>CHRTR06</td>
<td>.624</td>
<td>.0080</td>
<td>-3.764*</td>
</tr>
<tr>
<td><strong>2008 (( N = 3759 ))</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>.638</td>
<td>.0080</td>
<td>6.841*</td>
</tr>
<tr>
<td>HISP</td>
<td>.232</td>
<td>.0073</td>
<td>-5.753*</td>
</tr>
<tr>
<td>BLCK</td>
<td>.050</td>
<td>.0038</td>
<td>-2.340*</td>
</tr>
</tbody>
</table>

(table 6 continues)
Table 6 (continued)

<table>
<thead>
<tr>
<th>Variables</th>
<th>( p )</th>
<th>( S_p )</th>
<th>z-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Sample Proportion)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N_AMER</td>
<td>.047</td>
<td>.0035</td>
<td>0.571</td>
</tr>
<tr>
<td>ASIAN</td>
<td>.033</td>
<td>.0030</td>
<td>-0.987</td>
</tr>
<tr>
<td>Male</td>
<td>.500</td>
<td>.0082</td>
<td>0.000</td>
</tr>
<tr>
<td>FEMALE</td>
<td>.500</td>
<td>.0082</td>
<td>0.000</td>
</tr>
<tr>
<td>SD</td>
<td>.115</td>
<td>.0051</td>
<td>1.374</td>
</tr>
<tr>
<td>ELL</td>
<td>.038</td>
<td>.0037</td>
<td>-4.054*</td>
</tr>
<tr>
<td>FRL</td>
<td>.345</td>
<td>.0078</td>
<td>-2.296*</td>
</tr>
<tr>
<td>CHRTR06</td>
<td>.624</td>
<td>.0080</td>
<td>-3.764*</td>
</tr>
<tr>
<td>2009 ( N = 3852 )</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>.651</td>
<td>.0080</td>
<td>9.170*</td>
</tr>
<tr>
<td>HISP</td>
<td>.225</td>
<td>.00719</td>
<td>-6.815*</td>
</tr>
<tr>
<td>BLCK</td>
<td>.053</td>
<td>.0040</td>
<td>-3.250*</td>
</tr>
<tr>
<td>N_AMER</td>
<td>.037</td>
<td>.0034</td>
<td>-2.663*</td>
</tr>
<tr>
<td>ASIAN</td>
<td>.034</td>
<td>.0030</td>
<td>-0.667</td>
</tr>
</tbody>
</table>

*(table 6 continues)*
Table 6 (continued)

<table>
<thead>
<tr>
<th>Variables</th>
<th>$p$</th>
<th>$S_p$</th>
<th>z-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Sample Proportion)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>.493</td>
<td>.0081</td>
<td>-0.370</td>
</tr>
<tr>
<td>FEMALE</td>
<td>.507</td>
<td>.0081</td>
<td>0.370</td>
</tr>
<tr>
<td>SD</td>
<td>.118</td>
<td>.0050</td>
<td>1.793*</td>
</tr>
<tr>
<td>ELL</td>
<td>.022</td>
<td>.0031</td>
<td>-5.450*</td>
</tr>
<tr>
<td>FRL</td>
<td>.342</td>
<td>.0078</td>
<td>-4.987*</td>
</tr>
<tr>
<td>CHRTR06</td>
<td>.353</td>
<td>.0077</td>
<td>-1.163*</td>
</tr>
</tbody>
</table>

*p < .05 (2-tailed).

Nearly all subgroups (i.e., *White, HISP, BLCK, ELL, FRL*, and *CHRTR06*) were significantly different from the proportion in the population (i.e., Arizona’s charter middle school students) for their subgroup across all three years (*SD* was significantly different for two of the three years) with the exception of *Male, FEMALE,* and *ASIAN* students. Multiple imputations were deemed necessary because of the proportion of missing data.

**Missing Data**

While cleaning the data it was discovered that there were missing data from the state and incomplete data from the telephone survey. The total number of schools with missing data was 46 which included 3115 students (over all three years). The ADE indicated that the missing data were due to the schools not uploading the information to
SAIS. The missing data from the telephone survey occurred from 113 schools not responding to the survey questions.

Missing values in a quantitative study can be a serious issue. The missing data themselves can inadvertently bias the results so the first step is to investigate how much data are missing and if there is a pattern of the missing values. The results determine what method should be used to overcome the missing data dilemma. If there is a relationship between the missing values and current data then it is possible to impute the data if necessary. Data “missing completely at random” means that the missing data are independent of other values within that variable and independent of other variables in the data set. This means that there is no pattern to the missing data, for example, perhaps an assessment was lost prior to data entry or a test taker became injured and couldn’t take the assessment. There is no rhyme or reason to the missing data and thus not related (or dependent) to any other variables in the study. Data “missing at random” means that there is some dependency on or relationship between one variable that has missing data to another variable. For example, in a pre- and post-test study, students who score very low on the pre-test may become intimidated and drop out of the treatment before the post-test. In this example, this would mean that the determination of which students ended up taking the post-test depended on their pre-test scores thus resulting in bias results unless the missing values are imputed (Enders, 2001; Goldstein, 1995; Hill & Goldstein, 1998; Leyland & Goldstein, 2001; Little & Rubin, 2002; McKnight, McKnight, Sidani, & Figueredo, 2007; Rabe-Hesketh & Skrondal, 2008; Raudenbush &
Bryk, 2002; Rubin, 1987; Rubin, 2004; Schafer, 1999; Tabachnick & Fidell, 2001; Yuan & Little, 2009).

There are steps to follow in addressing the issue of missing data and assessing the amount of missing data. It was determined that the number of missing data on schools in this study would jeopardize the robustness of the study, therefore some action was required. The missing data was too large to go on as is with the study (Hox, 2002; Little & Rubin, 2002; McKnight et al., 2007; Raudenbush & Bryk, 2002; Rubin, 1987; Snijders & Bosker, 1999).

First, variables with missing data were recoded using dummy codes for missing and non-missing values. The values for the variable, CERT, for example, was re-coded in a different variable for this investigation as “0” for missing and “1” for a datum.

Secondly, independent sample t-tests were run on the variables that have missing data with another variable in the study (i.e. a continuous normally distributed variable [mathematics score] as the dependent variable) to determine the significance of the missing data. For the independent sample t-tests, $H_0: \mu_1 = \mu_2$, $\mu_1$ is the mean mathematics achievement for the group that has the missing data and $\mu_2$ is the mean mathematics achievement for the group that has no missing data (Tabachnick & Fidell, 2001). If the t-test shows statistical significance, as was the instance with the data from this study, then the data are “missing at random.” If there was no significant difference between the two groups (those with missing data and those without missing data) then this would mean that the data was “missing completely at random.” If this is the case then nothing can be determined about these missing data – not even determine that they may be different from
the data that remain. It was concluded that the number of missing data from schools would jeopardize the robustness of the study therefore some form of imputation would be required (Hox, 2002; Little & Rubin, 2002; McKnight et al., 2007; Raudenbush & Bryk, 2002; Rubin, 1987; Snijders & Bosker, 1999). Descriptive statistics and histograms were run on all variables that have missing data. Reflections and transformations to normal distributions were run on the continuous variables that were skewed (Tabachnick & Fidell, 2001).

Thirdly, once the missing data were determined to be “missing at random” the next step was to recognize which other variables available correlated with the variable containing the missing data. Pearson correlations were run in SPSS on the continuous variables and Spearman \( r \) correlations were run on the dichotomous variables with those non-normal continuous variables to look for strong correlations between variables. This process determines which variables would be used as predictors in the regression models used to estimate the missing values (Tabachnick & Fidell, 2001).

Lastly, the other available variables that are highly correlated were used in a regression model to impute the missing values. Linear and logistic regressions were used to impute plausible values for the missing data with 20 iterations using the computer software, WinMICE, Version 0.1. WinMICE is a Windows program for Multivariate Imputation for Chained Equations (WinMICE) by Gert Jacobusse. For each variable the imputation was repeated five times in WinMICE creating five plausible values for each missing cell. The five plausible values were brought into SPSS to average - determining the final parameter estimate (Cheong, & Congdon, 2004; Raudenbush, Bryk, Rubin,
When comparing the descriptive statistics of the parameter estimates, the “new” full data set closely resembled the original data. Table 7 reports descriptive statistics of the school level predictors prior to the multiple imputation process and with the full data set.

Table 7

*Descriptive Statistics of School Predictors Prior to Multiple Imputation (MI) and After MI*

<table>
<thead>
<tr>
<th>Variables</th>
<th>Prior to MI</th>
<th>Full Data Set</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>M</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2007</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OUTFLD</td>
<td>114</td>
<td>0.36</td>
</tr>
<tr>
<td>CONV</td>
<td>123</td>
<td>0.09</td>
</tr>
<tr>
<td>CERT</td>
<td>191</td>
<td>57.89</td>
</tr>
<tr>
<td>HQ</td>
<td>184</td>
<td>86.08</td>
</tr>
<tr>
<td>EXPER</td>
<td>192</td>
<td>7.26</td>
</tr>
<tr>
<td>HGHRED</td>
<td>188</td>
<td>56.51</td>
</tr>
<tr>
<td>CLASS</td>
<td>100</td>
<td>18.68</td>
</tr>
<tr>
<td>2008</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OUTFLD</td>
<td>103</td>
<td>0.31</td>
</tr>
<tr>
<td>CONV</td>
<td>111</td>
<td>0.08</td>
</tr>
<tr>
<td>CERT</td>
<td>186</td>
<td>60.68</td>
</tr>
<tr>
<td>HQ</td>
<td>181</td>
<td>87.22</td>
</tr>
</tbody>
</table>

*(table 7 continues)*
Table 7 (continued)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Prior to MI</th>
<th>Full Data Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>EXPER</td>
<td>186</td>
<td>8.43</td>
</tr>
<tr>
<td>HGHRED</td>
<td>183</td>
<td>58.10</td>
</tr>
<tr>
<td>CLASS</td>
<td>99</td>
<td>18.78</td>
</tr>
<tr>
<td>2009</td>
<td></td>
<td></td>
</tr>
<tr>
<td>OUTFLD</td>
<td>111</td>
<td>0.2973</td>
</tr>
<tr>
<td>CONV</td>
<td>118</td>
<td>0.08</td>
</tr>
<tr>
<td>CERT</td>
<td>191</td>
<td>58.71</td>
</tr>
<tr>
<td>HQ</td>
<td>190</td>
<td>85.40</td>
</tr>
<tr>
<td>EXPER</td>
<td>191</td>
<td>7.95</td>
</tr>
<tr>
<td>HGHRED</td>
<td>189</td>
<td>58.58</td>
</tr>
<tr>
<td>CLASS</td>
<td>100</td>
<td>18.79</td>
</tr>
</tbody>
</table>

$^a$OUTFLD = Teachers Teaching Out-of-Field, CONV = School Converted from a Traditional Public School, CERT = Number of Certified Teachers per School, HQ = Number of Highly Qualified Teachers per School, EXPER = Average Years of Teaching Experience per School, HGHRED = Average Number of Teachers with Higher Education, and CLASS = Actual Number of Students per Classroom per School. $^b$Statistics have been rounded to the nearest 100th.

There were fewer than 30 student scale scores that needed to be imputed for mathematics and reading. The replacement parameters were computed using the same process as was used for the school level parameters.
Outliers

Outliers were found in the data. The outliers are from the target population and seem to be unique to certain schools when disaggregated by year. For example, the charter schools located on Native American reservations had a large amount of Native American student population compared to other charter schools throughout the state of Arizona. Another example is charter schools that have a curriculum of only college prep courses (e.g., academies) had a higher percentage of teachers with teaching experience than others. Frequencies were run on the dichotomous variables (i.e., RACE, SD, ELL, FRL, CHRTR06, CONV, OUTFLD) for a comparison of means and medians that showed no difference between the two descriptors. All continuous variables (i.e., EXPER, CLASS, CERT, HQ, HGHRED) were standardized. All $z$ scores that were greater (+/-) than 3.0 were inspected for errors in inputting data and/or errors occurring during the multiple imputation process. The standardized parameter estimates that were beyond 3.0 were deleted from one set of the $z$ scores to compare to the $z$ scores that contained the outliers. Pearson $r$ correlations were run on both sets of $z$ scores with the outcome variables (i.e., mathematics and reading) in comparison to see if the outliers were skewing the data (See Table 8). Stevens (2002) states that with a large sample size ($n > 100$) a few $z$ scores greater than 3.0 is reasonable. As a result, the outliers do not seem to be affecting the data so they were retained in the sample without alteration. The predictors containing the outliers were investigated and it was determined that the data were entered correctly and did not occur during the multiple imputation process (Stevens, 2002; Tabachnick & Fidell, 2001).
Table 8

Correlation of Predictors Containing Outliers and the Mathematics and Reading Outcome (z Scores)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Cases without Outliers</th>
<th>Full Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Math</td>
<td>Reading</td>
</tr>
<tr>
<td>2007</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EXPER</td>
<td>.172**</td>
<td>.182**</td>
</tr>
<tr>
<td>HGHRED</td>
<td>.105**</td>
<td>.106**</td>
</tr>
<tr>
<td>2008</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EXPER</td>
<td>.106**</td>
<td>.125**</td>
</tr>
<tr>
<td>HGHRED</td>
<td>.213**</td>
<td>.211**</td>
</tr>
<tr>
<td>2009</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EXPER</td>
<td>.067**</td>
<td>.113**</td>
</tr>
<tr>
<td>HGHRED</td>
<td>.239**</td>
<td>.232**</td>
</tr>
</tbody>
</table>

**p < .01 (2-tailed).

Normality Assumption

It was concluded from an examination of histograms and normal probability plots of the residuals that they are normally dispersed and independent for both the mathematics and reading as the dependent variables, thereby confirming normal distribution.

The distributions of the variables were also examined using normal probability plots for all continuous variables (i.e., school level predictors with file split by year). All
variables were reasonably normally distributed except for \textit{EXPER} and \textit{HQ} which was reflected in their skewness and kurtosis statistics (Stevens, 2002). Tabachnick and Fidell (2001) state, that although non-normal kurtosis can underestimate the variance of the variable, with a large sample size the positive (i.e., approximately over 100 cases) or negative kurtosis (i.e., approximately over 200 cases) may not cause underestimations.

The negative skewness of the \textit{HQ} variable is explained in the frequencies showing that a large percentage of schools have a majority of teachers who are highly qualified. With a large sample, significant skewness is not likely to make a substantive difference in the analysis (Tabachnick & Fidell, 2001).

\textit{Linearity Assumption}

Relationships among variables were examined for linearity through scatterplots and Pearson’s $r$ statistic. All relationships appear linear in nature.

\textit{Multicollinearity and Singularity}

To check for multicollinearity, a squared multiple correlation was run in SPSS. This correlation runs one variable as the dependent variable and the rest as the independent variables. The higher the squared multiple correlation is, the more likely multicollinearity is present – if the correlation reaches 1.0 then you have singularity. Condition indices (the square root of the maximum eigenvalue [i.e., variance matrix] divided by the minimum eigenvalue) determine the dependency of one variable on the other variables. This will alert the researcher of variance inflation in the standard error of the parameter estimate of a variable. When the index is high then the standard error of the parameter estimate is unstable (Tabachnick & Fidell, 2001). Collinearity takes place
when you have a variable with a high condition index (i.e., > 30.0) and it also has a high correlation (> .50) with two or more variables (Belsley, Kuh, & Welsch, 2004).

Screening for multicollinearity and singularity was completed for all independent variables by running squared multiple correlations (split by year). The condition indices were higher than 30 for all three years (i.e., ranging from 35.090 – 38.545) and the variance proportions for the squared multiple correlations (where each variable serves as the dependent variable for the others) was higher than 50 for the variable HGHRED. As a precautionary measure, a second regression was run without the HGHRED variable to compare diagnostic tests. Without the HGHRED variable the condition indices were fair (ranging from 26.005-27.833) and the variance proportions for the squared multiple correlations did not approach 1.0 (ranging from .01 - .63) as compared to the model with the HGHRED variable. A Pearson’s r correlation was run to see which variables correlated with HGHRED. The results revealed that HGHRED was correlated to HQ (r = .415) and EXPER (r = .285). It was determined by the researcher that the removal of the HGHRED variable from the following sets of regression models reduced multicollinearity as a whole and, therefore, multicollinearity was no longer a threat. As a result, the variable HGHRED was not used for the HLM/CCREM analysis. Finding a high correlation between HGHRED variable with HQ and a correlation with EXPER (i.e., average years teaching is 7.77 years) makes logical sense because a teacher that has been teaching for several years is more likely to have attended higher education courses and acquire the highly qualified status than a new teacher. Other researchers have found that teachers with higher education is either not a statistically significant predictor in student
achievement or had a negative effect on reading achievement (Buddin and Zamarro; Croninger, Rice, Rathbun, and Nishio, 2005; Munoz & Chang, 2007)

**Sample**

There were 266 charter schools in the study that were open longer than four years as of 2003 and that had grades 6 through 8 during the time period of 2007-2009. The data were extracted by the Arizona Department of Education using a unique identifier for each student in SAIS. The original data were 18133 data points for all the years combined from 10043 students. This means that not every student had three time points (one data point for each year). There were 4786 students that have one time point, 2424 students that have two time points, and 2833 students that have three time points totaling 10043 students.

One of the strengths of HLM is that empirical Bayesian (EB) estimations are based on the reliability of the coefficients for groups with few within group observations; however, in this case there seemed to be too many missing data points for students for EB to produce tenable residuals. EB, based on the coefficients’ reliability, uses a weighting procedure for the sampling mean and overall mean estimates. This is a shrinkage procedure toward model-based estimates and the EB residuals are shrunk towards the zero. If the reliability estimate (which relies on the sample size) is low, more shrinkage takes place. If the reliability is high then less shrinkage has to occur to produce the estimates of the coefficient. This is useful when researcher is missing a few within observations (McCoach & O’Connell, 2008). However, when you are missing too many observations, EB tends to pull the estimates for the unbalanced data close to the sampling
average. If there are too many missing data then more shrinkage will take place; therefore, the estimates will be too close to the sampling average and thus the residuals will pull toward zero. Since a high portion of students have missing data over time then too much weight will be given to the overall mean when obtaining EB estimates for the overall parameters causing the residuals to be tenuous. The alternate in this case is to pull a random sample of the students that only have 1 data point to use in the final HLM/CCREM analyses.

The original data, as mentioned earlier, had 4768 students with only one observation. This was nearly one half of the overall data. This means that two data points would have to be estimated in HLM/CCREM for this large sample and would ultimately receive a higher weight in the overall estimation process. After the initial analyses the residual file for level one was found to be tenuous; therefore a random sample of 20% was pulled in SPSS from the students who only had one data point in level one.

Although in the literature there are no conclusions drawn as to a definite sample size needed to carry out a reliable HLM study with precise model estimates, generally when using HLM you want approximately 25 schools with approximately 25 students in each school to have robust model estimates (Paterson & Goldstein, 1991). See Table 9 for a total of students at each data point. This table shows full data set compared to the data set with the 20% random sample for those that had 1 data point. This study originally had 266 schools and when the 20% random sample was extracted the total number of schools went down to 261. For 2007, there are 222 schools total with 69 schools that have greater than 20 students in each school, for the 2008 data, there are 194 schools total with 91
schools that have greater than 20 students in each school, and for the 2009 data there are 201 schools total with 75 schools that have greater than 20 students in each school, see Table 10. After a 20% random sample was extracted from those 4768 students using SPSS, the residuals of the resulting models were tenable. Distributions of the variables (means and standard deviations) based on the selected sample were very comparable (representative) to the entire data set for the students with only 1 time-unit, see Table 11.

Table 9

Summary of Sample Sizes for the Linear Growth Study

<table>
<thead>
<tr>
<th>Data Points</th>
<th>Number of Students</th>
<th>Cumulative Number of Students</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full Data</td>
<td>Data Sample</td>
</tr>
<tr>
<td>1</td>
<td>4786</td>
<td>957</td>
</tr>
<tr>
<td>2</td>
<td>2424</td>
<td>2424</td>
</tr>
<tr>
<td>3</td>
<td>2833</td>
<td>2833</td>
</tr>
</tbody>
</table>

*Note.* Full data: \( N = 18133 \) observations, \( N \) students = 10043. Sample data: \( n = 14304 \) observations, \( n \) students = 6214.
Table 10

**Number of Students Nested within Schools**

<table>
<thead>
<tr>
<th>Number of Students School</th>
<th>Number of Schools with Specified Number of Students</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2007</td>
</tr>
<tr>
<td></td>
<td>Full</td>
</tr>
<tr>
<td></td>
<td>$n = 225$</td>
</tr>
<tr>
<td>&gt; 20</td>
<td>101</td>
</tr>
<tr>
<td>&lt; 20</td>
<td>124</td>
</tr>
</tbody>
</table>

*Note.* Total of schools included in the full data was 266; the total schools in the sample data was 261. There is a discrepancy in school samples sizes per year because many Arizona charter schools close or start up in any given year.

Table 11

**Descriptive Statistics of the Full Data and the 20% Sample of Students with One Data Point**

<table>
<thead>
<tr>
<th>Variables</th>
<th>Full Data</th>
<th>Sample Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>WHITE</td>
<td>.54</td>
<td>.498</td>
</tr>
<tr>
<td>HISP</td>
<td>.30</td>
<td>.457</td>
</tr>
<tr>
<td>N_AMER</td>
<td>.05</td>
<td>.228</td>
</tr>
<tr>
<td>BLACK</td>
<td>.08</td>
<td>.270</td>
</tr>
<tr>
<td>ASIAN</td>
<td>.02</td>
<td>.155</td>
</tr>
</tbody>
</table>

*(table 11 continues)*
Table 11 (continued)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Full Data</th>
<th>Sample Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>FEMALE</td>
<td>.47</td>
<td>.499</td>
</tr>
<tr>
<td>SD</td>
<td>.11</td>
<td>.308</td>
</tr>
<tr>
<td>ELL</td>
<td>.06</td>
<td>.230</td>
</tr>
<tr>
<td>FRL</td>
<td>.41</td>
<td>.492</td>
</tr>
<tr>
<td>CHRTR06</td>
<td>.31</td>
<td>.464</td>
</tr>
<tr>
<td>OUTFLD</td>
<td>.20</td>
<td>.399</td>
</tr>
<tr>
<td>CONV</td>
<td>.06</td>
<td>.228</td>
</tr>
<tr>
<td>CERT</td>
<td>63.25</td>
<td>21.484</td>
</tr>
<tr>
<td>HQ</td>
<td>88.92</td>
<td>15.78</td>
</tr>
<tr>
<td>EXPER</td>
<td>7.16</td>
<td>2.810</td>
</tr>
<tr>
<td>HGHRED</td>
<td>58.81</td>
<td>7.45</td>
</tr>
<tr>
<td>CLASS</td>
<td>19.52</td>
<td>4.482</td>
</tr>
</tbody>
</table>

*Note.* The $N$ count for the full data was 4786 and for the sample data was 957.

**Hierarchical Linear Cross-Classified Random Effects Model Results**

When data is naturally nested (i.e., time units nested in students and students nested in schools) then hierarchical linear modeling is the statistical procedure to use. However, not all data is naturally nested as is the case with this study. Student mobility over the time period for this study has required a specialized use of HLM called
cross-classified random effects model (CCREM). With this procedure, observation times are nested within student as well as school, where student and school are crossed on the same level (i.e., level two) (Beretvas, 2008; McCoach & O’Donnell, 2008; Raudenbush & Bryk, 2002). It is easiest to think of this process in a matrix where time units are in the cells, students are the rows, and schools are the columns (Raudenbush & Bryk, 2002). The HLM software for Windows, Version 6.08, was used for this CCREM. The overall structure of the model constitutes two levels. On level one the outcomes (mathematics and reading scores treated separately) are expressed as an estimate for the average achievement at exit year, their growth over time, the effect of all time varying variables, and random errors (Raudenbush, 1993). Estimates from the level one model are then expressed as a function of students and school practices in a randomized cross-classified model where students (rows) are crossed with schools (columns) (Raudenbush & Bryk, 2002).

The process of fitting the model started with an unconditional model (i.e., no predictors were introduced on either of the two levels) as suggested by Raudenbush and Bryk (2002). This model is to set baseline statistics for the average achievement in the exit year (i.e., 2009) and student’s individual growth. The variances of these parameters are partitioned into across-students and across-schools component (i.e., \( \tau \)) estimates. Correlations among the estimated parameters are also provided (Raudenbush & Bryk, 2002). Level one and level two predictors were added one at a time and retained in the model based on whether the coefficient estimate for each predictor was statistically significant at the .05 alpha level. The effect of each predictor added to the model was
treated as randomly varying across schools and across students; however, if the variance of the effect for a particular predictor was found to be not significantly different from zero (a $\chi^2$ test-statistic was insignificant) the effect of the predictor was treated as fixed for future models. The BIC was calculated for each model to determine the model parsimony (see Tables 18 and 24). Based on these criteria the following models (i.e., unconditional, baseline [Model 1], and the full model) were run in the HLM/CCREM computer program.

**MATHEMATICS**

*Unconditional Model*

**Level 1:**

$$\text{MATH}_{ijk} = \pi_{0jk} + \pi_{1jk}(\text{ANNUALGRWTH})_{ijk} + e_{ijk}, \quad e_{ijk} \sim N(0, \sigma^2)$$

$i =$ year 2007, 2008, 2009  
$j = 1, 2, \ldots, J$ an index for students  
$k = 1, 2, \ldots, K$ an index for schools

**Level 2:**

$$\pi_{0jk} = \theta_{000} + b_{00k} + c_{0/j0}$$  
$$\pi_{1jk} = \theta_{100} + b_{10k} + c_{1/j0}$$

$$b_{00k} \sim N(0, \tau_{b00k})$$  
$$c_{0/j0} \sim N(0, \tau_{c0/j0})$$  
$$b_{10k} \sim N(0, \tau_{b10k})$$  
$$c_{1/j0} \sim N(0, \tau_{c1/j0})$$
Where:

\( MATH_{ijk} \) is the mathematics achievement at time \( i \) for student \( j \) in school \( k \).

\( \pi_{0jk} \) is the predicted average mathematics achievement for student \( j \) in 2009 from the specific combination of schools \( k_{2007}, k_{2008}, \) and \( k_{2009} \).

\( \pi_{1jk} \) is the annual mathematics achievement growth rate for student \( j \) from the specific combination of schools \( k_{2007}, k_{2008}, \) and \( k_{2009} \). The predictor \( ANNUALGRWTH (time – time_{2009}) \) is centered at the exit time point, 2009, for ease of interpretation and, thus, is the focus of this study.

\( \theta_{000} \) is the predicted average students’ mathematics achievement at year 2009 across all students and across all schools.

\( \theta_{100} \) is the annual growth rate of mathematics achievement across all students and across all schools.

\( b_{00k} \) is student random effects associated with the average mathematics achievement in 2009. It is assumed normally distributed with a mean of 0 and a variance of \( \tau_{b00k} \).

\( b_{10k} \) is student random effects associated with the annual growth rate. It is assumed normally distributed with a mean of 0 and a variance of \( \tau_{b10k} \).

\( c_{0j0} \) is school random effects associated with the aggregated mathematics achievement in 2009. It is assumed normally distributed with a mean of 0 and a variance of \( \tau_{c0j0} \).

\( c_{1j0} \) is school random effects associated with the aggregate annual growth rate. It is assumed normally distributed with a mean of 0 and a variance of \( \tau_{c1j0} \).
\(e_{ijk}\) is the random within-subject residual assumed normally distributed with a mean of 0 and a variance of \(\sigma^2\).

Table 12 presents the results of the linear growth in mathematics achievement.

Table 12

*Linear Growth Model in Mathematics Achievement (Unconditional Model).*

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>SE</th>
<th>(t)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean MATH Achievement in 2009, (\pi_{0jk})</td>
<td>555.405</td>
<td>2.144</td>
<td>259.033***</td>
</tr>
<tr>
<td>ANNUALGRWTH, (\pi_{1jk})</td>
<td>16.866</td>
<td>0.743</td>
<td>22.703***</td>
</tr>
</tbody>
</table>

Student Random Effect

<table>
<thead>
<tr>
<th></th>
<th>Variance</th>
<th>(df)</th>
<th>(\chi^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance in average MATH achievement</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>across students for 2009, (b_{00k})</td>
<td>1962.763</td>
<td>5256</td>
<td>26372.009***</td>
</tr>
<tr>
<td>Variance in ANNUALGRWTH rate</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>across students, (b_{10k})</td>
<td>75.104</td>
<td>5256</td>
<td>6902.415***</td>
</tr>
<tr>
<td>Level 1 error, (e_{ijk})</td>
<td>471.919</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

School Random Effect

<table>
<thead>
<tr>
<th></th>
<th>Variance</th>
<th>(df)</th>
<th>(\chi^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance in aggregate MATH achievement</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>across schools for 2009, (c_{0j})</td>
<td>891.198</td>
<td>198</td>
<td>2463.839***</td>
</tr>
<tr>
<td>Variance in aggregate ANNUALGRWTH</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>rate of students across schools, (c_{1j})</td>
<td>72.902</td>
<td>198</td>
<td>829.975***</td>
</tr>
</tbody>
</table>

*(table 12 continues)*
Table 12 (continued)

Correlations

| Average MATH Achievement at 2009 and ANNUALGROWTH Rate across Students, $r(\tau_{b00\ell|1}(\tau_{b10\ell}))$ | 0.083 |
|---------------------------------------------------------------|-------|
| Average MATH Achievement at 2009 and ANNUALGROWTH Rate across Schools, $r(\tau_{c00/0}(\tau_{c11/0}))$ | 0.360 |

Fit Statistics

<table>
<thead>
<tr>
<th>Deviance</th>
<th>144903.158</th>
</tr>
</thead>
<tbody>
<tr>
<td>BIC</td>
<td>144989.273</td>
</tr>
</tbody>
</table>

***p < .001

The results from the fixed effects show that the average student mathematics achievement at 2009 was 555.405, $t(14302) = 259.033$, $p < .001$, and every year the average charter school student’s mathematics achievement will increase by 16.87 points, $t(14302) = 22.703$, $p < .001$.

The within cell variance, $e_{ijk}$, was 471.919 and the within cell IUCC is 0.1419 which indicates that approximately 14% of the total mathematics scores variance is attributed to error within each year.

The results from the unconditional model show that a statistically significant variation exists across students’ average mathematics achievement, $\tau_{b00\ell} = 1962.763$, $\chi^2(5256) = 26372.009$, $p < .001$. The intra-unit class correlation (IUCC) of test scores over time between students was estimated as 0.5901. This indicates that there is approximately
59\% variation in mathematics achievement over time between students who attended different charter schools.

The $\chi^2$ test statistic of the variation in mathematics achievement growth rate across students was significant, $\tau_{b10k} = 75.104$, $\chi^2 (5256) = 6902.425$, $p < .001$, meaning there is significant variation in learning rates between students. A student with a growth rate measured by one standard deviation, $8.67 (SD = \sqrt{75.104})$, above the average is expected to grow at the rate of 25.54 points ($16.87 + 8.67 = 25.54$) a year on mathematics achievement. A student with a growth rate measured by one standard deviation below the average student ($16.87 - 8.67 = 8.20$) is still expected to grow at the rate of 8.20 points per year.

A statistically significant variation also exists among students in mathematics achievement across schools, $\tau_{c0j0} = 891.198$, $\chi^2 (198) = 2463.839$, $p < .001$. The IUCC for the correlation of test scores over time from different students who attended the same charter school was estimated to be .2680. This indicates that there is approximately 27% variation of mathematics achievement amongst students across charter schools.

The $\chi^2$ test statistic of the variation in aggregate mathematics achievement growth rate of students across schools was significant, $\tau_{c1j0} = 72.902$, $\chi^2 (198) = 829.975$, $p < .001$, meaning there is significant variation in aggregate student learning rates across schools. In a school with an aggregate student growth rate measured by one standard deviation, $8.553 (SD = \sqrt{75.104})$, above the average of the aggregate student growth rate for that school is expected to be 25.41 points ($16.87 + 8.54 = 25.41$) a year on mathematics achievement. In a school with an aggregate student growth rate measured by
one standard deviation below the average \((16.87 - 8.54 = 8.33)\) the expected aggregate growth rate is 8.33 per year.

The correlation between the average mathematics achievement at year 2009 and the annual growth rate across students is \(r = 0.083\). The low correlation indicates that the growth rate is similar across students. The positive correlation (albeit very weak) is an indication that high growth is associated with high achievement across students.

The correlation between the average mathematics achievement at year 2009 and the annual growth rate across schools is \(r = 0.360\). This relationship is low to moderate in strength and it shows the schools with high aggregate achieving students’ are also have high students aggregate growth rate in mathematics achievement.

The deviance for model fit was 144903.158 and the BIC was 144989.273. This creates a baseline statistic to use as comparison as the model is built. The BIC should be reduced as predictors are added to the model which would indicate that the model is a better fit.

**Random-Coefficient Model**

The following predictors were added to the unconditional model to see if they could help explain some of the variability in average achievement and growth rates across students and across schools. This is the first step in model building to answer the question of how school practices affect student mathematics achievement.

The following model (i.e., Model 1) has time varying covariates (i.e., \(EXPER\), \(CERT\), and \(HQ\)) which are school practices that were added as part of the level one predictors. All predictors at each level were analyzed separately to determine whether
they could help explain part of the overall variance (Raudenbush & Bryk, 2002). If the coefficient estimate for each predictor was not statistically significant at the .05 alpha level then the predictor did not remain in the model. *HGHRED* (time-varying predictor) was eliminated from the study after the test for multicollinearity. As explained earlier, this predictor was found to be highly correlated with highly qualified teachers, $r = .415$, (i.e., HQ predictor) and teachers with average teaching experience, $r = .285$, (i.e., EXPER predictor with an average of 7.77 years). This makes sense because one of the criteria for the “highly qualified” classification for teachers is to have an advanced degree and teachers that have been teaching for at least eight years have had time to complete some higher education courses.

Raudenbush & Bryk (2002) state when the preliminary $t$-test ratios for the effects of predictors are near or less than 1.0 the predictors should be excluded from the model. In the preliminary analysis *CERT* (time-varying predictor, grand-mean centered) was eliminated after it was determined not to be a significant predictor of student mathematics achievement, $t(14301) = 0.888$, $p > .05$ (two-tailed). From the research, teachers close to receiving certification (i.e., awarded an emergency certification) are as effective with their students as those who have certification - if they are teaching their specific content area (Darling-Hammond et al., 2001; Goldhaber & Brewer, 2000). Similarly, other researchers using quantitative methods to test whether teaching with a certificate was significantly different from teachers that do not have certification found that teacher certification was not a significant predictor (Croninger et al. 2005; Buddin and Zamarro, 2009). Teacher certification was not required in Arizona charter schools and many charter
schools did not have the funds to pay experienced teachers what they requested, so these two factors (i.e., the lack of certification requirement and school funds) led to many Arizona charter schools hiring less experienced teachers with an emergency teaching certificate. The mean percentage of certified teachers in Arizona charter schools is 58-60% (see Table 7 in Chapter IV for detailed data of mean and standard deviations disaggregated by year).

The preliminary analysis for HQ (time-varying predictor, centered on the median), yielded a $t(14301) = 2.040, p = 0.041$ (two-tailed). However, it was also eliminated after it was determined not to be a significant predictor of student mathematics achievement when paired up in the model building with other variables, $t(14290) = 1.733, p > 0.05$ (two-tailed). EXPER proved to be a significant predictor and was grand-mean centered for the ease of interpretation. The following model is the unconditional model plus the teacher experience predictor (added as a random predictor) to estimate the effect on average student mathematics achievement.

**Model 1**

**Level 1:**

$$\text{MATH}_{ijk} = \pi_{0jk} + \pi_{1jk}(\text{ANNUALGRWTH})_{ijk} + \pi_{2jk}\text{EXPER}_{ijk} + e_{ijk}, \quad e_{ijk} \sim N(0, \sigma^2)$$

\[ i = 2007, 2008, 2009 \]
\[ j = 1, 2, \ldots, J \text{ an index for students} \]
\[ k = 1, 2, \ldots, K \text{ an index for schools} \]
Level 2:

\[
\pi_{0jk} = \theta_{000} + b_{00k} + c_{0j0}
\]

\[
\pi_{1jk} = \theta_{100} + b_{10k} + c_{1j0}
\]

\[
\pi_{2jk} = \theta_{200} + b_{20k} + c_{2j0}
\]

Where:

\( MATH_{ijk} \) is the mathematics achievement at time \( i \) for student \( j \) in school \( k \) with average teacher experience.

\( \pi_{0jk} \) is the predicted average mathematics achievement for student \( j \) in 2009 from the specific combination of schools \( k_{2007}, k_{2008}, \text{and} \ k_{2009} \), adjusting for teacher experience effect.

\( \pi_{1jk} \) is the annual mathematics achievement growth rate for student \( j \) from the specific combination of schools \( k_{2007}, k_{2008}, \text{and} \ k_{2009} \) adjusting for the average teacher experience effect. The predictor \( ANNUALGRWTH \) is centered at the exit time point, 2009, for ease of interpretation.

\( \pi_{2jk} \) is the predicted average effect of teacher experience on student \( j \) mathematics achievement from the specific combination of schools \( k_{2007}, k_{2008}, \text{and} \ k_{2009} \) controlling for annual growth. This predictor was grand mean centered.

\( EXPER_{ijk} \) is the average teacher experience at year \( i \) associated with student \( j \) in school \( k \). It is grand mean centered.

\( \theta_{000} \) is the predicted average students’ mathematics achievement at year 2009 controlling for teacher experience effect across all students and across all schools.
\( \theta_{100} \) is the annual growth rate of mathematics achievement adjusting for teacher
effect across all students and across all schools.

\( \theta_{200} \) is the effect of teacher experience on students’ mathematics achievement in
2009 across all students and across all schools.

\( b_{00k} \) is student random effects associated with the average mathematics
achievement in 2009. It is assumed normally distributed with a mean of 0
and a variance of \( \tau_{b00k} \).

\( b_{10k} \) is student random effects associated with the annual growth rate. It is
assumed normally distributed with a mean of 0 and a variance of \( \tau_{b10k} \).

\( b_{20k} \) is student random effects associated with teacher experience effect. It is
assumed normally distributed with a mean of 0 and a variance of \( \tau_{b20k} \).

\( c_{0j0} \) is school random effects associated with the aggregated mathematics
achievement in 2009. It is assumed normally distributed with a mean of 0
and a variance of \( \tau_{c0j0} \).

\( c_{1j0} \) is school random effects associated with the aggregate annual growth rate. It
is assumed normally distributed with a mean of 0 and a variance of \( \tau_{c1j0} \).

\( c_{2j0} \) is school random effects associated with the aggregate teacher experience
effect. It is assumed normally distributed with a mean of 0 and a variance
of \( \tau_{c2j0} \).

\( e_{ijk} \) is the random within-subject residual assumed normally distributed with a
mean of 0 and a variance of \( \sigma^2 \).

Table 13 presents the results of the coefficient estimates for Model 1.
### Table 13

**Coefficient Model (Model 1)**

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>SE</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean MATH Achievement in 2009, $\pi_{0jk}$</td>
<td>556.207</td>
<td>2.185</td>
<td>254.598***</td>
</tr>
<tr>
<td>ANNUALGRWTH, $\pi_{1jk}$</td>
<td>15.509</td>
<td>0.825</td>
<td>18.806***</td>
</tr>
<tr>
<td>EXPER, $\pi_{2jk}$</td>
<td>2.925</td>
<td>0.511</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Student Random Effect</th>
<th>Variance</th>
<th>df</th>
<th>$\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance in average MATH achievement across students for 2009, $b_{00k}$</td>
<td>1997.996</td>
<td>2706</td>
<td>7317.243***</td>
</tr>
<tr>
<td>Variance in ANNUALGRWTH across students, $b_{10k}$</td>
<td>99.362</td>
<td>2706</td>
<td>3530.932***</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Student Random Effect</th>
<th>Variance</th>
<th>df</th>
<th>$\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance in teacher EXER effect on MATH achievement across students, $b_{20k}$</td>
<td>2.281</td>
<td>2706</td>
<td>2970.010***</td>
</tr>
<tr>
<td>Level 1 error, $e_{ijk}$</td>
<td>424.115</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

(table 13 continues)
Table 13 (continued)

<table>
<thead>
<tr>
<th>School Random Effect</th>
<th>Variance</th>
<th>df</th>
<th>$\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance in average MATH achievement</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>across schools for 2009, $c_{0j0}$</td>
<td>800.716</td>
<td>141</td>
<td>1391.565***</td>
</tr>
<tr>
<td>Variance in ANNUALGRWTH of</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>students across schools, $c_{1j0}$</td>
<td>79.162</td>
<td>141</td>
<td>612.890***</td>
</tr>
<tr>
<td>Variance in teacher EXPER effect on</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MATH achievement across schools, $c_{2j0}$</td>
<td>30.476</td>
<td>141</td>
<td>647.354***</td>
</tr>
</tbody>
</table>

Correlations

Average MATH achievement in 2009 & ANNUALGRWTH
across students, $r(\tau_{b00k}, \tau_{b10k})$ 0.138

Average MATH achievement in 2009 & teacher EXPER effect
across students, $r(\tau_{b00k}, \tau_{b20k})$ -0.431

ANNUALGRWTH & teacher EXPER effect across students,
$r(\tau_{b10k}, \tau_{b20k})$ -0.443

Correlations

Average MATH achievement in 2009 & ANNUALGRWTH
across schools, $r(\tau_{c0j0}, \tau_{c1j0})$ 0.398

Average MATH achievement in 2009 & teacher EXPER effect
across schools, $r(\tau_{c0j0}, \tau_{c2j0})$ 0.009

(table 13 continues)
The results from Model 1 show that the average mathematics achievement of an Arizona Grade 8 charter school student who has a teacher with an average amount of teaching experience (i.e., 7.77 years) in the exit year (i.e., 2009) was 556.21 on AIMS for mathematics. The charter school students have an annual growth rate of 15.51 scale scores after adjusting for teacher experience. The mean effect of teacher experience ($M = 7.77$ years) on students’ mathematics achievement scores is 2.92 points.

The within cell variance was, $\varepsilon_{ijk} = 424.115$ and the proportional reduction in variance (i.e., $\sigma^2_{(Model 1)} - \sigma^2_{(Full Model)} / \sigma^2_{(Model 1)}$) for the within variance of this model from the unconditional model due to the added predictor, $EXPER$, was 0.101. This is an indication that approximately 10% of the within variance was explained by the addition of teacher experience to the model. The IUCC proportion of variability between mathematics achievement scores from one year to the next for a student, $j$, who attended the same charter school within the years 2007-2009 (i.e., within cells) was estimated as 0.131.
There was statistically significant variation across students’ average mathematics achievement in 2009 even when adjusting for teacher experience effects, $\tau_{b00k} = 1997.996$, $\chi^2 (2706) = 7317.243$, $p < .001$. The proportional reduction in the variance of student average achievement of this model from the unconditional model was -0.017 across students. The predictor added to Model 1 is a school variable so it is reasonable that the reduction in variance across students be a negligible amount (less than 2%) (McCoach & Black, 2008). The student-IUCC is the correlation of achievement over time for a student, $j$, who attended different charter schools. This was estimated to be 0.620 and indicates that there is approximately 62% of the total mathematics achievement variation that lies between students.

The $\chi^2$ test statistic of the mathematics achievement growth rate adjusting for $EXPER$ across students was significant, $\tau_{b10k} = 99.362$, $\chi^2 (2706) = 3530.932$, $p < .001$, meaning there is significant variation in student learning rates. A student with a growth rate measured by one standard deviation ($SD = \sqrt{99.362} = 9.968$) above the average is expected to grow at the rate of 25.48 points (i.e., $15.51 + 9.97$) a year on mathematics achievement. A student with a growth rate measured by one standard deviation below the average student is expected to grow at the rate of 5.54 (i.e., $15.51 – 9.97$) per year.

The variability in the effect of teacher experience on mathematics achievement in grade 8 (i.e., exit year, 2009) across students was also statistically significant, $\tau_{b20k} = 2.281$, $\chi^2 (2706) = 2970.010$, $p < .001$. This means that on average, Grade 8 students taught by a teacher (with 7.77 years of experience) whose effect is measured by one standard deviation ($SD = \sqrt{2.281} = 1.510$) above the average teaching experience effect
will have an expected student average achievement of 560.63 (556.21 + 2.925*1.51 = 560.63). Students taught by a teacher with an experience effect that is measured by one standard deviation below the average teacher experience effect will have an expected average achievement of 551.79 (556.21 + 2.925*[-1.51] = 551.79).

The variation among aggregate students’ mathematics achievement in 2009 with a teacher with average experience across schools was statistically significant, \( \tau_{c00} = 800.716, \chi^2 (141) = 1391.565, p < .0001 \). This indicates that there is variance in average students’ mathematics achievement yet to be explained across schools. The proportional reduction across-school variance of this model from the unconditional model was .102 across schools. This indicates that by adding the \textit{EXPER} predictor that approximately 10% of the variance was explained across schools. The school-IUCC is the correlation of mathematics achievement over time from different students who attended the same charter school. This was estimated to be .248 which indicates that there is approximately 25% variation between charter schools.

The \( \chi^2 \) test statistic of the aggregate mathematics achievement growth rate across schools was significant, \( \tau_{c10} = 79.162, \chi^2 (141) = 612.890, p < .001 \), meaning there is significant variation in student learning rates across schools. In a school with aggregate student growth rate measured by one standard deviation (\( SD = \sqrt{79.162} = 8.897 \)) above the average is expected to show a growth rate of 24.41 points (i.e., 15.51 + 8.90 = 24.41) a year on mathematics achievement. In a school with aggregate student growth rate measured by one standard deviation below the average it is expected to show a growth rate of 6.61 points (i.e., 15.51 – 8.90 = 6.61) per year.
The effect of teacher experience on students’ aggregate mathematics achievement in grade 8 (i.e., exit year, 2009) across schools showed statistically significant variation, $\tau_c^{20}=32.48$, $\chi^2(141) = 647.354$, $p < .001$. On average, Grade 8 students attending a school with teachers (with 7.77 years of experience) whose experience effect measured by one standard deviation ($SD = \sqrt{30.476} = 5.52$) above the average teaching experience effect will have an expected aggregate student mathematics achievement of 572.36 (i.e., $556.21 + 2.925\times5.52 = 572.36$). Students attending a school where the level of teaching experience effect measured by one standard deviation below the average will have an expected aggregate mathematics score of 540.06 (i.e., $556.21+ 2.925\times[-5.52] = 540.06$).

There is a weak relationship between average mathematics achievement in 2009 and annual growth rate across students, $r = 0.138$. This positive correlation implies that high achieving students show high growth; yet this is not a strong relationship. There is a moderate negative relationship between average mathematics achievement in 2009 and teacher experience effect across students, $r = -0.431$. This correlation shows that the teacher experience effect on mathematics achievement is more influential for students with low average achievement. Finally, the correlation between the annual growth rate and teacher experience effect across students, $r = -0.443$, showed a moderate negative relationship and is an indication that high teacher experience effect on mathematics achievement tends to be more pronounced for students with a lower growth rate.

The correlation between average mathematics achievement in 2009 and annual growth rate across schools was, $r = 0.398$. This moderate relationship across schools indicates that high aggregate mathematics achievement is associated with high growth
rates across schools. The correlation between average mathematics achievement in 2009 and teacher experience effect on math achievement across schools, $r = 0.009$, shows that there is practically no relationship. Finally, the correlation between aggregate annual growth rate and teacher experience effect on math achievement across schools was $r = -0.187$. This negative weak relationship shows that the effect of teacher experience on math achievement tends to be more pronounced in schools with lower aggregate growth rates across schools.

The deviance for model fit was 144656.99 and the BIC was 144810.086. The BIC difference of Model 1 from the Unconditional Model was 179.187 which is an indication that Model 1 is a very strong model (Raftery, 1995). This model was considered the base model for the best fit statistics (See Table 18 for an overall summary of the best fit statistics). The Level two predictors were added one at a time until reaching the best fit model (i.e. Full model) (Raudenbush & Bryk, 2000).
Full Model

The following model is the Full model. The student characteristics are added to the model to more closely define the “average” student who attends an Arizona charter school, but the focus of the study is how the school practices effect student achievement at the exit year (i.e., 2009) and over time. All level two predictors were added one at a time. If the coefficient estimate was not statistically significant at .05 alpha level then the predictor was pulled from the analysis. Each predictor was entered as a random factor unless the effect was not statistically significant. If this were the case the predictor was placed in the model as a fixed effect. The BIC was determined for each predictor added to see if the predictor contributed to a parsimonious model.

EXPER and CLASS were grand mean centered for ease of interpretation in this next model. HQ and CERT were removed early in the building process due to non-significant t-ratios warranting them as not significant predictors (as mentioned in detail in the section prior to the Model 1 results). The school characteristic, CONV, although statistically significant \( \delta_{02} = 15.778, t(14291) = 3.155, p < 0.01, \) indicated that students who attended an Arizona charter middle school that was converted from a traditional public school scored nearly 16 points higher than the average student (as described by this model) in mathematics; this predictor did not contribute to the parsimony of the model (i.e., the BIC was higher with this variable included in the model than the last model indicating that the last model was a better fit), therefore it was removed from the model. OUTFLD had to be removed as a predictor because it was not statistically significant, \( \delta_{03} = -6.372, t(14288) = -1.815, p = .069, \) although, this negative
effect concurs with the Goldhaber et al (2000) study. **OUTFLD** did not add to the parsimony of the model as measured by the BIC and deviance indices. The student variable, **ELL**, was initially a predictor for **ANNUALGRWTH** but was later pulled from that portion of the model because as predictors were added to the model, **ELL** became statistically insignificant under **ANNUALGRWTH**, \( \gamma_{11} = 2.869, t(14291) = 1.917, p = .055 \), and more importantly it did not add to the parsimony of the model. **FEMALE** was removed when it was discovered that this statistically significant predictor, \( \gamma_{09} = -2.869, t(14294) = -2.529, p = .012 \), did not add to the parsimony of the model. In addition, the comparison of reliability of the student effects with the gender predictor in the model, reliability **FEMALE**\((b_{00k}) = 0.48\), to the model without **FEMALE**, reliability\((b_{00k}) = 0.92\), ranged 54 percentage points in favor of the model without **FEMALE**. This concurs with NAEP Arizona Grade 8 data regarding gender differences for mathematics. The Arizona NAEP trend line shows that gender is not statistically significant across the years NAEP was administered in Arizona, including 2009 (See Appendix H).

**Full Model.**

**Level 1 (TIME):**

\[
\text{MATH}_{ijk} = \pi_{0jk} + \pi_{1jk}(\text{ANNUALGRWTH})_{ijk} + \pi_{2jk}\text{EXPER}_{jk} + e_{ijk}, \quad e_{ijk} \sim \mathcal{N}(0, \sigma^2)
\]

\(i = 2007, 2008, 2009\)

\(j = 1, 2, \ldots, J\) an index for students

\(k = 1, 2, \ldots, K\) an index for schools

**Level 2 model (STUDENT and SCHOOL):**

\[
\pi_{0jk} = \theta_{000} + \gamma_{01}(\text{HISP})_{0j} + \gamma_{02}(\text{N\_AMER})_{0j} + \gamma_{03}(\text{BLCK})_{0j} + 
\]
$\gamma_{04}^{(ASI\text{AN})_{04j}} + \gamma_{05}^{(SD)_{05j}} + \gamma_{06}^{(ELL)_{06j}} + \gamma_{07}^{(FRL)_{07j}} +$

$\gamma_{08}^{(CHRTR06)_{08j}} + \delta_{01}^{(CLASS)_{01k}} + b_{00k} + c_{0j0}$

$\pi_{1jk} = \theta_{100} + b_{10k} + c_{1j0}$

$\pi_{2jk} = \theta_{200} + b_{20k} + c_{2j0}$

*Where:*

\( \text{MATH}_{ijk} \) is the mathematics achievement at time \( i \) for student \( j \) in school \( k \) with average teacher experience.

\( \pi_{0jk} \) is the predicted average mathematics achievement for student \( j \) in 2009 from the specific combination of schools \( k_{2007}, k_{2008}, \text{and } k_{2009} \), adjusting for school practices and student characteristics’ effects.

\( \pi_{1jk} \) is the annual mathematics achievement growth rate for student \( j \) from the specific combination of schools \( k_{2007}, k_{2008}, \text{and } k_{2009} \) adjusting for the average teacher experience effect. The predictor \( \text{ANNUALGRWTH} \) is centered at the exit time point, 2009, for ease of interpretation.

\( \pi_{2jk} \) is the predicted effect of teacher experience on student \( j \) in mathematics achievement in 2009 from the specific combination of schools \( k_{2007}, k_{2008}, \text{and } k_{2009} \). This predictor was grand mean centered.

\( \text{EXPER}_{ijk} \) is the average teacher experience at year \( i \) associated with student \( j \) in school \( k \). It is grand mean centered.
\( \theta_{000} \) is the predicted average students’ mathematics achievement at year 2009 controlling for student characteristics and school practices across all students and across all schools.

\( \gamma_{0q} \) are fixed effects of student characteristics’ predictors, \( X_{qj} \); where \( q = 1, 2, 3, \ldots, Q \) is an index for student’s characteristics.

\( \delta_{0r} \) are fixed effects of school practices’ predictors, \( Y_{rk} \); where \( r = 1, 2, 3, \ldots, R \) is an index for school practices.

\( \theta_{100} \) is the average annual growth rate in mathematics achievement adjusting for teacher experience effect across all students and all schools.

\( \theta_{200} \) is the effect of teacher experience on students’ mathematics achievement in 2009 across all students and all schools.

\( b_{00k} \) is students’ random effects associated with the average mathematics achievement in 2009. It is assumed normally distributed with a mean of 0 and a variance of \( \tau_{b00k} \).

\( b_{10k} \) is student random effects associated with the annual growth rate. It is assumed normally distributed with a mean of 0 and a variance of \( \tau_{b10k} \).

\( b_{20k} \) is student random effects associated with teacher experience effect. It is assumed normally distributed with a mean of 0 and a variance of \( \tau_{b20k} \).

\( c_{0j0} \) is school random effects associated with the aggregate mathematics achievement in 2009. It is assumed normally distributed with a mean of 0 and a variance of \( \tau_{c0j0} \).
$c_{1j0}$ is the school random effects associated with the annual growth rate. It is assumed normally distributed with a mean of 0 and a variance of $\tau_{c1j0}$.

$c_{2j0}$ is school random effect associate with teacher experience effect. It is assumed normally distributed with a mean of 0 and a variance of $\tau_{c2j0}$.

$e_{ijk}$ is the random within-subject effect assumed normally distributed with a mean of 0 and a variance of $\sigma^2$.

The results for the model are in Table 14.

**Table 14**

*Random-Coefficient Model (Full Model).*

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>SE</th>
<th>$t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean MATH Achievement in 2009, $\pi_{0jk}$</td>
<td>547.217</td>
<td>6.078</td>
<td>90.034***</td>
</tr>
<tr>
<td>HISP, $\gamma_{01}$</td>
<td>-16.098</td>
<td>1.613</td>
<td>-9.979***</td>
</tr>
<tr>
<td>N_AMER, $\gamma_{02}$</td>
<td>-19.532</td>
<td>3.533</td>
<td>-5.528***</td>
</tr>
<tr>
<td>BLCK, $\gamma_{03}$</td>
<td>-22.079</td>
<td>2.491</td>
<td>-8.865***</td>
</tr>
<tr>
<td>ASIAN, $\gamma_{04}$</td>
<td>14.123</td>
<td>3.104</td>
<td>4.550***</td>
</tr>
<tr>
<td>SD, $\gamma_{05}$</td>
<td>-48.052</td>
<td>1.808</td>
<td>-26.570***</td>
</tr>
<tr>
<td>ELL, $\gamma_{06}$</td>
<td>-26.991</td>
<td>2.911</td>
<td>-9.271***</td>
</tr>
<tr>
<td>FRL, $\gamma_{07}$</td>
<td>-13.746</td>
<td>1.454</td>
<td>-9.455***</td>
</tr>
<tr>
<td>CHRTR06, $\gamma_{08}$</td>
<td>5.522</td>
<td>1.201</td>
<td>4.596***</td>
</tr>
<tr>
<td>CLASS, $\delta_{01}$</td>
<td>1.391</td>
<td>0.298</td>
<td>4.665***</td>
</tr>
</tbody>
</table>

(table 14 continues)
Table 14 (continued)

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>SE</th>
<th>( t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANNUALGRWTH, ( \pi_{1jk} )</td>
<td>15.953</td>
<td>0.795</td>
<td>20.058***</td>
</tr>
<tr>
<td>EXPER, ( \pi_{2jkl} )</td>
<td>2.445</td>
<td>0.457</td>
<td>5.348***</td>
</tr>
</tbody>
</table>

Student Random Effect

| Variance in average MATH achievement across students for 2009, \( b_{00k} \) | 1704.303 | 2697 | 6752.545*** |
| Variance in ANNUALGRWTH across students, \( b_{10k} \) | 94.026 | 2706 | 3458.699*** |
| Variance in teacher EXPER effect on achievement across students, \( b_{20k} \) | 1.340 | 2706 | 2892.239** |
| Level 1 error, \( e_{ijk} \) | 423.180 |

School Random Effect

| Variance in aggregate MATH achievement across schools for 2009, \( c_{0j0} \) | 495.675 | 132 | 1126.842*** |
| Variance in aggregate ANNUALGRWTH rate across schools, \( c_{1j0} \) | 75.640 | 141 | 629.590*** |
| Variance in aggregate teacher EXPER effect across schools, \( c_{2j0} \) | 24.019 | 141 | 647.078*** |

(table 14 continues)
Table 14 (continued)

Reliabilities of coefficient estimates

| Average MATH achievement across students for 2009 | 0.924 |
| Aggregate MATH achievement across schools for 2009 | 0.779 |

<table>
<thead>
<tr>
<th>School Random Effect</th>
<th>Variance</th>
<th>df</th>
<th>$\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance in aggregate MATH achievement across schools for 2009, $c_{0j0}$</td>
<td>495.675</td>
<td>132</td>
<td>1126.842***</td>
</tr>
<tr>
<td>Variance in aggregate ANNUALGRWTH rate across schools, $c_{1j0}$</td>
<td>75.640</td>
<td>141</td>
<td>629.590***</td>
</tr>
<tr>
<td>Variance in aggregate teacher EXPER effect across schools, $c_{2j0}$</td>
<td>24.019</td>
<td>141</td>
<td>647.078***</td>
</tr>
</tbody>
</table>

Reliabilities of coefficient estimates

| Average MATH achievement across students for 2009 | 0.924 |
| Aggregate MATH achievement across schools for 2009 | 0.779 |
| Average ANNUAL GRWTH in MATH achievement across students for 2009 | 0.400 |

(table 14 continues)
The coefficient estimation for the intercept of the Full Model is explained as an Arizona Grade 8 white English proficient student who does not have a learning disability and pays for school lunch. This student attends a charter school that started from scratch with an average class size of 18 students, did not attend a charter school in 2006 (Grade 5) and has a teacher with 7.77 years of teaching experience. The average mathematics scale score for this student was approximately 547 in 2009. (As mentioned earlier, the predictors \( \text{EXPER} \) and \( \text{CLASS} \) were grand mean centered for ease of interpretation).

The student characteristic coefficients are reflective of Arizona NAEP scores. See Appendices I for Arizona NAEP 2009 Mathematics scores for race, gender, students with disabilities, English language learners, and students eligible for the free and reduced lunch program. Just as reported in NAEP, with the exception of Asian students, Arizona White students scored higher than all other races/ethnicities. Students eligible for the National Free and Reduced Lunch Program scored similarly on the NAEP; however, students with disabilities scored lower on AIMS, \( \gamma_{05} = -48.052, t(14292) = -26.570, p < \)
0.001, than English language learners, $\gamma_{06} = -26.991$, $t(14292) = -9.271$, $p < 0.001$. This is reverse on the NAEP.

Attending a charter school in 2006 (one year prior to this study – grade 5) is positively related to mathematics achievement in 2009, $\gamma_{08} = 5.522$, $t(14292) = 4.596$, $p < 0.001$. This concurs with research on student mobility stating that switching schools negatively affects student achievement (Solmon, Paark, & Garcia, 2001). Class size has a positive effect on student mathematics achievement in 2009, $\delta_{01} = 1.391$, $t(14292) = 4.665$, $p < 0.001$, but it does not have as profound of an effect as the other school predictors in Table 14. This fixed effect of average class size (i.e., 18 students per classroom) in 2009 indicates that a student placed in a classroom with at least 18 students would cause his/her predicted mathematics achievement score to increase to 548.61 (i.e., $547.22 + 1.39 = 548.61$).

The annual growth rate of mathematics achievement, adjusting for teacher experience, for an average (i.e., as defined by this study) Grade 8 charter school student is 15.95 points.

The variance within cells was $e_{ijk} = 423.180$, with a standard deviation of 20.57. The within cell proportional reduction of the variance of this model in comparison to Model 1 was .001, meaning that by adding these predictors 0.13% of the within variance is explained. This is a negligible amount (less than 2%) (McCoach & Black, 2008). This is reasonable considering AIMS is administered approximately the same day every year in the same manner (Arizona Department of Education, personal communication, September 9, 2009). For this model, the IUCC indicates that the correlation between
mathematics achievement scores from one year to the next for a student, \( j \), who attended the same charter school within the years 2007-2009 was \( r = 0.1613 \).

The variance of the average mathematics achievement in 2009 across students was statistically significant, \( \tau_{b00k} = 1704.303, \chi^2 (2697) = 6752.545, p < .001 \), indicating that there is more variance to be explained. The proportional reduction of variance from the Full model compared to Model 1 was 0.147 which means that approximately 15% of the variance between students is explain by the predictors added to this model. The IUCC of mathematics achievement for students was .650, meaning that a substantial proportion of variability (65%) remains unexplained over time for a student, \( j \), who attend different schools. This substantiates the problem with trying to assess student achievement for students that move from school to school. This model showed a positive effect on mathematics achievement for attending a charter school in Grade 5 but, yet, the proportion of variability for a student who attends different schools is extensive.

The variance of the growth rate, adjusting for teacher experience, across average mathematics achievement of (i.e., as defined by this study) Grade 8 charter school students was statistically significant, \( \tau_{b10k} = 94.026, \chi^2 (2706) = 3458.699, p < .001 \), signifying there is more variance to be explained in the growth rate coefficient across the student. A student with a growth rate one standard deviation (\( SD = \sqrt{94.026} = 9.70 \)) above the average growth rate (15.95) is expected to grow at the rate of 25.65 points (i.e., 15.95 + 9.70 = 25.65) a year on mathematics achievement. A student with a growth rate one standard deviation below the average student growth rate (15.95) is expected to grow at the rate of 6.25 (i.e., 15.95 – 9.70) per year. The proportional reduction of variance of
annual growth across students from Model 1 to the Full Model (i.e., $\tau_{b10k(\text{Model 1})} - \tau_{b10k(\text{Full Model})}$) was .054, indicating that 5% of the annual growth variance across students is explained by adding the Full model predictors.

Teachers’ experience has a significant effect on average students mathematics scores ($\pi_{j2k} = 2.445, t[14292], p < .001$). This effect, however, varies across students, $\tau_{b20k} = 1.340, \chi^2 (2706) = 2892.239, p < .01$. This means that some teachers with average years experience are more effective than others. So on average, a Grade 8 student (as defined by this study) that has a teacher with 7.77 years of experience that is more effective by one standard deviation above the average (i.e., $SD = \sqrt{1.340} = 1.158$) would have an expected mathematics achievement score of 550.05 ($547.22 + 2.445 \times 1.158 = 550.05$) and the achievement score of a student that has a teacher that is not as effective (one standard deviation below the average) their achievement would have an expected 544.39 ($547.217 + 2.445 \times [-1.158] = 544.39$).

The reduction of variance of teacher experience effect across students from Model 1 to the Full Model (i.e., $\tau_{b20k(\text{Model 1})} - \tau_{b20k(\text{Full Model})} / \tau_{b20k(\text{Model 1})}$) was 0.413. This indicates that 41% of the teacher effect variance across students is explained by adding the Full model predictors.

Although there is still significant variability to be accounted for across schools in terms of their aggregate students’ mathematics achievement at 2009, $\tau_{c00} = 495.675, \chi^2 (132) 1126.842, p < .001$, the proportional reduction of variance across schools was .381 (38%) when comparing the Full model to Model 1. This means that 38% of the variance across schools is explained by the predictors included in this model. The school – IUCC
was 0.190, meaning that the proportion of variability that remains unexplained is 19% between mathematics achievement over time for different students attending the same school.

The annual aggregate growth for mathematics achievement across schools for an average Grade 8 student was statistically significant, $\tau_{c1,0} = 75.640, \chi^2(141) = 629.590, p < .001$. The annual aggregate student growth rate in a school with one standard deviation ($SD = \sqrt{75.64} = 8.70$) above the average school is expected to grow at the rate of 24.74 points (i.e., $15.95 + 8.70 = 24.65$) a year on mathematics achievement. The annual aggregate student growth rate in a school with one standard deviation below the average school is expected to grow at the rate of 7.25 (i.e., $15.95 - 8.70 = 7.25$) per year. The reduction of variance between the variance of annual aggregate growth across schools from Model 1 to the Full Model was .044, indicating that 4% of the variance for annual growth across schools is explained by adding the Full model predictors. Needless to say, there is quite a bit of variance yet to be explained across schools from factors not considered in this study. Mathematics growth rate can vary from one school to another based on the students’ mathematics ability and courses offered at the school; for example, if charter schools are targeting a certain population (e.g., special education or college bound students) then the variance between schools will be greater.

The aggregate effect of teacher experience on students’ mathematics achievement in grade 8 (i.e., exit year, 2009) across schools showed statistically significant variation, $\tau_{c2,0} = 24.019, \chi^2(141) = 647.078, p < .001$, considerably more than across students. The coefficient estimate showed that an average grade 8 student who has a teacher with
average teaching experience (7.77 years) has a gain in mathematics achievement scores of 2.45 points. Some teachers with 7.77 years of experience are more effective than others. The effect of teacher experience for Grade 8 students across schools measured by one standard deviation ($SD = \sqrt{24.019} = 4.90$) above the average is 4.90 indicating that an expected aggregate student achievement would be 559.20 ($547.22 + 2.445 \times 4.90 = 559.20$). On the aggregate school level, Grade 8 students that have teachers with 7.77 years of experience who are less effective than the average teacher measured by one standard deviation (-4.90) would be expected to have an aggregate achievement score of 535.24 ($547.22 + 2.445 \times [-4.90] = 535.24$).

Thus, empirically, it is critical that charter schools hire experienced teachers that are effective because the range on mathematics achievement for an average Grade 8 student from one standard deviation above and below the mean is expected to be 535.24 to 559.20 scale score points. Across schools, the difference of effectiveness from teaching experience may result in a 23.96 gain in scale scores.

See Table 15 to view the range of mathematics achievement scores influenced by teacher experience effect across students and across schools. The effect of teacher experience across students is a small range indicating high consistency; whereas the effect of teacher experience across schools showed a large range emphasizing the necessity to work with teachers to become more effective in teaching mathematics.
The proportional reduction of variance of the teacher experience effect across schools from Model 1 to the Full Model was .212 indicating that 21% of the teacher effect variance across schools is explained by adding the Full model predictors. This indicates that the effect is more profound on individual students. The added predictors reduced a greater amount of variance (41%) for teacher experience effect on student achievement across students but reduced only one fifth (21%) of the variance in the aggregate effect of teacher experience across schools.
After determining the reduction in variance and the IUCC, the next step was to look at the relationship between mathematics achievement to the annual growth rate, achievement to teacher experience effect, and the relationship of the growth rate and teacher experience effect.

The correlations among average mathematics achievement (i.e., the intercept), the growth rate of mathematics achievement, and the effect of teacher experience on mathematics achievement across students are found in Table 16. A low positive correlation was found ($r = 0.161$) between student’ growth rate and mathematics achievement at year 2009. This is an indication that higher achievement is associated with higher growth rate yet the relationship is only fair in strength.

There was a moderate negative correlation ($r = -0.463$) between the average mathematics achievement and teacher experience effect on mathematics achievement for 2009 across students. This is an indication that there was a more pronounced effect of teacher experience on lower achieving students than higher achieving students. Experienced teachers can produce better results with low achieving students.

The correlation between student growth rate and teacher experience effect across students was also a moderate negative correlation ($r = -0.531$). This indicates that teacher experience is more effective with students that have a lower growth rate. Empirically this study shows that, for mathematics achievement, students with a lower growth rate are influenced by more experienced teachers.
When examining the correlations among average mathematics achievement, the growth rate of mathematics achievement, and the effect of teacher experience on mathematics achievement across schools there is somewhat a different picture painted than was the case with the across student correlations (see Table 17). The across students correlations showed that teacher experience effect has the greatest impact on lower achieving students and that the students that were influenced the most by the teacher experience effect were those that had a lower growth rate. With the across school correlations, the correlation between the aggregate mathematics achievement in a school and the annual growth rate is moderate and positive, $r = .525$, meaning that across schools higher achievement is associated with higher growth rate. This result is interesting because individually the relationship was very low but across the schools the aggregate growth is more prominent for the higher achieving students.
The correlation between the aggregate mathematics achievement and the teacher experience effect is negligible, $r = .064$, indicating there is no relationship between teacher experience effect and student achievement across schools; although this relationship was at least moderate on the student level ($r = -.463$). This is an example of a reversal paradox where you see one relationship when you disaggregate the data and the reverse relationship when you aggregate the data (e.g., looking at individual students with no indication of school membership as oppose to aggregating to the school level). When you aggregate the data to the school level (i.e., membership to a school is accounted for) many factors can come into play. For example, the majority of the students in one school (e.g., the higher achieving students) could be so large that it overshadows the relationship seen with the minority students (e.g., lower achieving students). This could look as though there is barely a relationship seen between teacher experience effect and mathematics achievement and that the only relationship seen is with the higher achieving students (Tu, Gunnell, & Gilthorpe, 2008). The relationship seen with individual students is hidden when only looking at the school level.

The correlation between the aggregate annual growth rate in a school and the effect of teacher experience across schools was low, $r = -0.184$, indicating that over time the growth that is seen across schools from teacher experience effect is coming from the students with a lower growth rate (certainly not as prominent as at the student level, $r = -0.531$). Apparently there are many other factors aside from teacher experience effect that play a role in the aggregate growth rate across school relationships not captured in this study.
Table 17

*Correlations for Mathematics Achievement across Schools.*

<table>
<thead>
<tr>
<th></th>
<th>Mean MATH Achievement</th>
<th>Annual Growth Rate</th>
<th>Teacher Experience Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean MATH Achievement</td>
<td>-</td>
<td>.525</td>
<td>.064</td>
</tr>
<tr>
<td>Annual Growth Rate</td>
<td>-</td>
<td></td>
<td>-.184</td>
</tr>
<tr>
<td>Teacher Experience Effect</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note: Schools (n = 261)*

The deviance for this model was 143485.137 and the BIC was 143724.344. The difference BIC between Model 1 and this model was $\Delta BIC = 1085.742$. A comparison of deviance and BIC fit statistics as the model progressed to the Full model is in Table 18.

The focus of this study is on school practices (as defined in Chapter II) which are the school predictors and how they affect student achievement; however, as the student level predictors were added to the model the difference in the BIC fit statistic was quite large (in favor of the later models). The difference in the BIC statistic for mathematics when $SD$ and $FRL$ were added was, $\Delta BIC = 603.519$. See Tables 18 for more details.

This is reasonable considering the student predictors are distinguishing between students. For example, students who have a learning disability or are English language learners will have a disadvantage in mathematics.

Once the student was described, the BIC difference statistic tapered off as one school predictor was added at a time, although, still reported a decline in the difference statistic with a “very strong” grade on the Rafterty (1995) “Grades of Evidence” table.
<table>
<thead>
<tr>
<th>Model</th>
<th>Deviance</th>
<th>Number of Parameters</th>
<th>BIC</th>
<th>ΔBIC</th>
<th>Evidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>MATH Unconditional ANNUALGRWTH Model</td>
<td>144903.158</td>
<td>9</td>
<td>144989.273</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Model 1 (ANNUALGRWTH + EXPER)</td>
<td>144656.993</td>
<td>16</td>
<td>144810.086</td>
<td>179.187</td>
<td>Very Strong</td>
</tr>
<tr>
<td>+ RACE</td>
<td>144416.891</td>
<td>20</td>
<td>144429.455</td>
<td>380.631</td>
<td>Very Strong</td>
</tr>
<tr>
<td>+ RACE, FEMALE, SD, FRL</td>
<td>143615.434</td>
<td>22</td>
<td>143825.936</td>
<td>603.519</td>
<td>Very Strong</td>
</tr>
<tr>
<td>+ RACE, FEMALE, SD, FRL, ELL</td>
<td>143527.143</td>
<td>23</td>
<td>143747.214</td>
<td>78.723</td>
<td>Very Strong</td>
</tr>
<tr>
<td>+ RACE, FEMALE, SD, FRL, ELL, CHRTR06</td>
<td>143506.139</td>
<td>24</td>
<td>143735.778</td>
<td>11.435</td>
<td>Very Strong</td>
</tr>
<tr>
<td>+ RACE, FEMALE, SD, FRL, ELL, CHRTR06, CLASS</td>
<td>143485.137</td>
<td>25</td>
<td>143724.344</td>
<td>11.434</td>
<td>Very Strong</td>
</tr>
</tbody>
</table>

*Note.* The rating of evidence is from Raftery (1995). *N = 14304*
The following section is the results from running the analyses using the reading achievement as the outcome. An unconditional model, a baseline model, and the full model are fully described including predictors that were removed from the model for various reasons. Correlations across students and across schools for reading achievement, the reading growth rate, and teacher experience effect are fully reported. Lastly, the fit statistics for reading achievement are reported showing the progression to the full model.

READING

This same analysis was run with the reading achievement scale scores from AIMS as was the mathematics scores. Model building started with an unconditional linear growth model (no level one or level two predictors) as suggested by Raudenbush and Bryk (2002). The purpose of the unconditional model is to give baseline statistics necessary for building a parsimonious model. In the model the time-varying predictors were added one by one, to level one, to assess their effect on reading achievement. Predictors with coefficient estimates that were significantly different from zero were kept in the model. This was done to create a base model (i.e., Model 1). Then Level two predictors were added one at a time to assess their effect on reading achievement (Raudenbush & Bryk, 2002; McCoach & O’Donnell, 2001). Each predictor effect was treated as a random effect across students and across schools; however if their variance component (i.e., tau) was not significantly different from zero, the current model was run again with those predictors as fixed effects. The following is the unconditional model. The BIC was determined for each model to determine the parsimony (see Tables 24).
Based on these criteria the following models were run in the HLM/CCREM computer program.

**Unconditional Model**

Level 1:

\[ \text{READ}_{ijk} = \pi_{0jk} + \pi_{1jk}(\text{ANNUALGRWTH})_{ijk} + e_{ijk}, \quad e_{ijk} \sim N(0, \sigma^2) \]

\( i = 2007, 2008, 2009 \)

\( j = 1, 2, \ldots, J \) an index for students

\( k = 1, 2, \ldots, K \) an index for schools

Level 2:

\[ \pi_{0jk} = \theta_{000} + b_{00k} + c_{0j0} \]

\[ \pi_{1jk} = \theta_{100} + b_{10k} + c_{1j0} \]

\[ b_{00k} \sim N(0, \tau_{b00k}) \]

\[ c_{0j0} \sim N(0, \tau_{c0j0}) \]

\[ b_{10k} \sim N(0, \tau_{b10k}) \]

\[ c_{1j0} \sim N(0, \tau_{c1j0}) \]

Where:

\( \text{READ}_{ijk} \) is the reading achievement at time \( i \) for student \( j \) in school \( k \).

\( \pi_{0jk} \) is the predicted average reading achievement for student \( j \) in 2009 from the specific combination of schools \( k_{2007}, k_{2008}, \text{and } k_{2009} \).

\( \pi_{1jk} \) is the annual reading achievement growth rate for student \( j \) from the specific combination of schools \( k_{2007}, k_{2008}, \text{and } k_{2009} \). The predictor
ANNUALGROWTH is centered at the exit time point, 2009, for ease of interpretation.

θ₀₀₀ is the predicted average students’ reading achievement at year 2009 across all students and across all schools.

θ₁₀₀ is the average annual growth rate of reading achievement across all students and across all schools.

b₀₀⁰ is the student random effects associated with the average reading achievement in 2009. It is assumed normally distributed with a mean of 0 and a variance of τ₀₀⁰.

b₁₀⁰ is the student random associated with the annual growth rate. It is assumed normally distributed with a mean of 0 and a variance of τ₁₀⁰.

c₀⁰ is school random effects associated with the aggregated reading achievement in 2009. It is assumed normally distributed with a mean of 0 and a variance of τ₀⁰.

c₁⁰ is the school random effects associated with the aggregate annual growth rate. It is assumed normally distributed with a mean of 0 and a variance of τ₁⁰.

e₀⁰ is the random within-subject effect assumed normally distributed with a mean of 0 and a variance of σ².

Table 19 presents the results of the linear growth in reading achievement.
Table 19

*Linear Growth Model in Reading Achievement (Unconditional Model).*

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>SE</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean READ Achievement in 2009, $\pi_{0jk}$</td>
<td>528.205</td>
<td>1.845</td>
<td>286.256***</td>
</tr>
<tr>
<td>Mean ANNUALGRWTH Rate per Year, $\pi_{1jk}$</td>
<td>12.641</td>
<td>0.518</td>
<td>24.405***</td>
</tr>
<tr>
<td>Student Random Effect</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance in READ achievement across students</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>for 2009, $b_{00k}$</td>
<td>1974.732</td>
<td>5256</td>
<td>24494.405***</td>
</tr>
<tr>
<td>Variance in ANNUALGRWTH rate across students, $b_{10k}$</td>
<td>26.034</td>
<td>5256</td>
<td>6031.726***</td>
</tr>
<tr>
<td>Level 1 error, $e_{ijk}$</td>
<td>522.432</td>
<td></td>
<td></td>
</tr>
<tr>
<td>School Random Effect</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance in aggregate READ achievement across schools for 2009, $c_{0j0}$</td>
<td>633.602</td>
<td>198</td>
<td>1656.764***</td>
</tr>
<tr>
<td>Variance in aggregate ANNUALGRWTH rate across schools, $c_{1j0}$</td>
<td>24.892</td>
<td>198</td>
<td>483.718***</td>
</tr>
</tbody>
</table>

*(table 19 continues)*
Table 19 (continued)

Correlations

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Average READING achievement at 2009 and ANNUALGRWTH rate across students, $r(\tau_{b00k}(\tau_{b10k}))$</td>
<td>0.933</td>
<td></td>
</tr>
<tr>
<td>Average READING achievement at 2009 and ANNUALGRWTH rate across schools, $r(\tau_{c0j0}(\tau_{c1j0})$</td>
<td>0.498</td>
<td></td>
</tr>
</tbody>
</table>

Fit Statistics

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Deviance</td>
<td>143529.317</td>
</tr>
<tr>
<td>BIC</td>
<td>143541.083</td>
</tr>
</tbody>
</table>

***$p < .001$

The results from the unconditional model for reading fixed effects show that the average charter school student for 2009 scored approximately 528.21, $t(14302) = 286.256$, $p < .001$, and every year the average charter school student’s reading achievement will increase 12.64 points, $t(14302) = 24.405$, $p < .001$.

The within cell variance was, $e_{ijk} = 522.43$ and the within cell IUCC was 0.1669. This means that there is approximately 17% of the total within (i.e., reading scores) variance that is attributed to error within each year.

The results from the unconditional model show that there is a statistically significant variation across students reading achievement for the exit year (i.e., 2009), $\tau_{b00k} = 1974.185$, $\chi^2 (5256) = 24494.405$, $p < .001$. The IUCC of test scores over time between students was estimated as 0.6308. This indicates that there is approximately 63%
variation in reading achievement over time between students who attended different charter schools.

The $\chi^2$ test statistic of the reading achievement growth rate across students was significant, $\tau_{b10k} = 26.034, \chi^2 (5256) = 6031.726, p < .001$, meaning there is significant variation in student learning rates. A student with a growth rate measured by one standard deviation, $5.10 (SD = \sqrt{26.034})$, above the average is expected to grow at the rate of 17.74 points ($12.64 + 5.10 = 17.74$) a year on reading achievement. A student with a growth rate measured by one standard deviation below the average student ($12.64 - 5.10 = 7.54$) is still expected to grow at the rate of 7.54 points per year.

A statistically significant variation also exists among students in reading achievement across schools, $\tau_{c0j0} = 633.602, \chi^2 (198) = 1656.764, p < .001$. The IUCC for the correlation of test scores over time from different students who attended the same charter school was estimated was 0.2024. This indicates that there is approximately 20% variation of reading achievement growth amongst students between charter schools.

The $\chi^2$ test statistic of the aggregate reading achievement growth rate across schools was significant, $\tau_{c1j0} = 24.892, \chi^2 (198) = 483.718, p < .001$, meaning there is significant variation in student learning rates across schools. In a school with an aggregate student growth rate measured by one standard deviation, $4.989 (SD = \sqrt{24.892})$, above the average of the aggregate student growth rate for that school is expected to be 17.63 points ($12.64 + 4.99 = 17.63$) a year on reading achievement. In a school with an aggregate student growth rate measured by one standard deviation below the average ($12.64 - 4.99 = 7.65$) the expected aggregate growth rate is 7.65 per year.
There is a high correlation of the average reading achievement and the annual growth rate across students is $r = 0.933$. This positive correlation is an indication that there is a strong relationship between high average reading achievement with high growth rates.

The correlation of the aggregate reading achievement in 2009 and the annual growth rate across schools is $r = 0.498$. This positive relationship indicates a moderate relationship between high aggregate reading achievement associated with high growth rates across schools.

The deviance for model fit was 143529.317 and the BIC was 143541.083.

**Random-Coefficient Model**

The purpose of the next model was to create a “base” model to begin building upon. Similar to the mathematics section, time- varying covariates were added to the unconditional model (i.e., $EXPER$, $HQ$, and $CERT$). All predictors were analyzed separately to determine whether they could help explain the variability in average achievement and growth rates across students and across schools. $HGHRED$ (time-varying school characteristic) was eliminated from the study after the test for multicollinearity. As Raudenbush & Bryk (2002) stated, $t$ ratios of predictors that are near or less than 1.0 should be excluded from the model. $CERT$ (time-varying predictor) was eliminated after it was determined not to be a significant predictor of student reading achievement, $t(14293) = 1.471, p > .05$ (two-tailed). This is what was found with the mathematics achievement as well. In Arizona charter schools the mean of teachers holding a teaching certificate was 58-60% (see Table 7 for details). $HQ$ (time-varying
predictor) was also removed from the study after it was determined that it was not a
significant predictor, $t(14301) = 0.751, p > .05$. The effect of teacher experience
(EXPER) on student reading achievement for 2009 was not statistically significant across
students, $b_{20} = 1.54, \chi^2(2705) = 2706.600, p > .05$, so it remained fixed across the
students and is grand mean centered. The following model (i.e., Model 1) served as the
base model for the Full model.

Model 1

Level 1:

\[
\text{READ}_{ijk} = \pi_{0jk} + \pi_{1jk}(\text{ANNUALGRWTH})_{ijk} + \pi_{2jk}\text{EXPER}_{ijk} + e_{ijk}, \quad e_{ijk} \sim N(0, \sigma^2)
\]

\(i = 2007, 2008, 2009\)
\(j = 1, 2, \ldots, J\) an index for students
\(k = 1, 2, \ldots, K\) an index for schools

Level 2:

\[
\pi_{0jk} = \theta_{000} + b_{00k} + c_{0j0}
\]
\[
\pi_{1jk} = \theta_{100} + b_{10k} + c_{1j0}
\]
\[
\pi_{2jk} = \theta_{200} + c_{2j0}
\]

Where:

$\text{READ}_{ijk}$ is the reading achievement at time $i$ for student $j$ in school $k$ with average
teacher experience.

$\pi_{0jk}$ is the predicted average reading achievement for student $j$ in 2009 from the
specific combination of schools $k_{2007}, k_{2008}, and k_{2009}$, adjusting for the
teacher experience effect.
\( \pi_{1jk} \) is the annual reading achievement growth rate for student \( j \) from the specific combination of schools \( k_{2007}, k_{2008}, \) and \( k_{2009} \), adjusting for the average teacher experience effect. The predictor \( \text{ANNUALGRWTH} \) is centered at the exit time point, 2009, for ease of interpretation.

\( \pi_{2jk} \) is the predicted average effect of teacher experience on student, \( j \), in reading achievement in 2009 from the specific combination of schools \( k_{2007}, k_{2008}, \) and \( k_{2009} \). This predictor was grand mean centered.

\( \text{EXPER}_{ijk} \) is the average teacher experience at year \( i \) associated with student \( j \) in school \( k \). It is grand mean centered.

\( \theta_{000} \) is the predicted average students’ reading achievement at year 2009 adjusting for teacher experience effect across all students and across all schools.

\( \theta_{100} \) is the average annual growth rate in reading achievement adjusting for the teacher experience effect across all students and across all schools.

\( \theta_{200} \) is the effect of teacher experience on students’ reading achievement in the exit year, 2009, across all students and across all schools.

\( b_{00k} \) is students random effects associated with the average reading achievement in 2009. It is assumed normally distributed with a mean of 0 and a variance of \( \tau_{b00k} \).

\( b_{10k} \) is students random effects associate with the annual growth rate. It is assumed normally distributed with a mean of 0 and a variance of \( \tau_{b10k} \).
$c_{0j0}$ is school random effects associated with the aggregate reading achievement in 2009. It is assumed normally distributed with a mean of 0 and a variance of $\tau_{c0j0}$.

$c_{1j0}$ is school random effects associated with the aggregate annual growth rate. It is assumed normally distributed with a mean of 0 and a variance of $\tau_{c1j0}$.

$c_{2j0}$ is school random effect associated with the aggregate teacher experience effect. It is assumed normally distributed with a mean of 0 and a variance of $\tau_{c2j0}$.

$e_{ijk}$ is the random within-subject residual assumed normally distributed with a mean of 0 and a variance of $\sigma^2$.

Table 20 presents the results of the regression-coefficient Model 1.
Table 20

Coefficient Model (Model 1)

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>SE</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean READ achievement in 2009, $\pi_{0jkl}$</td>
<td>528.150</td>
<td>1.804</td>
<td>292.834***</td>
</tr>
<tr>
<td>ANNUALGRWTH, $\pi_{1jkl}$</td>
<td>11.996</td>
<td>0.534</td>
<td>22.459***</td>
</tr>
<tr>
<td>EXPER, $\pi_{2jkl}$</td>
<td>1.912</td>
<td>0.284</td>
<td>6.743***</td>
</tr>
</tbody>
</table>

Row - Student Random Effect

<table>
<thead>
<tr>
<th></th>
<th>Variance</th>
<th>df</th>
<th>$\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance in average READ achievement across students for 2009, $b_{0jk}$</td>
<td>2002.796</td>
<td>5256</td>
<td>25445.425***</td>
</tr>
<tr>
<td>Variance in ANNUALGRWTH across students, $b_{10k}$</td>
<td>42.291</td>
<td>5256</td>
<td>6228.444***</td>
</tr>
<tr>
<td>Level 1 error, $e_{ijk}$</td>
<td>502.079</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Column - School Random Effect

<table>
<thead>
<tr>
<th></th>
<th>Variance</th>
<th>df</th>
<th>$\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance in average READ achievement across schools for 2009, $c_{0j0}$</td>
<td>568.971</td>
<td>141</td>
<td>864.393***</td>
</tr>
<tr>
<td>Variance in ANNUALGRWTH of students across schools, $c_{1j0}$</td>
<td>23.924</td>
<td>141</td>
<td>375.005***</td>
</tr>
<tr>
<td>Variance in teacher EXPER effect on READ achievement across schools, $c_{2j0}$</td>
<td>3.987</td>
<td>141</td>
<td>261.747***</td>
</tr>
</tbody>
</table>

(table 20 continues)
Table 20 (continued)

Correlations

<table>
<thead>
<tr>
<th>Correlation</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average READ achievement in 2009 &amp; ANNUALGRWTH across students, $r(\tau_{b00k}, \tau_{b10k})$</td>
<td>0.792</td>
</tr>
<tr>
<td>Average READ achievement in 2009 &amp; ANNUALGRWTH across schools, $r(\tau_{c0j0}, \tau_{c1j0})$</td>
<td>0.513</td>
</tr>
<tr>
<td>Average READ achievement in 2009 &amp; teacher EXPER effect across schools, $r(\tau_{c0j0}, \tau_{c2j0})$</td>
<td>-0.235</td>
</tr>
<tr>
<td>Aggregate ANNUALGRWTH &amp; teacher EXPER effect across schools, $r(\tau_{c10k}, \tau_{c20k})$</td>
<td>-0.486</td>
</tr>
</tbody>
</table>

Fit Statistics

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deviance</td>
<td>143439.429</td>
</tr>
<tr>
<td>BIC</td>
<td>143563.817</td>
</tr>
</tbody>
</table>

***$p < .001$

The results from Model 1 show that the average reading achievement of an Arizona Grade 8 charter school student who has a teacher with an average number of teaching experience (i.e., 7.77 years) in the exit year (i.e., 2009) was 528.15 on the reading AIMS. The charter school students have an annual growth rate of 12.00 scale scores while adjusting for teacher experience effect.

The within cell variance, $e_{ijk}$, was 502.079 and the proportional reduction in variance for the within variance of this model from the Unconditional model due to the added predictor, EXPER was 0.039. This is an indication that approximately 4% of the
variance between time periods was explained by teacher experience. The IUCC for within cells was estimated as 0.163. This indicates that the proportion of variability between reading achievement scores from one year to the next for a student, \( j \), who attended the same charter school within the years 2007-2009 is approximately 16%.

There was statistically significant variation across students’ reading achievement in 2009 with average teacher experience, \( \tau_{100k} 2002.796, \chi^2 (5256) = 25445.425, p < .001 \). The proportional reduction in student variance of this model from the Unconditional model was -0.014 across students. The predictor added to Model 1 is fixed across students so it is reasonable that the reduction in variance across students be a negligible amount (less than 2%) (McCoach & Black, 2008). The student- IUCC is the correlation of achievement over time for a student, \( j \), who attended different charter schools. This was estimated to be 0.652 and indicates that there is approximately 65% total variation that lies between students.

There is substantial variability across students’ annual growth rate adjusting for \( EXPER, \tau_{b10k} = 42.291, \chi^2 (5256) = 6228.444, p < .001 \). A student with a growth rate measured by one standard deviation (\( SD = \sqrt{42.291} = 6.503 \)) above the average is expected to grow at the rate of 18.50 points (i.e., 12.00 + 6.50) a year on reading achievement. A student with a growth rate measured by one standard deviation below the average student is expected to grow at the rate of 5.50 (i.e., 12.00 – 6.50) per year. The reduction of variability was -.6245 (-62%). Grand mean centering the teacher experience predictor was necessary for a lucid interpretation (Dedrick et al., 2009; Enders & Tofighi, 2007; Holt, 2008; Raudenbush & Bryk, 2002). However, this caused the variance of the
annual growth rate to increase. As a result, the teacher experience effect is reflected in the reduction of variability statistic (i.e., from the unconditional model to the baseline model, where these adjustments took place).

The variation among students’ reading achievement in 2009 with average teacher experience across schools was statistically significant, \( \tau_{c0j0} = 568.971, \chi^2 (141) = 864.393, p < .001 \). This indicates that there is variance in average reading achievement yet to be explained across schools. The proportional reduction across-school variance of this model from the Unconditional model was 0.102 across schools. This indicates that by adding the EXPER predictor that approximately 10% of the variance was explained across schools. The school-IUCC of reading achievement over time from different students who attended the same charter school was estimated to be 0.185 which indicates that there is approximately 19% variation between charter schools.

The annual aggregate growth of students across schools adjusting for EXPER was, \( \tau_{c1j0} = 23.924, \chi^2 (141) = 375.005, p < .001 \), meaning there is significant variation in student learning rates across schools. In a school with aggregate student growth rate measured by one standard deviation \( (SD = \sqrt{23.924} = 4.891) \) above the average is expected to show a growth rate of 16.89 points (i.e., 12.00 + 4.89 = 16.89) a year on reading achievement. In a school with aggregate student growth rate measured by one standard deviation below the average it is expected to show a growth rate of 7.11 points (i.e., 12.00 – 4.89 = 7.11) per year. The reduction in variability was 0.0389 which indicates that by adding the teacher experience predictor it explained 4% of the aggregate student growth across schools.
The effect of teacher experience on students’ reading achievement in grade 8 (i.e., exit year, 2009) across schools showed statistically significant variation, $\tau_{c/0} = 3.987, \chi^2 (141) = 261.747, p < .001$. On average, Grade 8 students attending a school with teachers who have a level of experience effect that is measured by one standard deviation ($SD = \sqrt{3.987} = 2.00$) above the average teaching experience effect will have an expected aggregate student reading achievement of 531.97 (i.e., $528.15 + 1.912 \times 2.00 = 531.97$). Students attending a school where the level of teaching experience effect is measured by one standard deviation below the average will have an expected aggregate reading score of 524.33 (i.e., $528.15 + 1.912 \times [-2.00] = 524.33$). Teacher experience effect does not seem to have as much of an impact on students’ reading achievement scores as it did on mathematics achievement. This may occur because reading is taught as a formal class only in the elementary grades (unless the student has a learning disability or is an English language learner). In middle school, reading is typically just assigned as homework to be completed on an individual basis.

The correlation of average reading achievement in 2009 and annual growth rate across students was $r = 0.792$. This indicates a moderate to strong relationship showing that students with higher achievement tend to have high growth rate.

The correlation between aggregate reading achievement in 2009 and aggregate annual growth rate across schools was, $r = 0.513$. This indicates that there is a moderate relationship across schools suggesting that schools with high aggregate achieving students tend to have students with high growth rates. The correlation between aggregate reading achievement in 2009 and teacher experience effect across schools, $r = -0.235$
shows that there is weak to moderate negative relationship. This relationship indicates that high effects of teacher experience have more of an influence on students with low reading achievement when you aggregate to the school level. Finally, there was a moderate negative correlation between aggregate annual growth rate and teacher experience effect across schools was $r = -0.486$. This relationship shows the effect of teacher experience tends to be more pronounced on schools with lower aggregate growth rates.

The deviance for model fit was 143439.429 and the BIC was 143563.817. The BIC difference of Model 1 from the Unconditional Model was -22.734. The negative BIC statistic is attributed to the grand mean centering of the teacher $EXPER$ predictor added to the model. Grand mean centering of this predictor ($EXPER$) causes the variance of the intercept and growth rate across students to increase because the variability of these two coefficients is different in the first year of the study (i.e., 2007) than in the exit year of the study (i.e., 2009). By adding the $EXPER$ predictor it indicates that the variability is greater between students when adjusting for the teacher experience effect. This model was considered the base model for the best fit statistics (See Table 24 for an overall summary of the best fit statistics).

*Full Model*

The following model is the Full model in which student and school practices were added to the model one at a time. If the coefficient estimate of the predictor was not statistically significant different at the .05 alpha level then the predictor was dropped from the model. Each predictor was added as a random effect to see if there was a
significant difference in the variance; if not, the predictor was fixed and the model was run again. The student characteristics were added to more clearly define the “average” student but the main focus of this study was the school practices. $CHRTR06$, although significant $\gamma_{08} = 3.304, t(14289) = 3.097, p < 0.01$, did not add to the parsimony (overall explanatory power) of the model so it was removed during the building process. This student characteristic was added to determine whether a student was new to the charter school system. Apparently for reading achievement in middle school grades this characteristic does not add to the model. $OUTFLD$ was removed from the model when it was found to be statistically insignificant, $\delta_{03} = -4.143, t(14287) = -1.732, p = .083$ nor did it make a more parsimonious model. $HQ$ and $CERT$ were removed because they were found not to be significant predictors as explained in detail when describing Model 1. Also, just as reported for Model 1 (the baseline model) the effect of teacher experience ($EXPER$) on student reading achievement for 2009 was not statistically significant across students, $b_{20} = 1.54, \chi^2(2705) = 2706.600, p > .05$, so it remained fixed across the students and is grand mean centered. $ASIAN$ was removed when the main effect was found to be statistically insignificant $t(14287) = 1.553, p > .05$. $CLASS$ and $EXPER$ were grand mean centered for ease of interpretation.

FULL MODEL

Level 1 (TIME):

$$READ_{ijk} = \pi_{0jk} + \pi_{1jk}(ANNUALGRWTH)_{ijk} + \pi_{2jk}EXPER_{ijk} + e_{ijk}, \quad e_{ijk} \sim N(0, \sigma^2)$$

$i = 2007, 2008, 2009$

$j = 1, 2, \ldots, J$ an index for students
\( k = 1, 2, \ldots, K \) an index for schools

Level 2 (STUDENT and SCHOOL):

\[
\pi_{0jk} = \theta_{000} + \gamma_{01}(\text{HISP})_{01j} + \gamma_{02}(\text{N_AMER})_{02j} + \gamma_{03}(\text{BLCK})_{03j} + \gamma_{04}(\text{FEMALE})_{04j} + \\
\gamma_{05}(\text{SD})_{05j} + \gamma_{06}(\text{ELL})_{06j} + \gamma_{07}(\text{FRL})_{07j} + \delta_{01}(\text{CONV})_{01k} + \delta_{02}(\text{CLASS})_{02k} + b_{00k} + c_{0j0}
\]

\[
\pi_{1jk} = \theta_{100} + \gamma_{11}(\text{FEMALE})_{11j} + \gamma_{12}(\text{SD})_{12j} + b_{10k} + c_{1j0}
\]

\[
\pi_{2jk} = \theta_{200} + c_{2j0}
\]

\[b_{00k} \sim \mathcal{N}(0, \tau_{b00k})\]
\[c_{0j0} \sim \mathcal{N}(0, \tau_{c0j0})\]
\[b_{10k} \sim \mathcal{N}(0, \tau_{b10k})\]
\[c_{1j0} \sim \mathcal{N}(0, \tau_{c1j0})\]
\[c_{2j0} \sim \mathcal{N}(0, \tau_{c2j0})\]

Where:

\( \text{READ}_{ijk} \) is the reading achievement at time \( i \) for student \( j \) in school \( k \) with average teacher experience.

\( \pi_{0jk} \) is the predicted average reading achievement for student \( j \) in 2009 from the specific combination of schools \( k_{2007}, k_{2008}, \text{and } k_{2009} \) adjusting for school practices and student characteristics’ effects.

\( \pi_{1jk} \) is the annual reading achievement growth rate for student \( j \) from the specific combination of schools \( k_{2007}, k_{2008}, \text{and } k_{2009} \), adjusting for the average teacher experience effect. The predictor \( \text{ANNUALGRWTH} \) is centered at the exit time point, 2009, for ease of interpretation.
\( \pi_{2jk} \) is the predicted average effect of teacher experience on student, \( j \), in reading achievement in 2009 from the specific combination of schools \( k_{2007}, k_{2008}, \) and \( k_{2009} \). This predictor was grand mean centered.

\( \theta_{000} \) is the predicted average students’ reading achievement at year 2009 controlling for student and school practices across all students and across all schools.

\( \gamma_{0q} \) are fixed effects of student characteristics’ predictors, \( X_{qj} \); where \( q = 1, 2, 3, \ldots, Q \) is an index for student’s characteristics.

\( \delta_{0r} \) are fixed effects of school practices’ predictors, \( Y_{rk} \); where \( r = 1, 2, 3, \ldots, R \) is an index for school practices.

\( \theta_{100} \) is the annual growth rate of average reading achievement adjusting for teacher effect across all students and across all schools.

\( \theta_{200} \) is the effect of teacher experience on students’ reading achievement in 2009 across all schools.

\( b_{00k} \) is the students’ random effects of reading achievement in 2009. It is assumed normally distributed with a mean of 0 and a variance of \( \tau_{b00k} \).

\( b_{10k} \) is the students’ random effects associated with the annual growth rate. It is assumed normally distributed with a mean of 0 and a variance of \( \tau_{b10k} \).

\( c_{0j0} \) is the school random effects of the aggregate reading achievement in 2009. It is assumed normally distributed with a mean of 0 and a variance of \( \tau_{c0j0} \).

\( c_{1j0} \) is the school random effects associated with the annual aggregate growth rate. It is assumed normally distributed with a mean of 0 and a variance of \( \tau_{c1j0} \).
\( c_{2,j0} \) is the school random effects associated with teacher experience effect. It is assumed normally distributed with a mean of 0 and a variance of \( \tau_{c,2,j0} \).

\( e_{ijk} \) is the random within-subject residual assumed normally distributed with a mean of 0 and a variance of \( \sigma^2 \).

The results for the model are in Table 21.

Table 21

*Random-Coefficient Model (Full Model).*

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>SE</th>
<th>( t )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean READ Achievement in 2009, ( \pi_{0jk} )</td>
<td>529.781</td>
<td>4.257</td>
<td>124.463***</td>
</tr>
<tr>
<td>HISP, ( \gamma_{01} )</td>
<td>-16.071</td>
<td>1.394</td>
<td>-11.528***</td>
</tr>
<tr>
<td>N_AMER, ( \gamma_{02} )</td>
<td>-20.994</td>
<td>2.958</td>
<td>-7.098***</td>
</tr>
<tr>
<td>BLCK, ( \gamma_{03} )</td>
<td>-15.832</td>
<td>2.170</td>
<td>-7.295***</td>
</tr>
<tr>
<td>FEMALE, ( \gamma_{04} )</td>
<td>7.763</td>
<td>1.239</td>
<td>6.268***</td>
</tr>
<tr>
<td>SD, ( \gamma_{05} )</td>
<td>-49.703</td>
<td>1.994</td>
<td>-24.930***</td>
</tr>
<tr>
<td>ELL, ( \gamma_{06} )</td>
<td>-33.408</td>
<td>2.526</td>
<td>-13.227***</td>
</tr>
<tr>
<td>FRL, ( \gamma_{07} )</td>
<td>-13.898</td>
<td>1.264</td>
<td>-10.997***</td>
</tr>
<tr>
<td>CONV, ( \delta_{01} )</td>
<td>12.143</td>
<td>3.352</td>
<td>3.622**</td>
</tr>
<tr>
<td>CLASS, ( \delta_{02} )</td>
<td>0.731</td>
<td>0.201</td>
<td>3.643***</td>
</tr>
</tbody>
</table>

*(table 21 continues)*
Table 21 (continued)

<table>
<thead>
<tr>
<th>Fixed Effect</th>
<th>Coefficient</th>
<th>SE</th>
<th>t</th>
</tr>
</thead>
<tbody>
<tr>
<td>ANNUALGRWTH, $\pi_{1jk}$</td>
<td>11.708</td>
<td>0.589</td>
<td>19.865***</td>
</tr>
<tr>
<td>FEMALE, $\delta_{11}$</td>
<td>1.916</td>
<td>0.547</td>
<td>3.500**</td>
</tr>
<tr>
<td>SD, $\delta_{12}$</td>
<td>-3.593</td>
<td>0.865</td>
<td>-4.154***</td>
</tr>
<tr>
<td>EXPER, $\pi_{2jkl}$</td>
<td>1.480</td>
<td>0.239</td>
<td>6.179***</td>
</tr>
</tbody>
</table>

Student Random Effect

<table>
<thead>
<tr>
<th></th>
<th>Variance</th>
<th>df</th>
<th>$\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance in average READ achievement across students for 2009, $b_{00k}$</td>
<td>1641.057</td>
<td>5247</td>
<td>21665.570***</td>
</tr>
<tr>
<td>Variance in ANNUALGRWTH across students, $b_{10k}$</td>
<td>24.420</td>
<td>5254</td>
<td>5878.109***</td>
</tr>
<tr>
<td>Level 1 error, $e_{ijk}$</td>
<td>507.191</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

School Random Effect

<table>
<thead>
<tr>
<th></th>
<th>Variance</th>
<th>df</th>
<th>$\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance in aggregate READ achievement across schools for 2009, $c_{0j0}$</td>
<td>256.548</td>
<td>132</td>
<td>649.924***</td>
</tr>
<tr>
<td>Variance in aggregate ANNUALGRWTH rate across schools, $c_{1j0}$</td>
<td>21.223</td>
<td>139</td>
<td>368.126***</td>
</tr>
</tbody>
</table>

(table 21 continues)
Table 21 (continued)

<table>
<thead>
<tr>
<th>School Random Effect</th>
<th>Variance</th>
<th>df</th>
<th>$\chi^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variance in aggregate teacher EXPER effect across schools, $c_{2/0}$</td>
<td>2.626</td>
<td>141</td>
<td>258.737***</td>
</tr>
</tbody>
</table>

Reliabilities of coefficient estimates

| Average READ achievement across students for 2009 | 0.907 |
| Aggregate READ achievement across schools for 2009 | 0.603 |
| Average ANNUAL GRWTH in READ achievement across students for 2009 | 0.126 |

Reliabilities of coefficient estimates

| Aggregate ANNUAL GRWTH in READ achievement across schools for 2009 | 0.112 |

Fit Statistics

| Deviance | 142017.203 |
| BIC      | 142029.949 |

***p < .001

The coefficient estimation for the intercept of the Full model is an Arizona Grade 8 English proficient white male student who does not have a learning disability, pays for school lunch, and attends a charter school that started from scratch with a class size less than 18 students. This student did not attend a charter school in 2006. He has a
teacher with 7.77 years of teaching experience. This student would have an average reading score of 529.78 in 2009.

The student characteristic coefficients are reflective of Arizona NAEP reading scores for race, gender, students with disabilities, English language learners, and students eligible for the free and reduced lunch program (See Appendix J). Just as reported in NAEP, with the exception of Asian students, Arizona White students scored higher than all other races/ethnicities. Students eligible for the National Free and Reduced Lunch Program scored similarly on the NAEP; however, students with disabilities scored lower on AIMS, $\gamma_{05} = -49.703, t(14292) = -24.930, p < 0.001$, than English language learners, $\gamma_{06} = -33.408, t(14292) = -10.997, p < 0.001$. This is reverse on the NAEP.

Attending a charter school that was converted from a traditional public school has a positive effect, $\delta_{01} = 12.143, t(14290) = 3.643, p < .01$, on students’ reading achievement. A class size of 18 student had a positive (albeit small) effect, $\delta_{02} = 0.731, t(14290) = 0.201, p < .001$ on student reading achievement.

The annual growth rate of reading achievement, adjusting for teacher experience, for average student (i.e., average as defined by this study) was 11.71 points. The annual growth rate for female students who attend a charter school holding teacher experience effect constant was 1.92 points faster than their male counterpart. The female students scored higher initially ($\gamma_{04} = 7.76$) in Grade 8, holding teacher experience effect constant, and they are expected to increase faster annually; whereas, students with disabilities rate of growth was slower than those students without a disability by 3.59 points for an expected annual growth rate of 8.12 points (i.e., $11.71 - 3.59 = 8.12$).
The variance within cells was $e_{ijk} = 507.191$. The within cell proportional reduction of the variance of this model in comparison to Model 1 was -.010, meaning that by adding these predictors, -1% of the variance is explained between time periods which is a negligible amount (less than 2%) (McCoach & Black, 2008). This is reasonable, as was with AIMS Mathematics, AIMS Reading was administered approximately the same day every year in the same manner (Arizona Department of Education, personal communication, September 9, 2009). For this model the IUCC within cells was estimated as 0.211, indicating that the proportion of variability between reading achievement scores from one year to the next for a student, $j$, who attended the same charter school within the years 2007-2009 was approximately 21%.

The average reading achievement across students in 2009 was statistically significant, $\tau_{b00k} = 1641.057$, $\chi^2 (5247) = 21665.570$, $p < .001$, indicating that there is more variance to be explained. The proportional reduction of variance due to the predictors added to the full model compared to Model 1 was 0.180 which means that approximately 18% of the variance between students is explained by the predictors added to this model. The IUCC of reading achievement for students was .684 meaning that the proportion of variability of reading achievement over time for a student, $j$, who attended different schools was 68%.

The variance of the growth rate of a male student that does not have a learning disability while adjusting for teacher experience effect was statistically significant, $\tau_{b10k} = 24.420$, $\chi^2 (5254) = 5878.109$, $p < .001$, signifying there is more variance to be explained. An average male student (without a learning disability) with a growth rate one standard
deviation ($SD = \sqrt{24.420} = 4.942$) above the average is expected to grow at the rate of 16.65 points (i.e., $11.71 + 4.94 = 16.65$) a year on reading achievement. An average male student (without a learning disability) with a growth rate one standard deviation below the average student is expected to grow at the rate of 6.77 (i.e., $11.71 - 4.94 = 6.77$) per year. The reduction of variance of annual growth across students from Model 1 to the Full Model (i.e., $\tau_{b10k(Model 1)} - \tau_{b10k(Full Model)} / \tau_{b10k(Model 1)}$) was 0.423, indicating that 42% of the annual growth variance across students is explained by adding the Full model predictors. Reading growth rate can vary from one student to another based on the students’ reading ability; for example, if a student has a learning disability it was shown from the model that the student would have a smaller gain (approximately -4 points) in reading over time than a student without a disability. Females tend to have a higher growth rate (2 points) than males in reading.

The aggregate Grade 8 reading achievement across schools at 2009 was $\tau_{c00} = 256.548, \chi^2 (132) = 649.924, p < .001$. The proportional reduction of variance across schools for students’ reading achievement at 2009 with average teacher experience was 0.549 when comparing the Full model to Model 1. This is a significant amount of variance (i.e., 55%) across schools explained by the Full model predictors. The school – IUCC was 0.107 meaning that the proportion of variability of reading achievement over time for different students attending the same school is 11%.

The annual growth for reading achievement across schools, while holding teacher experience effect constant, among average Grade 8 male students without a disability was statistically significant, $\tau_{c10} = 21.223, \chi^2 (139) = 368.126, p < .001$. The aggregate annual
student growth rate in a school measured by one standard deviation ($SD = \sqrt{21.223} = 4.61$) above the average school is expected to grow at the rate of 16.32 points (i.e., $11.71 + 4.61 = 16.32$) a year on reading achievement. The aggregate annual student growth rate in a school measured by one standard deviation below the average school is expected to grow at the rate of 7.10 (i.e., $11.71 - 4.61 = 7.10$) per year. The reduction of variance of the aggregate annual growth across schools from Model 1 to the Full Model (i.e., $\tau_{c1j0(\text{Model 1})} - \tau_{c1j0(\text{Full Model})}/\tau_{c1j0(\text{Model 1})}$) was 0.113, indicating that 11% of the variance for annual growth across schools is explained by adding the Full model predictors. The reading growth rate can vary from one school to another based on the students’ reading levels; for example, if charter schools are targeting a certain population (e.g., special education or college bound students) then the variance between schools will be greater.

The aggregate effect of teacher experience for the exit year of 2009 across schools of average students was also statistically significant, $\tau_{c2j0} = 2.63, \chi^2 (141) = 258.737, p < .001$. The reduction of variance of teacher experience effect across schools from Model 1 to the Full Model (i.e., $\tau_{c2j0(\text{Model 1})} - \tau_{c2j0(\text{Full Model})}/\tau_{c2j0(\text{Model 1})}$) was 0.341, indicating that 34% of the teacher experience effect variance across schools is explained by adding the predictors to the Full model.

After determining what the reduction in variance was by adding predictors and establishing the IUCC, the next step was to look at the relationship between achievement to the growth rate, achievement to teacher experience effect, and the relationship of the growth rate and teacher experience effect.
For across-students correlations (Table 22) there is an extremely high correlation ($r = 0.945$) between the student’s growth rate in reading and their reading achievement in 2009. This means that students with higher reading achievement also show greater growth.

Table 22

*Correlations for Reading Achievement across Students.*

<table>
<thead>
<tr>
<th>Mean READ Achievement</th>
<th>Annual Growth Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean READ Achievement</td>
<td>-.945</td>
</tr>
<tr>
<td>Annual Growth Rate</td>
<td>-</td>
</tr>
</tbody>
</table>

*Note: Students ($n = 6214$)*

The correlations across schools for reading achievement are also very different from the correlations seen across students, see Table 23. The relationship between the aggregate growth rate in schools and the aggregate reading achievement of the students is moderate to strong, $r = 0.694$. The positive correlation indicates that the greater growth is seen from higher achieving students in the schools although not as strong as the relationship seen across students ($r = 0.945$).

The correlation across schools between teacher experience effect and aggregate student reading achievement is moderate, $r = -0.231$, and indicates that the lower achieving students are more influenced by teacher experience.

Finally, there is a moderate negative correlation ($r = -0.451$) between the aggregate annual student growth rate in reading achievement across schools and teacher
experience effect on reading achievement. This correlation illustrates that the teacher experience effect on reading achievement has a greater influence on the students who have a lower growth rate.

Table 23

*Correlations for Reading Achievement across Schools.*

<table>
<thead>
<tr>
<th></th>
<th>Mean READ Achievement</th>
<th>Annual Growth Rate</th>
<th>Teacher Experience Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean READ Achievement</td>
<td>-</td>
<td>.694</td>
<td>-.231</td>
</tr>
<tr>
<td>Annual Growth Rate</td>
<td>-</td>
<td>-</td>
<td>-.451</td>
</tr>
<tr>
<td>Teacher Experience Effect</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

*Note.* Schools (*n* = 261)

The deviance for this model was 142017.203 and the BIC was 142029.949. The difference between this BIC and the BIC prior to this model (i.e., Model 1) was 1533.868. A comparison of deviance and BIC fit statistics is in Table 24. The focus of this study is on school practices (as defined in Chapter II) which are the school predictors and how they affect student achievement; however, as the student level predictors were added to the model the difference in the BIC fit statistic was quite large (in favor of the later models). The greatest difference in BIC statistic for reading was when the predictors *SD*, *ELL*, and *FRL* were added, $\Delta BIC = 1080.465$. See Tables 24 for more details. This is reasonable considering the student predictors are distinguishing between students. For example, students who have a learning disability or are English language learners will
have a disadvantage in reading. Once the student was described, the BIC difference statistic tapered off as one school predictor was added at a time, although, still reported a decline in the difference statistic with a “very strong” grade on the Rafterty (1995) “Grades of Evidence” table.
Table 24

Bayesian Information Criterion Estimates - Reading

<table>
<thead>
<tr>
<th>Model</th>
<th>Deviance</th>
<th>Number of Parameters</th>
<th>BIC</th>
<th>ΔBIC</th>
<th>Evidence</th>
</tr>
</thead>
<tbody>
<tr>
<td>READ Unconditional ANNUALGRWTH</td>
<td>143529.317</td>
<td>9</td>
<td>143541.083</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>Model</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Model 1 (ANNUALGRWTH + EXPER)</td>
<td>143439.429</td>
<td>13</td>
<td>143563.817</td>
<td>-22.734</td>
<td>Weak</td>
</tr>
<tr>
<td></td>
<td>143223.431</td>
<td>16</td>
<td>143235.772</td>
<td>328.045</td>
<td>Very Strong</td>
</tr>
<tr>
<td>+ RACE</td>
<td>143155.491</td>
<td>18</td>
<td>143167.950</td>
<td>67.822</td>
<td>Very Strong</td>
</tr>
<tr>
<td>+ RACE, FEMALE</td>
<td>142040.728</td>
<td>22</td>
<td>142251.231</td>
<td>916.719</td>
<td>Very Strong</td>
</tr>
<tr>
<td>+ RACE, FEMALE, SD, FRL, ELL</td>
<td>142030.495</td>
<td>23</td>
<td>142043.199</td>
<td>208.032</td>
<td>Very Strong</td>
</tr>
<tr>
<td>+ RACE, FEMALE, SD, FRL, ELL, CONV</td>
<td>142017.203</td>
<td>24</td>
<td>142029.949</td>
<td>13.250</td>
<td>Very Strong</td>
</tr>
</tbody>
</table>

Note: The rating of evidence is from Raftery (1995). N = 14304.

*The predictor added to this model (i.e., EXPER) was grand mean centered which increases the variance for the intercept and slope.
In summary of Chapter IV, the school practice that had the most affect on students was the effect from teacher experience. The greater impact was seen when looking at the relationships between teacher experience effect and mean achievement in both content areas (i.e., mathematics and reading achievement) of lower achieving students. Also, a stronger relationship was seen across students between the teacher experience effect and the annual growth rate of students with a lower growth rate in mathematics. Surprisingly, attending a charter school that was converted from a traditional public school had a positive impact on student achievement. In the next chapter these three points along with other results were summarized and compared to current research. Recommendations for future research based on the findings from this study were also given.
CHAPTER V
Discussion

This study was an investigation of how Arizona charter middle school practices (as defined in Chapter II) may affect attending students’ mathematics and reading achievement over the course of three years (i.e., grades 6 through 8). The goal of this study was to determine: 1) if the effects from school practices, while controlling for student characteristics, were significantly affecting students’ mathematics and reading achievement (i.e., to determine with 95% confidence if the effects were large enough to warrant further investigation); 2) whether these practices and characteristics explained some of the variation in the achievement scores and in the growth rate across students and across Arizona charter middle schools; and 3) what kind of relationship (positive or negative) was seen by these characteristics.

The data from this study are nested (i.e., time points for each student in their school); although, because of the student mobility the data is not a natural hierarchy. It is likely that each school a student attends will have some effect on their achievement and if the student mobility issue isn’t addressed it is impossible to link one year’s achievement scores to the next without over/underestimation. Hierarchical linear cross-classified random effects modeling (HLM/CCREM) was the analysis used to allow for this change in schools to accurately assess the gains of each student from one school to the next (Beretvas, 2008; May & Supovitz, 2006; Raudenbush & Bryk, 2002). This chapter is comprised of five sections: a summary of the findings; a comparison to results
of previous studies; a listing of limitations; recommendations for future research; and concluding remarks.

Summary of Findings

This study gave an in-depth look at Arizona charter middle school students from 2007-2009. The following research questions guided the study:

1. How do school practices, while controlling for student characteristics, affect average mathematics and reading achievement for Grade 8 students at the exit year (i.e., 2009)?

2. What is the average growth rate in mathematics and reading achievement of students at Arizona charter middle schools?

Student characteristics helped to explain variability in the growth rate across students and across schools.

A HLM/CCREM study allows for analyses across students and across schools. This section consists of a brief summary of the findings for each predictor using mathematics and reading achievement as the outcome for across students and across schools. The predictors for each content area are: [aggregate] achievement in 2009, teacher experience effect, and the annual [or aggregate] growth rate. This is followed by a synthesized summary of the entire model for each content area (i.e., mathematics and reading).

Mathematics Achievement

The first research question guiding this study was to determine the effect of school practices, while controlling for student characteristics, on student mathematics
achievement at the exit year (i.e., 2009) adjusted for the teacher experience effect. The results indicate that attending a charter school for Grade 5 and having a class size of approximately 18 students showed positive effects ($p < .001$) on mathematics achievement. The school characteristic, teacher experience effect, is a time-varying predictor meaning that every year the amount of teacher experience is altered due to retention and changes in teaching staff. Teacher experience was adjusted around the grand mean of 7.77 years (i.e., overall average of all schools). This characteristic showed a statistically significant positive effect on average mathematics achievement and was able to be analyzed across students and across schools (as detailed below).

**Across students.** When the variance was assessed for average mathematics achievement across students, the precision estimate (i.e., reliability) of the parameters was very high (0.92) indicating a highly reliable estimate of the true average mathematics achievement. The IUCC, however, of mathematics achievement over time for a student who attended different schools was moderate which seems to be an indicator of student mobility causing a high amount of variance not accounted for in this study.

**Across schools.** The reduction of variance in the aggregate mathematics achievement across schools adjusting for average teacher experience effect was moderate as a result of the full model predictors (i.e., RACE, SD, ELL, FRL, CHRTR06, and CLASS) added to the baseline model. Also the full model IUCC of mathematics achievement over time for different students attending the same school was reduced from the baseline model. The precision estimate (i.e., reliability) of the parameters for
mathematics achievement across schools was moderate to high which is lower than the reliability across students indicating that the schools were more homogenous; thus making it more difficult to distinguish differences across schools.

*Teacher experience effect across students.* The added predictors in the full model reduced the amount of variance in the teacher experience effect across students by 41%. It was evident from the correlation between teacher experience and the annual growth rate that the students with a lower growth rate in mathematics achievement benefited from teacher experience. It was also clear that students with low mathematics achievement were influenced by teacher experience from the correlation between teacher experience and mathematics achievement.

*Teacher experience effect across schools.* The effect of teacher experience aggregated across schools showed an expected 24 point scale score difference (measured by one standard deviation above and below the mean) on aggregated mathematics achievement for schools. This emphasizes the point that a highly effective teacher can make an impact on students yet there is a lot of variation seen across schools. As a result from this variation, low correlations were seen when comparing teacher experience effect and mathematics achievement - even to the point of being negligible. This created a reversal paradox from the relationship seen across students (which is fully described in Chapter IV).

*Growth Rate on Mathematics Achievement*

The second research objective of the study was to assess the average annual growth rate of students during Grades 6 – 8 in Arizona charter middle schools. The
analysis showed that the average growth rate in mathematics achievement over the years 2007-2009, adjusting for teacher experience effect in students, was approximately 16 scale score points per year.

Across students. The reliability estimate of the growth rate across students was high. The correlation between the teacher experience effect and the growth rate of students with a low growth rate also showed a moderate relationship. Yet the reduction of variance due to the full model predictors was very low. This indicates that there is unexplained variance not being captured for student growth across students by the predictors in this study.

Across schools. The precision measure for the aggregate annual growth rate was fairly high indicating that the model was a reliable estimate of the true aggregate mathematics achievement; yet, the reduction of variance across schools was very low from the baseline model to the full model. This means there is unexplained variance in the growth rate not accounted for by the predictors in the full model for aggregate student growth across schools. This is reasonable considering that in the middle school years mathematics courses offered at a school vary from basic mathematics to advanced courses especially if a charter school targets a specialized population (e.g., special education or college bound students). The correlation of aggregate mathematics achievement and aggregate annual growth rate across schools revealed that schools with higher aggregate mathematics achievement show the greater gains.
Reading Achievement

The following are the results from the research question of how school practices, while controlling for student characteristics, affect student reading achievement in grade 8. A most unexpected finding was the advantage the students have if they are attending a school that converted from a traditional public school - nearly 12 points in reading ($p < 0.01$) (and 16 points in mathematics but it was removed because it was not contributing to the parsimony of the model). Class size had a positive effect on reading achievement as well. Teacher experience was treated as a time-varying predictor just as in the mathematics analysis and therefore was able to be analyzed across schools as detailed below. The teacher experience effect did not show a statistically significant effect across students on reading achievement.

Across students. The reliability estimate for reading average achievement across students was very high (0.91). Yet, the IUCC of reading achievement over time for a student who attended different schools was also high which is an indication of additional variation from student mobility that are not captured by this model.

Across schools. The proportion of variability for reading achievement over time controlling for teacher experience effect of different students attending the same school was reduced from the baseline model IUCC. The reduction of variance from the predictors added to the full model (i.e., RACE, FEMALE, SD, ELL, FRL, CONV, and CLASS), adjusting for teacher experience effect, for the aggregate reading achievement scores across schools was 55%. The reliability estimate of average reading achievement
across schools was moderate, indicating that the schools were more homogenous than the students; thus making it more difficult to distinguish differences across schools.

Teacher experience effect across schools. The reduction of variance for the effect of teacher experience across schools was moderate for reading achievement. There was a moderate negative correlation between the aggregate annual student growth rate across schools and teacher experience effect on reading achievement. This correlation illustrates that the effect of experienced teachers are influential on the aggregate reading achievement of students who have a lower growth rate.

Growth Rate on Reading Achievement

The annual growth rate during 2007-2009 of reading achievement, adjusting for the effect of teacher experience, for an average student (as defined in Chapter IV) was 11.71 scale score points. It was found in this study that the average female student has a higher average reading achievement than the average male student and shows greater growth over time. Whereas students with disabilities not only have lower average reading achievement (just as in mathematics), they progress at a slower rate in reading. The proportion of variability between reading achievement scores from one year to the next for a student who attended the same charter school within the years 2007-2009 was low to moderate.

Across students. There was a very high correlation ($r = 0.945$) between the student’s growth rate in reading and their reading achievement in 2009. This means that higher achieving students also have a higher growth rate. The reduction of variance due to the full model predictors was moderate for the annual growth rate across students.
Across schools. The relationship between the aggregate growth rate in schools and the aggregate reading achievement of the students is moderate to strong. The positive correlation indicates that the greater growth is seen from higher achieving students in the schools and is reflective of the correlation across students.

Review of Mathematics and Reading Findings

Mathematics. The evidence from the effect of teacher experience on low performing students in mathematics achievement was substantial and warrants some attention from charter school administrators. The effect of teacher experience on mathematics achievement was represented by the following: the reliability estimate was very high for average achievement; the correlation between mathematics achievement and teacher experience effect was strong for lower achieving students; and the correlation between the growth rate and teacher experience was strong for students with a low growth rate.

The variance of the effect of teacher experience across students was minimal. It ranges about 5.66 scale score difference measured by one SD above and below the mean. This indicates that the effect of teacher experience combined with its high consistency (small variance) emphasizes the importance of teacher experience on low performing students in mathematics.

The variance of the teacher experience effect across schools was much greater than across students totaling 24 scale score points (measured by one SD above and below the mean). This range was reflected in the correlations between mathematics achievement at the exit year and teacher experience resulting in a negligible amount. This reversal
paradox seen in contrast to the same correlation across students is a cautionary note that multi-level modeling was the appropriate procedure to use to assess this data. Otherwise, if another procedure was used instead of multilevel modeling this information would have been lost through aggregation and misspecification of the model.

Attending a charter school in Grade 5 had a positive impact on Grade 8 mathematics achievement; however, it was difficult to account for the variance between students that attended more than one school during this time period, whether the student attended another charter school or they switched back to a traditional public school. Students attending a school with an average class size of 18 students had a small advantage. Overall, the parameter precision of this model proved itself to be a reliable estimate of the true mathematics mean score across students and across schools; however, the reliability of the annual growth rate was not as tenable.

Reading. The correlation between reading achievement and growth over time showed that the higher achieving students had greater gains over the years, although the teacher experience effect showed a stronger relationship on those students with a lower reading growth rate. Attending a charter school that converted from a traditional school showed an impact on reading achievement; however, when the demographics of those schools were looked at closely they seemed to reveal a specialized sub-population of Arizona students (fully described in the next section). Also attending a class with an average class size of 18 students showed a positive effect on students’ reading achievement, albeit a small effect. The differences between students were difficult to assess for reading achievement perhaps because of mobility (as reported by the IUCC)
and was reflected in the low reliability estimate of the reading growth rate. Overall, the precision of the parameters of this model proved itself to be a reliable estimate of the true reading mean score across students and across schools.

The following section compares the results from this study to the research described in Chapter II. Nearly all of the results from this study support the current research. There was only one exception - the results from attending a charter school that was converted from a traditional public school. All results are fully elaborated on in the next section.

Comparison to Current Research

Charter Attendance in 2006

Current research reveals that regardless of how long a charter school was in operation a student entering into the system seemed to perform off their academic track (whether negatively or positively depending on which content area – reading and mathematics) for the first few years and then return to perform at the original growth rate (Bifulco & Ladd, 2006; Lavertu & Witte, 2009). Solmon et al. (2001) found that there was a 2.12 gain in mathematics and a 3.87 gain in reading over a three year period for students that entered the charter school system and continued in a charter school for three years. (The Stanford Achievement Test, Ninth Edition was used for their outcome scores.) Solmon et al. (2001) also found that the first year entering into the charter system has a negative effect on student achievement but the negative effect is reduced over time, two years for reading and three years for mathematics. The transition from changing schools may have an effect on student achievement initially whether it has a negative
effect from experiencing a different curriculum, experiencing different teaching styles, having trouble adapting to the new environment or whether the change has a positive effect such as a student who is excited about the change in schools and perhaps motivated to do well in their studies.

In light of this research, a student predictor was added (i.e., CHRT06) to designate if the student attended a charter school in 2006. If a student’s first year in the charter school system was in Grade 5 (2006), by the following year he/she may be able to settle into a routine that is comfortable, and perform as he/she may have before the transition. The purpose of this variable was to establish entrance into the charter system. As the results showed (see Table 4) nearly half of the students entered the charter system during the study period (i.e., 2007-2009) which apparently affected their achievement scores. Empirically, it was revealed in this study that students who attended a charter school in 2006 did score higher than the average student – nearly 5.5 points higher on mathematics achievement. Attending a charter school in 2006 (one year prior to this study) had a positive effect on reading achievement, 3 points higher; however, this predictor did not add to the parsimony of the model.

Teacher Experience

In Munoz and Chang’s study (2007) of teacher characteristics on Grade 9 students’ reading academic growth, teacher experience proved to be ineffective (p>.05) on student reading achievement and the prediction in students’ growth rate. The same results were found in this study for reading achievement across students. Munoz and Chang grand mean centered the predictor, as in this dissertation, but did not give the
mean statistic in their study so the definition of teacher experience is unclear. Similarly, Buddin and Zamarro (2009) found positive but small effects, $p < .05$, for both reading and mathematics when studying a California urban elementary school over a four year period. Buddin and Zamarro defined teacher experience as less than 3 years. The mean teacher experience in this study was more than double that used in Buddin and Zamarro’s study.

Empirically, the results from this study are consistent with current research. The findings showed that teacher experience has an effect on aggregate student mathematics and reading achievement across schools (although not at the same level). Examining the correlations closely confirms the importance of the effect from teacher experience on lower achieving student scores on AIMS. In mathematics the relationships of teacher experience effect with achievement and annual growth are stronger on an individual student basis (across students) of those with a lower growth rate. In reading, the relationship of teacher experience effect and aggregate annual growth are stronger at a school level (across schools) for students in a school with low growth rates. It is reasonable that teacher experience would have more of an impact on students for mathematics achievement than for reading because in the middle school grades (grades 6 through 8) the broad subject of mathematics is broken out into different areas of specialization (e.g., basic math versus Algebra I) whereas reading is not taught as a separate course after the elementary grades unless a student has a learning disability or is an English language learner.
Although the range of the teacher experience effect on mathematics was greater across schools (approximately 24 point scale score difference) than across students (approximately 6 point scale score difference), these are substantial increases of points on AIMS. Hiring all mathematics teachers with 8+ years of experience may be somewhat unrealistic (based on the arguments in Chapter III [e.g., lack of funds and job security]) but perhaps assigning teachers with more experience as lead teachers would be beneficial in the mathematics division of schools or assigning mathematics teacher with more experience to teach struggling students in mathematics. Monitoring student growth from year to year is crucial (especially for low achieving students) and working with teachers to become more effective with low achieving students is the key for academic success in mathematics.

The average years of experience for Arizona charter middle school teachers is approximately 8 years of teaching experience. This average may be lower than for teachers teaching in Arizona traditional public schools or even teaching in other states’ charter schools. Contributing factors that may cause low averages are lack of funds to hire experienced teachers (as mentioned earlier) or poor school management which may cause high teacher turnover in the system. Although the state of Arizona allows traditional school teachers to teach at a charter school for three years without losing seniority in traditional school districts, this may not be enough to motivate experienced teachers who have seniority in a traditional school to switch to a charter school for any length of time (or at all for that matter). Focusing on teacher retention and effectiveness seem to be key for Arizona charter schools. This can benefit the school in many ways,
both directly (e.g., student achievement school-wide) and indirectly (e.g., money targeted for hiring and training new teachers can go to other needs in the school) (Buddin & Zamarro, 2009). In addition, if the inexperienced teachers stay in the profession for an extended period of time they may produce the same positive effect on student achievement.

Class Size

The Public Elementary and Secondary School Student Enrollment and Staff Counts from the Common Core of Data: School year 2007-2008 reported that Arizona secondary schools (this includes all Arizona public schools) had the second largest students-to-teacher ratio (20.8) in the country. The national average was 11.9 students-to-teacher ratio for secondary classrooms (Noel & Sable, 2009). The average class size for Arizona charter middle schools is approximately 18 ($M = 18.4, SD = 5.3$). Although proven to be a significant predictor in mathematics achievement, in this study the results showed a modest positive impact for mathematics scores. The mathematics class size coefficient estimate was $\delta_{01} = 1.39$. In reading, the class size coefficient estimate was even smaller, $\delta_{02} = 0.73$. It was stated in the RPP International report (2000) that unless the class size is less than 16 students per classroom the impact is minimal. Similarly, the Project Star program (1999) reported that a causal relationship exists between a class size less than 20 students and positive achievement results (Boyd-Zaharias, 1999; Egelson et al., 1996; Hanushek, 2003).

Buddin and Zamarro (2009) found a similarly small significant effect, although a negative effect, for class size in both reading and mathematics of students from an urban
elementary school (i.e., Grades 2 – 5) when they conducted a longitudinal study in California, reporting that a five-student drop in class size would only increase reading and mathematics levels by one percentage point. Their coefficient estimates for reading were $\psi_{\text{READ}} = -0.167$ (p < .05) and $\psi_{\text{MATH}} = -0.222$ (p < .05) for mathematics; although, the definition of class size was unclear in the Buddin and Zamarro report and class size may have a different effect on elementary students as opposed to middle school students—especially in reading. Nonetheless, in this study as well as the other research studies, there is no empirical study that shows a large effect attributed to class size. Reducing class size may not be the sole answer in raising achievement; teachers would need to use teaching strategies appropriate for small class sizes. In addition, Achilles (2002) states that fostering a class size effect entails at least six criteria (i.e., small classes as early as kindergarten, student spending all day in a small class, at least three consecutive years of small classes, peer-tutoring, use cohorts so students are familiar with each other, and the appropriate legislation to support small class sizes). Blatchford et al. (2003) found in the United Kingdom that unless teachers are trained to handle variations in class size, small amounts of students will not benefit academically beyond the first year of entering into a new school system.

*Converted versus Start-Up*

There are many suggestions from previous studies (fully described in Chapter II) as to why a traditional school may convert (e.g., to serve a certain sub-population of students, to avoid a state take-over because of failing to meet average yearly progress for NCLB, or to offer a specialized curriculum) (Buddin & Zimmer, 2005; RPP
International, 2000). A converted school has some advantages, for example, the school may be able to keep the same teaching staff thereby keeping experienced teachers on the payroll to which the students (assuming most of the students stay with the converted school) may already be familiar. Lavertu and Witte (2009) stated that the large number of converted schools and those charter schools that have been in operation for a number of years drive the achievement scores to go up when looking at charter schools as a whole.

Likewise, attending an Arizona charter school that was converted from a traditional public school has shown to be advantageous from the results of this study - approximately 12 points higher reading achievement controlling for all other predictors (16 points higher for mathematics but this predictor was pulled from the model after it was found not to contribute to the overall explanatory power of the model).

In Buddin and Zimmer’s (2005) study of California charter schools they found that students who attended converted charter schools scored lower than those who attended start-up charter schools (approximately 2.2 percentile points difference on reading and 0.4 percentile points difference on mathematics). The difference between the Buddin and Zimmer study and this study is in the demographics. These researchers reported that in California secondary charter schools that were converted from a traditional public school, the majority of the students enrolled were black students, a smaller proportion were white non-Hispanic students, and that Hispanic students were split between the “start-up” charter schools and converted charter schools. More of these students were also eligible for the free/reduced school lunch program. Parent education
was approximately the same for both converted charter schools and “start-up” charter schools.

In Arizona, approximately 7.5% of Arizona charter schools converted from a traditional public school. The conversion schools’ student makeup is approximately 77% White students, 16% Hispanic, while Black, Native American, and Asian account for the other 7%. Twelve percent of the students with disabilities and 4% of the ELL students attend charter schools that were converted from traditional public schools. Of the students attending converted charter schools in Arizona, 17% are eligible for free/reduced school lunch. This is a very different picture of student demographics in a converted school compared to what Buddin and Zimmer found in California. Historically, White non-Hispanic students score higher than Black and Hispanic students in mathematics and reading achievement. So the imbalance found from the student demographics in this study compared to the Buddin & Zimmer study could explain the differences in the results.

Not only are the student demographics of the Arizona converted charter schools different from the schools in Buddin & Zimmer’s study, they are also quite different from Arizona “start-up” charter schools, which are 56% White non-Hispanic, 29% Hispanic, 15% are Black, Native American, and Asian (combined). Perhaps Arizona’s converted charter schools are geared toward a special sub-population of their students. Nevertheless, from the empirical results of this study (i.e., 12 points in reading and 16 points in mathematics) there seems to be a substantial advantage to attending an Arizona
charter school that was converted from a traditional public school as opposed to attending a “start-up” charter school.

In summary, all of the results from the factors in this study were supported by current research. For instance, this study confirms that a class size of 18 students has a positive impact on attending students. This class size is right in between the findings of the Project Star study (1999) stating that a positive result was found with less than 20 students and the RPP International study (2000) which reported that less than 16 students resulted in positive outcomes. It was also found in this study that if a student entered the charter school system in Grade 5, which would give the student at least four years to adjust to the charter school system (far longer than other studies reported), entering the charter system would have a positive effect on their grade 8 mathematics achievement. Teacher experience was revealed to have an impact on lower achieving students in both mathematics and reading achievement (only at the aggregate school level for reading) over time which seems to parallel current research. The only contradictory finding to this study was found when comparing Buddin and Zimmer’s study (2005) on traditional public schools that converted to charter schools; however, the differences were attributed to dissimilar demographics. In addition, there were differences in the demographic makeup of Arizona converted charter schools to Arizona start-up charter schools which may indicate that the schools were converted for a specialized population.

Limitations

This study is exclusive to Arizona charter schools. As mentioned earlier, Arizona’s demographics may vary from other states’ charter schools. For example, the
demographics of Arizona’s converted charter schools are very different than what was found in California and likely to be different from other states (Buddin & Zimmer, 2005). Also, gender showed no significant difference on mathematics achievement neither on the state assessment nor on NAEP in the state of Arizona, which may be different from other parts of the country and thus may impact the gender results in other states’ charter school data. Aside from the differences in demographics, states have various charter laws, mathematics and reading standards, and state assessments; therefore, the findings are confined to Arizona and are only inferred to the Arizona charter school population. This limits the inferences to the larger population one might draw from the conclusions of this study.

This study is quasi-experimental in nature because Arizona schools, with enrollment intact, were used as units; therefore causal effects were not to be concluded (McMillan & Schumacher, 2001; O’Connell, & McCoach, 2008).

The focus of this study was the effects of the charter school practices for the allotted time period of only three years (i.e., 2007-2009). The assessment was changed in 2005 and in 2010; therefore, this confined the study to three years.

AIMS is administered by the classroom teacher; therefore, teacher effect may be an issue for students. Because this is a quasi-experimental research study using students assigned to classrooms, teacher effect on the class as a whole is an issue of internal validity. Maturation is an issue with repeated measures designs because of the natural cognitive development as students advance from grade 6 through grade 8 (McMillan & Schumacher, 2001).
The reading and mathematics scale scores may be a reflection of classroom instruction as well as tutoring which was not accounted for in this study. Prior reading and mathematics achievement was not accounted for and although a value-added model is used to measure growth within the charter school system during 2007 through 2009 to try to control for student characteristics, there is still the potential for unobserved characteristics to have an impact on the achievement scores of students (Charter School Achievement Consensus Panel, 2006; Hoxby & Murarka, 2008). Some schools and/or teachers may take longer than a year to have an impact on a student which could underestimate the growth of student achievement especially in the first few years of entering the charter school system.

Selection issues are a problem with assessing charter schools because parents choose to send their children to a certain school; however, by addressing student level data over time helps to alleviate some of this problem. The purpose of longitudinal data is to view student differences in achievement one year to the next year thereby deemphasizing the initial background variables of students that may have influence the decision to attend a certain charter school (Buddin & Zimmer, 2005; Solmon et al., 2001).

**Recommendations for Future Research**

The study and the methodology used for analysis of mathematics and reading achievement (as defined by this study) of Arizona Grade 6-8 charter school students more closely defines the structure of successful Arizona charter schools but there are more elements to a successful school than the variables described in this study. This study was
conducted to help fill in a gap that has been open in Arizona education for the last 15 years. From the results, one can see that the Grade 8 students from a charter school that converted from a traditional public school scored higher in reading. In future research, it would be beneficial to look at converted charter schools more closely to get an indication of their curriculum, teaching methods, class size, etc. that may be used as a guide to other charter schools.

This study concurred with the research that student achievement is negatively affected when a student enters the charter school system. This study confirms that at least at the fourth year of attendance (i.e., 2009) after the initial entrance in grade 5 into the charter school system there is a positive effect on mathematics achievement. However, there is not enough evidence from this study to confirm how long it takes before there are positive achievement results prior to the four year benchmark. In the future it would be beneficial to re-analyze this data and add an “entrance” predictor to the model to indicate when the student entered into the system if not 2006 (i.e., 2007, 2008, or 2009).

It would also be advantageous to add a “switching” schools indicator to the model. This would designate how often a student moved from one charter school to the next and how long they stayed in the charter school system as opposed to returning to a traditional public school.

Another direction for future research prompted by this study would be to take a closer look at Arizona charter schools by city location (i.e., city versus suburban) accounting for student characteristics to see if there is a difference in school practices across the state.
Lastly, there were a few predictors reported in Chapter IV (e.g., teachers teaching out-of-field, charter school attendance for Grade 5 students) that had statistically significant coefficient estimates but were eliminated from the model due to the fit statistics – meaning that the addition of those predictors did not add to the parsimony of the model. It may be advantageous to revisit those predictors in a different context.

Concluding Remarks

Arizona has a somewhat unique set of charter laws compared to most states. The unlimited amount of charters that can be accepted each year and the length of the charter contracts (i.e., 15 years) gives the educators teaching in charter schools the time to fully develop specialized programs in their schools. This study was an analysis of the performance of Arizona charter middle school students over a span of three academic years when the state assessment had not undergone any alterations, thereby stabilizing the assessment from years 2006 through 2009 in mathematics and reading.

The results present evidence of school practices that effect Arizona charter school students’ achievement in mathematics and in reading. The most prominent effect was teacher experience and the influence this makes on individual student growth of lower performing students struggling with mathematics. This empirical evidence concurs with current research and should be a consideration for authorizers of charter schools. The students struggling in mathematics need the attention of an experienced teacher and at the same time perhaps the school administrators could focus on retaining the teachers with less experience and working with them to develop effective skills to work with lower achieving students. A similar relationship was found between teacher experience and
aggregated student growth rate in reading achievement across schools of students with a low growth rate.

Also, attending a charter school in Grade 5 had a considerable positive effect on Grade 8 mathematics achievement. This finding raises some questions and would lead to more research in order to distinguish whether the reasoning behind this result was because of longevity of a student in the charter system as a whole or early exposure to the charter school curriculum and teaching methods influencing their academic achievement.

For reading achievement, the school characteristic that stood out the most was attending converted charter schools as opposed to start-up schools and the positive effect on reading achievement that was seen. Although, the number of students attending a converted charter school are a small sub-set of the Arizona charter middle school population, perhaps the teaching strategies, curriculum choices, administrator decisions (e.g., teachers’ qualifications), etc. in these schools could benefit other charter schools.

Arizona charter school policymakers and administrators will find the results from this study useful in terms of providing empirical evidence to support certain initiatives (e.g., requesting more funds to hire teachers with teaching experience to balance out their staff). This study can inform policymakers, the Arizona Board of Education, and the Arizona State Board for Charter Schools about the expected growth rate of Arizona charter middle school students which could be used to substantiate legislature when amending Arizona Education Charter Laws and Rules.

Not only are the results reported from the effect of each predictor in the model but also those predictors that were excluded from the model because of the fit statistics (e.g.,
highly qualified or teachers teaching out-of-field) were accounted for in this study. Those predictors in particular could be researched further in a separate model. Secondly, this study gives researchers a look at the demographics of Arizona charter schools and how the students attending charter middle schools perform on mathematics and reading achievement assessments. Arizona’s charter school population may be different from other states in some ways. For example, students attending a converted charter school from a traditional public school tend to score higher on achievement tests (mathematics and reading) due to the specialized population. Lastly, the complex analysis used was hierarchical linear cross-classified random effects modeling which is appropriate for student mobility (an issue within Arizona charter schools). This method is rarely used in education research, perhaps because of the complexity, but is the recommended method in order to be able to generalize to the population when the data is not naturally nested. This was confirmed in this study when a reversal paradox was found between the student level data and the school level data. A regression would not have accounted for that vital information found regarding lower achieving students in mathematics. This study could be used as a template for researchers on setting up a HLM/CCREM study and how to report the results.

Arizona’s charter schools have been in operation since 1995. With the implementation of AIMS, the state now has standardized data to compare schools and show growth within schools. The longevity of the charter contracts and the longitudinal data available from the state lays the foundation for research potential. This study not only provides useful information to researchers assessing the differences in charter
schools but it lays the groundwork for future research that is needed to fill a fifteen year gap in Arizona education.
APPENDIX A

ACCOUNTABILITY IN ARIZONA CHARTER SCHOOLS
Appendix A

Accountability in Arizona Charter Schools

Academic Accountability:

- Must demonstrate alignment to Arizona's Academic Standards.
- Must participate in state mandated annual nationally norm referenced testing program.
- Must participate in the Arizona criterion referenced testing program (AIMS—Arizona Instrument to Measure Standards) in grades 3, 5, 8, 10 and 12.
- Must state clear performance objectives including percentage of mastery and provide curriculum samples with a clear crosswalk between the curriculum and the AZ Academic Standards in their charter application before a charter can be granted.
- Subject to sanctions for non-compliance

Financial Accountability:

- Adhere to State statute for submission of an annual budget.
- Every charter school must submit a detailed business plan as part of their charter application.
- Must conduct an annual external audit both programmatic and financial with an independent certified CPA.
- Must annually demonstrate compliance with the uniform system of financial records for charter schools (USFRCS for charter schools) or must demonstrate compliance with generally accepted accounting principals (GAAP) if they have received an allowed exception from the USFRCS.
- Must submit annual financial reports to the Superintendent of Public Instruction regarding funding by program for inclusion in the Superintendent's Annual Report.

General Accountability:

- All charter schools must comply with all state, local and federal laws regarding health, safety and civil rights. This includes, but not limited to, compliance with city and county ordinances in relation to the safety, quality and location of their facilities.
- All charter schools must have their current Certificate of Occupancy with an E-I rating and the current Fire Marshall's Permit on file with their sponsor.
- All charter schools must comply with all provisions of the individuals with Disabilities Education Act (IDEA) as well as comply with any restrictions or regulations related to acceptance of federal funding for start-up or programmatic functions.
- Each charter school must submit annual demographic and ethnicity data for the Superintendent of Public Instruction's Annual Report, as well as periodic enrollment counts throughout the year by which their apportionments are adjusted.
- Each charter school is required to keep a public file of education qualifications and work experiences of all current and former teaching staff available for any parent to view.
- Each charter school is required to have a five-year contract compliance review by their sponsoring entity.
- Each charter school must also submit annual school profile data by school site for Arizona school report cards.
- Charter school teaching staff and /or volunteers who work with students must have a fingerprint clearance card issued through the AZ Department of Public Safety for tracking purposes.
- All charter school staff must be background checked upon employment

APPENDIX B

TITLE 7. EDUCATION
ARTICLE 2. NEW CHARTERS

R7-5-201. Application for a New Charter

A. By March 31st of each year, the Board shall approve and make available in writing at its office and online at its website an application for a new charter for a specified fiscal year.

B. A person desiring to establish a charter school shall submit an unbound original application package and 5 bound copies of the application package to the Board.

C. An applicant for a new charter shall ensure that the submitted application package contains the following in the order listed:

1. Cover Sheet form;
2. Title Page form;
3. Target Population form;
4. Curricular Emphasis. A narrative describing the proposed charter school’s program of instruction including its philosophy, special emphasis, and methods of instruction and assessment in relation to achieving the school’s mission;
5. Goals form;
6. Curriculum Sample. A reading, writing, and math sample for each grade level to be served. Each sample will include a student assessment, description of instruction, description of student activities, and an indication of alignment with the Arizona Academic Standards;
7. Monitoring of Program of Instruction. A narrative and examples regarding dissemination of information to teachers, tracking of students’ progress toward mastery of state standards, and integration of Arizona Academic Standards into instructional practices;
8. Special education delivery models to be used;
9. Business Plan. A detailed business plan including:
   a. Business description,
   b. Marketing plan,
   c. Management plan,
d. Resume of applicant,

e. Background information form,

f. Valid fingerprint clearance card for the principals and authorized representative,

g. Affidavit form,

h. Copy of Arizona filing required to conduct business in Arizona by the Arizona
Corporation Commission or Arizona Secretary of State,

i. Financial plan,

j. Start-up budget with assumptions form,

k. Three- year operating budget form, and

l. First year month-by-month cash flow form;

10. Compliance Assurances form;

11. Certificate of Workshop Attendance or Workshop Waiver form;

12. Bibliography; and


**R7-5-202. Time-frames for Granting or Denying a New Charter**

A. For granting or denying a charter, the time- frames required by A.R.S. § 41-1072 et seq. are:

1. Administrative completeness review time- frame: 25 days;

2. Substantive review time-frame: 175 days; and

3. Overall time- frame: 200 days.

B. An administratively complete application package for a charter school consists of all the information and documents listed in R7-5-201.

C. The administrative completeness review time-frame, as described in A.R.S. § 41-1072(1) and listed in subsection (A)(1), begins on the date the Board receives an application package.

1. If the application package is not administratively complete when received, the Board shall provide to the applicant a notice of deficiency that states the documents and information that are missing.

2. Upon written notice to the applicant that the application package is incomplete, the Board shall close the applicant’s file.

3. If the application package is administratively complete, the Board shall send a written notice of administrative completeness to the applicant.

C. If the Board does not provide a notice of deficiency or administrative completeness to the applicant within the administrative completeness review time-frame, the application package is deemed administratively complete.

D. A substantive review time-frame, as described in A.R.S. § 41-1072(3) and listed in subsection (A)(2), begins when an application package is determined to be administratively complete.

E. Within the time provided in subsection (A)(3), the Board shall provide the applicant with written notice of its decision to grant or deny a charter.

1. The Board shall deny a charter if it determines that the application package does not meet the requirements of statute or rule or the applicant is not sufficiently qualified to operate a charter school. The written notice shall include the basis for the denial. The applicant may:
i. Submit a new application under R7-5-201 for consideration by the Board; or
ii. Appeal the Board’s decision as prescribed in A.R.S. Title 41, Chapter 6, Article 10.

2. The Board shall grant a charter if it determines that the application package meets the requirements of statute and rule and the applicant is sufficiently qualified to operate a charter school.

**R7-5-203. Review of Application Package and Technical Assistance**

The review of a complete application package is as follows:

A. The Technical Review panel shall score the preliminary application package using the scoring criteria provided in the application.
B. The Board staff shall conduct background investigations of the applicant.
C. The Board shall notify the applicant if the preliminary application package fails to meet the expectations as evaluated by the Technical Review Panel. The Board shall include with the notice the comments of the Technical Review Panel, which will serve as technical assistance, and suggestions for improving the application package.
D. An applicant who receives notification of failure to meet the expectations as evaluated by the Technical Review Panel may, within 20 days of the postmark date on the notice, submit a revised application package or a letter requesting that the preliminary application package be forwarded to the Board.
E. If a revised application package or letter is not submitted to the Board within 20 days of the postmark date on the notice of failure to meet the expectations, the Board shall close the applicant’s file. An applicant whose file is closed and who wants to obtain a charter shall apply again under R7-5-201.
F. If a revised application package is submitted, the Technical Review Panel shall score the revised application package using the scoring criteria provided in the application.
G. If a revised application package fails to meet the expectations as evaluated by the Technical Review Panel, the Board shall notify the applicant of the intent to close the file. The Board shall include with the notice the comments of the Technical Review Panel.
H. An applicant who receives notification of the Board’s intent to close the file may, within 20 days of the postmark date on the notice, submit a letter requesting that the revised application package be forwarded to the Board.
I. An applicant whose file is closed and who wants to obtain a charter shall apply again under R7-5-201.
J. The Board shall consider an application package if the Technical Review Panel determines that the application package meets or exceeds the expectations or if the applicant requests under subsection (4) or (8) that the Board consider an application package that fails to meet the expectations. In conducting its consideration of an application package, the Board shall:
   1. Review a copy of the application package scored by the Technical Review Panel;
   2. Review a copy of the scoring rubric completed by the Technical Review Panel;
   3. Review all information obtained through verification and investigation of an applicant’s background including employment, education, fingerprint clearance card, and assessment of creditworthiness;
   4. Hear a brief presentation by the applicant; and
5. Listen to the applicant’s responses to Board questions.
K. The Board shall provide an applicant, with at least seven days written notice of the date, time, and place of the meeting at which the Board will consider the applicant’s application package.

R7-5-204. Execution of a Charter
A. After the Board grants a charter, and before the contract is signed, the charter holder shall submit to the Board the following:
1. Completed I.R.S. Form W-9, Request for Taxpayer Identification Number and Certification, obtained from the Board;
2. School site location information;
3. General Statement of Assurances form obtained from the Board;
4. Copy of the statement filed with the Secretary of State under A.R.S. § 38-431.02; and
5. Copy of lease agreement, if any, for each school site.
B. A new charter shall be signed by the Board President or designee and the charter holder or authorized representative within 12 months after the Board grants the charter.
C. A charter that is not timely signed expires. If the holder of an expired charter wants to obtain a new charter, the holder shall apply again under R7-5-201.
D. A charter holder shall begin providing educational instruction within six months after signing the charter or within 18 months after the Board grants the charter, whichever occurs later.
E. A charter holder shall submit to the Board written proof that the charter school is in compliance with federal, state, and local rules, regulations, and statutes relating to health, safety, and insurance at least 10 days before the first day of operation of the charter school by submitting:
1. School site contact information;
2. Certificate of occupancy for each school site;
3. Fire marshal report for each school site;
4. Insurance policy binder issued by an insurance company licensed to do business in Arizona;
5. County health certificate for each site at which students will be taught;
6. Evidence of a public meeting, required by A.R.S. §15-183(C)(5), at least 30 days before the charter holder opens a site for the charter school; and
7. Certificate of attendance of the authorized representative or principal at the special education training for new charters offered by the Arizona Department of Education, Exceptional Student Services Division.
F. A charter is effective for 15 years from the first day of operation of the charter school unless revoked under A.R.S. § 15-183(I).

ARTICLE 3. RESERVED

ARTICLE 4. AMENDMENT TO A CHARTER

R7-5-401. Amendment to a Charter
A. A charter holder that wishes to amend its charter shall submit to the Board
1. A completed charter amendment form approved by the Board,
2. The support documentation indicated on the charter amendment form, and
3. Evidence that the proposed charter amendment has been approved by the charter school’s governing body.
B. For approving or disapproving an amendment, the time-frames required by A.R.S. § 41-1072 et seq. are:
1. Administrative completeness review time-frame: 20 days.
2. Substantive review time-frame: 40 days.
3. Overall time-frame: 60 days.
C. A charter holder shall conform to the terms of the charter until an amendment is approved by the Board.

APPENDIX C

STATE SUMMARY BY GRADE OF PUPIL ENROLLMENT CHARTERS ONLY,

FY2006-07
Appendix C

State Summary By Grade Of Pupil Enrollment Charters Only, Fy2006-07

<table>
<thead>
<tr>
<th>Grade Level</th>
<th>Total State Enrollment</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>White (Non-Hispanic)</td>
</tr>
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<td>Kindergarten</td>
<td>8,709</td>
</tr>
<tr>
<td>Grade One</td>
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<tr>
<td>Grade Two</td>
<td>6,263</td>
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<td>Grade Three</td>
<td>6,263</td>
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<tr>
<td>Grade Four</td>
<td>6,263</td>
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<td>Grade Five</td>
<td>6,263</td>
</tr>
<tr>
<td>Grade Six</td>
<td>6,263</td>
</tr>
<tr>
<td>Grade Seven</td>
<td>6,263</td>
</tr>
<tr>
<td>Grade Eight</td>
<td>6,263</td>
</tr>
<tr>
<td>Total Elementary</td>
<td>59,323</td>
</tr>
</tbody>
</table>

| Grade Nine    | 6,061                  | 5,779                 | 5,779                           | 5,779                      |
| Grade Ten     | 7,173                  | 6,815                 | 6,815                           | 6,815                      |
| Grade Eleven  | 8,158                  | 7,733                 | 7,733                           | 7,733                      |
| Grade Twelve  | 11,356                 | 10,381                | 10,381                          | 10,381                     |
| Total Secondary | 52,748               | 48,952                | 45,471                          | 42,131                     |
| Grand Total   | 92,071                 | 82,074                | 77,487                          | 74,612                     |

Additional Data:

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<thead>
<tr>
<th>Prior Year State Enrollment</th>
<th>Resident Average Daily Membership for Charter Schools</th>
</tr>
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<tbody>
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<td>FY2005-06</td>
<td>FY2006-07</td>
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<tr>
<td>40th Day</td>
<td>100th Day</td>
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<td>Elementary:</td>
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<td>57,568</td>
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<tr>
<td>High School:</td>
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<td>Total:</td>
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<td>90,490</td>
<td>90,490</td>
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1 Pupil Enrollment: An unduplicated count of students enrolled on October 1, 2006.
2 Enrollment for charter schools. Detail pages in Volume II provide enrollment for each charter school.
3 Average Daily Membership as defined by ARS § 15-902.
4 Detail pages in Volume II provide ADM for each charter school.

APPENDIX D

STATE SUMMARY BY GRADE OF PUPIL ENROLLMENT CHARTERS ONLY,

FY2007-08
Appendix D

State Summary By Grade Of Pupil Enrollment Charters Only, Fy2007-08

<table>
<thead>
<tr>
<th>Grade Level</th>
<th>FY2007-08</th>
<th>Racial/Ethnic</th>
<th>American Indian or Alaskan Native</th>
<th>Pacific Islander or Asian</th>
<th>Total State Enrollment</th>
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<tr>
<td></td>
<td></td>
<td>White (Non-Hispanic)</td>
<td>Black (Non-Hispanic)</td>
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<td>512</td>
<td>2,068</td>
<td>171</td>
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<td>Grade Four</td>
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<td>1,822</td>
<td>218</td>
<td>220</td>
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<td>Grade Seven</td>
<td>3,539</td>
<td>374</td>
<td>1,711</td>
<td>306</td>
<td>205</td>
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<td>6,047</td>
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<th>Resident Average Daily Membership for Charter Schools1 FY2006-07</th>
<th>FY2007-08</th>
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1 Average Daily Membership as defined by ARS § 15-902.
2 Detail pages in Volume II provide ADM for each charter school.

APPENDIX E

STATE SUMMARY BY GRADE OF PUPIL ENROLLMENT CHARTERS ONLY,

FY2008-09
### Appendix E

State Summary By Grade Of Pupil Enrollment Charters Only, Fy2008-09

**FY 2008-09 Race/Ethnicity**

<table>
<thead>
<tr>
<th>Grade Level</th>
<th>White (Non-Hispanic)</th>
<th>Black (Non-Hispanic)</th>
<th>Hispanic</th>
<th>American Indian or Alaskan Native</th>
<th>Pacific Islander or Asian</th>
<th>Total State Enrollment</th>
</tr>
</thead>
<tbody>
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<td>Grade Two</td>
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<td><strong>Total Elementary</strong></td>
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<td>Grade Ten</td>
<td>3,063</td>
<td>443</td>
<td>2,958</td>
<td>421</td>
<td>146</td>
<td>7,031</td>
</tr>
<tr>
<td>Grade Eleven</td>
<td>3,570</td>
<td>569</td>
<td>3,866</td>
<td>480</td>
<td>139</td>
<td>8,624</td>
</tr>
<tr>
<td>Grade Twelve</td>
<td>4,773</td>
<td>1,020</td>
<td>6,653</td>
<td>782</td>
<td>198</td>
<td>13,426</td>
</tr>
<tr>
<td><strong>Total Secondary</strong></td>
<td><strong>14,281</strong></td>
<td><strong>2,555</strong></td>
<td><strong>15,615</strong></td>
<td><strong>2,014</strong></td>
<td><strong>612</strong></td>
<td><strong>34,877</strong></td>
</tr>
<tr>
<td><strong>Grand Total</strong></td>
<td><strong>52,008</strong></td>
<td><strong>7,232</strong></td>
<td><strong>35,349</strong></td>
<td><strong>4,517</strong></td>
<td><strong>3,274</strong></td>
<td><strong>102,380</strong></td>
</tr>
</tbody>
</table>

Additional Data:

**Prior Year State Enrollment**

- **Elementary:** 62,754
- **High School:** 35,631
- **Total:** 98,385

**Resident Average Daily Membership for Charter Schools**

<table>
<thead>
<tr>
<th></th>
<th>FY2007-08</th>
<th>FY2008-09</th>
</tr>
</thead>
<tbody>
<tr>
<td>40th Day 10th Day</td>
<td>40th Day 10th Day</td>
<td></td>
</tr>
<tr>
<td>Elementary</td>
<td>62,754</td>
<td>38,697</td>
</tr>
<tr>
<td>High School</td>
<td>35,631</td>
<td>34,892</td>
</tr>
<tr>
<td>Total</td>
<td>98,385</td>
<td>73,589</td>
</tr>
</tbody>
</table>

1. Resident Average Daily Membership as defined by A.R.S. § 15-902.

APPENDIX F

ARIZONA’S INSTRUMENT TO MEASURE STANDARDS (AIMS)

STATE BOARD APPROVED AIMS PERFORMANCE LEVEL DESCRIPTORS
Appendix F

Arizona’s Instrument to Measure Standards (AIMS)
State Board Approved
AIMS Performance Level Descriptors

Falls Far Below
Students who score in this level may have significant gaps and limited knowledge and skills that are necessary to satisfactorily meet the state’s reading, math, and writing standards. Students will usually require a considerable amount of additional instruction and remediation in order to achieve a satisfactory level of understanding.

Approaches the Standard
Students who score in this level show partial understanding of the knowledge and application of the skills that are fundamental for proficient work. Students who approach the standard possess some understanding and skills necessary to begin working on the content required of the student who meets the standards. Due to incomplete understanding, additional instruction and remediation may be necessary in order to achieve a satisfactory level of achievement.

Meets the Standard
Students who score in this level demonstrate a solid academic performance on subject matter as reflected by the reading, math, and writing standards. Students who perform at this level are prepared to begin work on materials that may be required for the next grade level. Attainment of at least this level is the goal for all students.

Exceeds the Standard
Students who score in this level illustrate a superior academic performance as evidenced by achievement that is substantially beyond the goal for all students. Students who exceed the standard have demonstrated exceptional and exemplary attainment of knowledge and skills.

Performance Level Descriptors describe the general performance of a student within a performance range (Exceeds, Meets, Approaches, and Falls Far below). In addition to the general Performance Level Descriptors listed below, there are specific descriptors at each grade level. These descriptors indicate some of the knowledge and skills a student may demonstrate on AIMS.

APPENDIX G

TELEPHONE/EMAIL SURVEY
Appendix G

Telephone/Email Survey

Dear charter school administrator,

My name is Carrie Giovannone and I am a doctoral student from Kent State University. I am working on a research study to assess the effectiveness of Arizona charter schools for my dissertation. In an effort to collect the last set of data I would like to ask you a few questions (below) regarding your charter school. This short survey should not take longer than five minutes to answer and is completely voluntary. Your responses will be reported as anonymous therefore no one will be able to track any data back to your school or students. If you should decide to participate please respond by December 11, 2009.

1) Is there a particular focus to your curriculum (e.g., Traditional, Performing Arts)?
2) Did your school originally start out as a charter school or was your school converted from a traditional public school?
3) What was the Grade 8 class size from the 2008-2009 school year (i.e., actual number of students in one grade 8 class - even if the class was combined with another grade)?
4) What was the Grade 7 class size from the 2007-2008 school year?
5) What was the Grade 6 class size from the 2006-2007 school year?

Many teachers are "highly qualified" (as defined by the Arizona Department of Education); however, some schools are set up where the teachers may still have to teach additional content areas to those in which they are high qualified.
6) Do your junior high school teachers (i.e., grades 6-8) have to teach content areas other than those they are "highly qualified" in?

Thank you for your cooperation. If you have any questions, please, don't hesitate to call me at (330) 518-0298. Also, feel free to call the advisor on this project, Dr. Rafa Kasim, at (330) 672-0601 with any questions or Dr. John West, Vice President of Research, Division of Research and Graduate Studies from Kent State University, Kent, Ohio at (330) 672-2704.

Carrie L. Giovannone
Doctoral Student, Evaluation & Measurement
Kent State University
APPENDIX H

NAEP, GRADE 8 MATHEMATICS – ARIZONA, GENDER
Appendix H

NAEP, Grade 8 Mathematics – Arizona, Gender

*No significant difference between male and female NAEP Arizona Grade 8 Mathematics scores across the years.

Note: The NAEP Mathematics scale ranges from 0 to 500. Some apparent differences between estimates may not be statistically significant.
APPENDIX I

NAEP, GRADE 8 MATHEMATICS, 2009 – ARIZONA
Appendix I

NAEP Grade 8 Mathematics, 2009 – Arizona

Note. NAEP Mathematics Scale = 0 - 500

Note. NAEP Mathematics Scale = 0 – 500
Appendix J

NAEP Grade 8 Reading, 2009 – Arizona

Note. NAEP Reading Scale = 0 - 500

Note. NAEP Reading Scale = 0 - 500
REFERENCES
References


stateStats&pSectionID=15&cSectionID=44


CER_charter_numbers.pdf


stateStats&pSectionID=15&cSectionID=44


Gill, B. P., Timpane, P. M., Ross, K. E., & Brewer, D. J. (2001). *Rhetoric versus reality: What we know and what we need to know about vouchers and charter schools.* Santa Monica, CA: RAND.


presented at the annual meeting of the American Educational Research Association conference, Denver, CO.


Tu, Y. K., Gunnell, D., & Gilthorpe, M.S. (2008). Simpson’s paradox, Lord’s paradox, and suppression effects are the same phenomenon – the reversal paradox. Emerging Themes in Epidemiology, 5(2). Retrieved September 1, 2010 from http://www.ete-online.com/content/5/1/2


