THE EFFECTS OF CHARTER SCHOOLS ON THE ACADEMIC ACHIEVEMENT OF CALIFORNIA STUDENTS

A Thesis

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by

Baxter R. Boeh-Sobon

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Department of Public Policy and Administration

Abstract

of

THE EFFECTS OF CHARTER SCHOOLS ON THE ACADEMIC ACHIEVEMENT

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Charter schools are a national controversy, and have been since they were first adopted in the early 1990s. Yet in nearly thirty years in operation, only half of the country knows what a charter school is, and perhaps more important, if they are effective. With the current administration putting school choice on a national platform, it is more important now more than ever to under charter schools.

This study asks, in terms of academic achievement, do charter schools perform as well as traditional public schools? Using school-level panel data from the California Department of Education's Academic Performance Index, this study uses fixed-effects analysis to test this question.

This study finds that charter schools perform at the same levels as traditional public schools, and potentially even slightly better. This study also examines demographic and socioeconomic indicators, and their relationship to academic achievement. I identified a number of policy recommendations aimed at improving charter school, reducing funding

disparities between charters and traditional schools, and ensuring underserved California's have the opportunity to benefit from a fulfilling education.

_______________________, Committee Chair
Robert W. Wassmer, Ph.D.

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Date

DEDICATION

I dedicate this work to my mother, Hail, an educator who taught be the value of a good education, the reward of hard work, and the meaning of being a Mensch. I could not be where I am today without your unending love and support. You are the best person I know, and I'm so fortunate to call you mom.

ACKNOWLEDGEMENTS

To my readers, Rob and Jenni. You gave me support, guidance, and encouragement. Thank you for everything!

And to Nino, my best friend. Your patience, love, and generosity means so much to me. I could not have done this without you.

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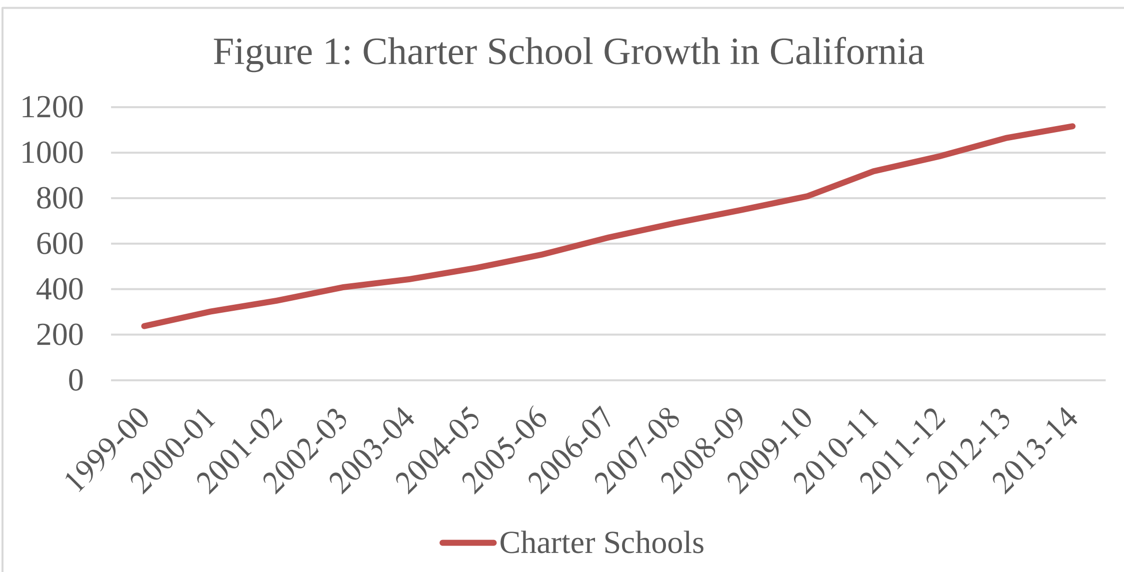
CHAPTER 1: Understanding Charter Schools

Why Examine Charter Schools?

California remains behind in academic achievement. In a 2016 study by Education Week Research Center, California's K-12 academic achievement ranked 30th in the nation, including Washington. D.C. (Quality Counts 2016, 2016). Previous annual reports by Education Week (Chalk 2015, Ebner 2014) show marginal improvement from years prior, when California ranked 33rd in both 2014 and 2015. While some may laud this increase in national ranking as an improvement, other Californian's remain concerned.

Dan Welch led the failed Vergara v. California lawsuit which challenged teacher protection laws (Noguchi, 2017). He stated, "California has refused to take meaningful action to address the education issues facing our state, so it was unsurprising to see California's poor grade remain the same year over year." Although his efforts failed, the sentiment remains prevalent. In Education Week's 2015 report, California's 33rd rank earned a D+ for K-12 student achievement, and its overall education ranking was 41st nationally (Noguchi, 2017). This overall examination of education, which includes equity, chance for success, and school finances, has not changed in 2016. California is still 41st nationally, with an overall score of 69.8 out of 100 (Quality Counts 2016, 2016). The concern remains prevalent to California educators, legislatures, parents, and those most affected: our children.

California has taken drastic measures to address this concern, from increasing education funding, to adopting a new approach to learning, (i.e. Common Core), to expanding support for school choice, namely through charter schools. These charter schools will be the focus of this research paper. Since adopted by California 25 years ago, charter schools – which are semi-independent systems, but publicly funded -- have become an increasingly popular option. Data collected by the National Alliance for Public Charter Schools (Figure 1) shows a steady increase in California charter schools since 2000. While charters only make up about 10 percent of California schools, the trend suggests Californian is looking for new solutions.



Data obtained from NAPCS at http://dashboard2.publiccharters.org/State/?state=CA

While charter school support has grown in California, national understanding of what they are and how they operate remains ambiguous. A 2014 national poll by Gallup and Phi Delta Kappa (PDK), a professional association for educators, reflects this lack of understanding. When survey questions proceeded with a brief explanation of charter schools, 70 percent of respondents said they were in support; that dropped to 63 percent when no description was provided (Bushaw and Calderon, 2014). When asked about school specifics however, respondents showed they generally misunderstood charters. Only half (50 percent) of respondents knew charter schools were public, and 48 percent knew they could not charge tuition. Most alarmingly, 68 percent of national respondents believed charters discriminated based upon student ability and 57 percent though charters could charge tuition. Simply put, misinformation exists. Now, with a renewed interest in school choice by the current federal administration, understanding charter schools is crucial. With the appointment of Betsy DeVos to the Department of Education, school choice has a large national platform, and the education of American children has not, in recent history, been so open to debate.

Under-achievement in California's K-12 education outcomes, and the general misunderstanding of how charters work, provide a catalyst for this study. This thesis asks, how does charter school academic achievement compare to the traditional public-school model? This thesis examines panel data pulled from the Department of Education's Academic Performance Index datasets, and will be discussed further in Chapter III. Comparing charter school success to the traditional public school will exemplify the root differences between these two academic models, helping Californians understand the issue. Understanding these differences can ultimately lead to better policy. Second, and most important, lasting and impactful improvements to California's education policy must be made. Clarifying achievement gaps between charter schools and traditional public schools can help legislatures allocate tax dollars to effectively address this state-wide concern.

To address these points methodically, I break this thesis into four chapters. The remainder of this chapter defines the differences between the charter model and the traditional public school (TPS) model, examines the development of the charter school, and expands on school choice and current political climate. Chapter two explores past charter school research on academic achievement in a comprehensive literature review. This information will naturally gather best practices for examining academic achievement. Chapter three lays out this paper's methodology and approach to understand charter school achievement. It defines data and parameters used, develops regression models necessary for a multi-year data examination, and explains the analysis process. Chapter four provides the results of the regression analysis, and potential policy implications. I explain this information and report significant findings, and provide general policy recommendations. It is important to note that while charter school achievement is a well-researched field, few studies focus on California. This thesis hopes to add to the growing literature in California charter research through a state-wide, longitudinal regression.

Development of the Charter School:

Although teachers' unions are often opposed to charter schools today, as they usually employ educators at-will, a teachers' union member first advocated for a new, charter-based system. In 1988, Albert Shanker, then president of the American Federation of Teachers, discussed an innovative approach to teaching students (Kahlenberg and Potter, 2014). He was inspired by a trip to a public school in Cologne, Germany, where teachers had greater say in school operations and ethnically diverse students performed in mixed-ability groups, presumably leading to achievement high above the German national average.

Mr. Shanker shared these principles with the American education system, in hopes of promoting social mobility and social cohesion (Kahlenberg and Potter, 2014). He envisioned unions would play a significant role in charter schools, and charters would showcase the principles of democracy to a diverse and integrated student population. Teachers would have a direct influence in the school, ensuring their investment and staying longer. Students, especially from a lower socio-economic background would see this democracy in action and work with a diverse group of peers, ideally motivating them to succeed.

These ideals led three educators to form the first charter school in St. Paul Minnesota in 1992 (Jacobs, 2015). City Academy aimed to teach the most under-served students in the state, namely drop-outs, students from low-income families, or those who lived in homes wracked with substance abuse. By 1993, the school graduated 17 students who otherwise would not have had an opportunity to learn. This idea of an innovative approach to teaching sparked charter school legislation across the nation. California became the second state to authorize charter schools in 1992, and in 1993 six more states signed on (Allen, 2017). By the end of the decade, 38 states had charter school legislation. Today, nearly 3 million children throughout 43 states and Washington, D.C. attend over 6800 charter schools (Facts About Charters, 2017).

Charter Schools and the Traditional Public School:

Simply put, charter schools are publicly-funded, non-religious institutions that offer greater freedom than the traditional public school ("Facts About Charters," 2017). They operate under a contract (or charter) which outlines administrative management, and holds the school accountable for achieving academic milestones. Ultimately, if a charter school fails to meet these milestones, the contract is revoked, and the school is closed. However, the recent Supreme Court ruling, Trinity Lutheran Church v. Comer, lifted restrictions on religious schools participating in public, government-funded programs (Barnum, 2017). Lower courts will decide how to interpret this, but critics argue it could open the way for public funding for religions schools through vouchers, or religious charter schools.

In many areas, charter schools and the counterpart traditional public school (TPS) model have many similarities. Both are publicly funded institutions of learning; both are currently non-religious (although subject to change); both have open enrollment policies for students, and cannot discriminate against potential pupils; neither can charge tuition; and both models participate in California standardized testing (O'Brien and Devarics, 2010). However, the two educational models have fundamental differences in academic philosophy and approach, administration, and even avenues of funding. This section examines these differences to help understand potential differences in academic achievement.

Academic Approach: Fostering Innovation

The most acclaimed difference in charter schools is their ability to foster innovation. Providing an innovative approach to learning was a founding philosophy when charter schools establishment in the early 1990s, and is a key argument in favor of the charter school model (Kahlenberg and Potter, 2014). Charter schools develop their own curriculum, including everything from establishing an educational philosophy to determining class size and school start times. Arguably, this flexibility allows for different, often targeted approaches for reaching students that do not succeed in the TPS model. Charter school curriculum is diverse, from foreign language emersion programs, to Montessori schools, to schools for English Language Learners (ELL), to schools with a focus on Science Technology Engineering and Math (STEM) ("Facts About Charters," 2017).

While this freedom allows charter schools to be creative in its curriculum, it also allows for educator flexibility. More to the point, charters can hire teachers at will, and is a major point of controversy. At will teachers are not part of teachers' unions, and do not receive job protection. This system provides less job security for educators, but also allows for greater flexibility in teaching methods.

Financial Management: The Privatization Concern

In addition to choosing curriculum and academic approach, a charter school is free to determine how it wants to manage finances. Most charter schools (67 percent) manage finances internally, while non-profit organizations manage 20 percent of charters ("Facts About Charters," 2017). The remaining 13 percent use for-profit management companies. Although for-profit companies must meet the same standards and are subject to the same oversight as other charter schools, concerns are still prevalent. California Assemblyman Kevin McCarty (D-Sacramento) stated that, "When we allow private companies to run public schools, we invite them to focus on shareholders and profit margins instead of on children and student achievement" (Calefati, 2017). A counter-argument is parents are these companies' customers, and they operate based on their desires or risk going out of business. Traditional public schools do not provide this option.

School Funding:

An adage of American journalism is to understand the root of an issue, simply "follow the money." This section briefly examines school funding in California, to first see if a disparity in funding between charter schools and the TPS model exists, to what extent, and whether that disparity could impact academic achievement.

In 1992, when charters received authorization to run in California, the Legislature authorized charter funding, which was to be comparable to the traditional public school TPS model (Estrada, 2012). This system had flaws however and money was not distributed effectively. At the time, school districts allocated funding to charter schools without ensuring if the money was following each student. Reforms made in 1998, 1999, 2005, and 2009 by the Legislature targeted reducing the funding gap, and clarifying the process through regimented funding categories (Ugo and Hill, 2017). While these funding categories helped maintain accountability, gaps remained as many charters lacked equal access to funds as the TPS model.

To fix this longstanding disparity, California Governor Jerry Brown overhauled education funding in 2013 by approving the Local Control Funding Formula (LCFF), which updated the school funding formula based upon student attendance to better align funding sources (Resmovits, 2017). Under this currently active policycharters are incorporated into structures which resemble their TPS school districts to receive funding, and support accountability (Ugo and Hill, 2017). The goals is to equalize funding for charter schools and public school districts. However, one provision in the LFCC, regarding high-needs student funding, unintentionally inculcates a funding gap.

Students designated as high-need can be low-income, English Language Learners (ELL), or students with disabilities ("Frequently Asked Questions," 2017). Under the LFCC provision, funding available for these students are calculated differently for charter schools and traditional public schools, placing caps on nearly one third of charter schools which don't meet these different criteria, effecting one third of California charters (Ugo and Hill, 2017). This difference aims to discourage TPS districts from converting to charters to alleviate budget issues. Ultimately, these charter schools receive an average of $450 less per pupil.

Before the LFCC, charter schools and the counterpart TPS model had a seven percent funding gap. (Estrada, 2012). This dropped to five percent under the new policy. A 2017 PPIC study (Ugo and Hill, 2017) measured achievement regarding this funding disparity, examining capped and non-capped charters. Results show that capped charters slightly underperformed when compared to charters that did not meet a cap; however, these results were not statistically significant. The study cautions drawing conclusions as the LFCC is not fully implemented, and more data is needed to determine an effect on academic achievement. However, the LFCC has generally helped to reduce the funding gaps prevalent between charter schools and the TPS model, but revenue disparity remains.

It is important to note the differences between direct and indirect funding sources. “Direct-funded” charters received their money from the state, where indirect, or “locally funded” charters authorizing school district or county office (EdData, 2017). According to EdData, these two funding models are treated differently in the California Department of Education’s main educational database. For example, direct-funded charter school dropout and graduation rates are not tracked, while locally funded charter schools are. This is likely because locally funded charters received funding the same way TPSs do, and are easier to track. While data parameters are discussed further in Chapter 3, the funding distinctions are important to note.

CHAPTER II: Literature Review

The inception of the charter school system spurred research regarding its impact on academic achievement. Today a huge body of literature exists on charter schools, many of which compare charters to the traditional school model. However, findings are often inconsistent. While some research shows academic achievement gains in charter schools (Hoxby and Rockhoff 2005; Sass 2006; Dobbie and Fryer 2009; Abdulkadirglu *et al.* 2011; Angrist *et al.* 2012; Rorrer and Ni 2012; Baude *et al.* 2014), other studies show no or diminished gains, or lower performance when compared to TPSs (Bettinger 2004; Bifulco and Ladd 2006; Zimmer and Buddin 2006; Zimmer *et al.* 2011). These differences may result from multiple factors. With the wide variety of research methods practiced and available data used, to the innumerous approaches in charters academic philosophies, to differences between state charter laws and funding, and differences in school makeup and geographical setting, such inconsistencies are bound to occur. While laws and funding disparity may influence academic achievement, it will not be the focus of this chapter, nor this study. This thesis hopes to add to this growing body of work using fixed-effects analysis and school-level panel data.

Before I complete my own regression study, this literature review examines some of the previous regression-based studies on charter school academic achievement to identify methodological best practices and summarize previous findings. In this chapter, I present a comparison of various methodology and results from past literature on charter schools. A table summarizing these comparisons is available in Appendix A.

Differences in Methodology:

Regression analysis is a data-driven, statistical tool used to understand relationships between identified variables. Variables are some quantifiable entity that are measurable, such as age, income, or education level. Regression models examine the relationships between dependent variables, the relationship output, and independent (or explanatory) variables, those inputs that influence the dependent variable. All studies in this literature review are regression based, and emplaced similar controls, making comparison between studies easier. However, the types of regression models used vary, and will be the focus for the first part of this chapter.

The most common methods used when examining academic achievement are random-effects models (using lottery-based random assignments), student fixed-effects analysis, and matching models. Lottery-based studies capitalize on the random nature of student admissions, often using denied students as a control group (Baude *et al.*, 2014). Hoxby and Rockhoff (2005), Zimmer and Buddin (2006), Dobbie and Fryer (2009), Abdulkadiroglu *et al.* (2011), and Angrist *et al.* (2012) have used this model with differing results. The random-effects model, often referred to as lottery testing, eliminates bias as it randomly assigns students to charter schools or TPSs through a lottery.

This lack of student attrition proves clarity on the impact of a charter school, but with noticeable limitations. Lottery-based testing is only usable on over-subscribed schools with waiting lists. Undersubscribed schools must be ignored, limiting the value of the analysis. A further concern develops from examining oversubscribed schools, as better preforming schools often have waitlists, while lower performing schools do not. These conditions make lottery-based studies hard to extrapolate to charter schools at large.

The greater body of literature, both in and out of this study, uses fixed-effects analysis. Holmes et al. (2003), Bettinger (2004), Booker *et al*. (2004), Bifulco and Ladd (2006), Sass (2006), Zimmer and Buddin (2006), Garcia *et al.* (2008), Zimmer *et al.* (2011), and Rorrer and Ni (2012) use student fixed-effects analysis. It is useful for categorizing and controlling variables, if they remain constant over time. Furthermore, the fixed-effects model is useful as it diminishes data self-selection bias by comparing the variables to themselves (Rorrer and Ni, 2012).

Fixed-effects uses panel data to examine student achievement over time, and compares student outcomes while attending a charter to before or after achievement in a TPS. Naturally, a student therefore must have attended both a charter school and TPS, and have switched during the time of analysis. These “switcher” students cannot represent all students however, and can limit the scope of a study. Baude *et al.* (2014) suggests that as charter schools become more established, less students are likely to start and stay with charter schools, especially those with high academic achievement. In fact, Rorrer and Ni (2012) identified that one-third of Utah charter school students never attended a traditional public school.

The matching model is less frequently used as lottery testing or fixed-effects analysis, but does have benefits. Rorrer and Ni (2012) used it as supplemental testing to their fixed-effects analysis to better isolate student achievement. Unlike the fixed-effect test that compares variables to themselves, the matching model matches charter school students to TPS students with similar demographics and prior achievement, to measure achievement gains. Ultimately, this approach provides a more inclusive examination of charter school students, without limits to switchers, or over and under-subscribed schools. However, it does not control for unobserved heterogeneity (such as parental involvement or motivation) as does fixed-effect analysis.

A more recent approach to examining charter school achievement is through an econometric, value-added model (often called VAMs). VAMs isolate achievement in classrooms, examining teacher performance instead of school-wide success. Because teaching style can alter dramatically between classrooms, this model originally aimed to identify variation between teachers. Baude *et al.* (2014) however uses a value-added assessment to focus on charter school achievement. Like fixed-effects, this model uses panel data to capture unobserved student-level factors. The econometric aspect of this model however also examines transitional costs associated with changing schools.

In the studies examined, the authors use multiple models to estimate the academic achievement of charter schools. Although each have their benefits and costs, the fixed-effect method is by far the most advantageous. It can account for unobserved variables in the data, providing greater validity. As longitudinal data accumulates this method will likely see continued use, along with more significant results.

Regression Findings

The reviewed literature presents findings as diverse as methods used. While inconsistent, some studies show less significant findings than others. This section categorically examines finding of each study. First, I present studies which show charters have a positive impact on academic achievement, or perform similarly to traditional public schools. Next, I examine those studies which suggest charter schools perform worse than traditional public schools, or show a decrease in student academic achievement. I then identify trends between positive and negative studies to understand best practices for my regression analysis. For specifics about the magnitude of coefficients and data parameters for all studies, see Appendix A.

Charters Have Positive Effects:

Most studies found that charter schools showed positive gains in student academic achievement when compared to the TPS model. Booker et al. (2004), Hoxby and Rockhoff (2005), Sass (2006), Zimmer and Buddin (2006), Garca *et al.* (2008), Dobbie and Fryer (2009), Abdulkadiroglu *et al.* (2011), Zimmer *et al.* (2011), Angrist *et al.* (2012), Rorrer and Ni (2012), and Baude *et al.* (2014) had findings that were similar in academic achievement when compared to traditional schools. Zimmer and Buddin (2006) examined San Diego and Los Angeles, two large urban school districts. While results were mixed, they found that charters and traditional public schools performed nearly the same. Results were statistically significant, showing charters perform -0.38

percentile points worse than TPS in reading, but 0.27 percentile points higher in math. A later study by Zimmer and et. al (2011) also found mixed results with a seven-way comparison between five states and two metropolitan cities. While not all findings were statistically significant, a clear pattern emerged. The high-density cities examined showed charter schools had a positive effect on academic achievement (Denver with 0.17, and Milwaukee with 0.05), while stat-wide results show statistically significant negative effects of charter schools (-1.18 in Ohio and -0.12 in Texas). As Texas and Ohio have large, non-urban areas, these may have skewed results. However, without more information it is best not to extrapolate.

Booker et al. (2004), Sass (2006), Abdulkadiroglu *et al.* (2011), Rorrer and Ni (2012), and Buade *et al*. (2014) found significant evidence that charters perform as well as TPSs, but only after a grace period of three to five years (depending on the study). In a charter's initial "infancy years," they perform slightly worse than their TPS counterpart. These findings are specifically worth noting when considering policies targeting charters. If charters experience a learning curve of up to five years, the state should review charter auditing policies to ensure charters do not close too early.

There were many similarities between these studies. All used student-level data, or some combination of student and school-level data, and all datasets were longitudinal. Most studies also used fixed-effects analysis, and examined switcher students to isolate differences in test scores for both charters and traditional public schools. Abdulkadiroglu *et al.* (2011) and Hoxby and Rockhoff (2009) instead use random-effects analysis for schools with waitlists. Abdulkadiroglu *et al.* (2011) saw statistically significant positive effects on charters, but compared them to pilot schools instead of TPSs. Although pilots are public schools operated through school districts, they are similarly to charter school structure. Hoxby and Rockhoff (2009) show positive magnitudes of 1.57 for math and 3.41 for reading, but these results are not statistically significant. The authors both attest to certain inherent bias in lottery-based testing, as it schools with waitlists are likely higher preforming schools already.

Negative Effects of Charter Schools:

While most of reviewed literature suggests charter schools and TPSs perform at similarly, a few studies suggested otherwise. Bifulco and Ladd (2006) found statistically significant results showing charter schools had negative effects on math (-0.16) and reading (-0.095) scores when compared to traditional public schools. Bettinger (2004) also showed charter schools do not improve test scores as well as TPSs. Charters show a statistically significant yet small magnitude of -0.01 for math scores and -0.013 for reading. Bettinger (2004) also found statistically significant, negative correlation between charters and academic achievement for math (-0.01) and reading (-0.013).

Interestingly, both studies use fixed-effects analysis with student-level panel data, which produced completely opposite results for most of studies. A possible explanation is that both studies are old, and use data from the 1990s. At this time, charter schools were not well established, and may have still been in there “infancy years” as Baude *et al.* (2014) put it, which could ultimately affect data quality.

While not showing a negative effect of charter schools, some studies showed differing trends based upon analyzed variables. Angrist *et al.* (2012), while showing an overall positive effect of charter schools (0.213) when compared to TPSs and positive achievement gains for urban charter schools (0.321), also showed non-urban charters as doing worse (-0.123) when compared to non-urban TPSs. Booker *et al.* (2004) and Garcia *et al.* (2008), while finding overall positive effects of charter school (0.109 and 17.67 in math for each study, respectively), saw mixed trends among switcher students. Both studies found statistically significant negative effects of student switching from TPSs to charters, but positive effects of students switching from charters to TPSs (see Appendix A for a breakdown of magnitudes).

Holmes *et al.* (2003) took a slightly different approach, examining the competitive effects of charter school proximity had on nearby TPSs, ultimately showing statistically significant gains (0.01) in achievement for those TPSs within a 10-kilometer radius. If anything, such findings suggest that the market-based competition of charter schools helps bolster overall achievement gains.

The multitude of differing results suggests that a significant consensus on charter schools' academic performance is not complete. This differentiation does not necessarily limit the validity of the individual findings, but does fuel the social commentary and controversy regarding charter schools. Researchers used multiple methodologies to examine academic achievement. But could other unobserved factors have influenced results? The next section examines differences in charter school law and funding by state.

Is it fair to compare? Differences in charter school laws and funding by state:

The studies in this literature review examine schools within multiple states, each with differing laws, and funding structures (and often funding disparities, both between states and school type). Beyond observable variations in data or issues with selection bias, these differences may have confounding impacts on studies, making them more challenging to compare. While this study does not intend to empirically examine these potential factors, nor determine how these differences could be controlled, it is at least worth noting differences in charter school funding and laws by state.

A noticeable difference between charter schools and traditional school models are the disparities in funding. It is logical that a charter which receives less money will have a harder time meeting similar performance standards as public institutions. However, not all states provide the same amount of funding to charters. A recent study calculated the funding disparity between states, finding that on average charter schools receive 28.4 percent less funding than TPS (Batdorff *et al*., 2014). Of the states in this literature review, Pennsylvania, California, Michigan, and Ohio received an “F” grade, Utah, Arizona, and Illinois received a “D” grade, and Texas received a “B” grade in terms of funding. With such great inequities in funding, it is understandable for disparities in charter performance by state.

While funding disparities differ by state, it is important to recall for this study that California revised funding in 2013 to reduce gaps between charter schools and traditional public schools. As discussed in Chapter 1, this LFCC streamlines funding for direct-funded charter schools, and funding received by charter school from public school districts (indirect funding). While the funding gap has decreased under the LFCC, disparity still exists, especially for students with disabilities. This new funding system is still being implemented however, and should be examined in future studies.

Although funding is important, state legislation may also have an impact on charter school success. Although Texas gives the most funding out of these states, their charter programs rank 27th in the nation by the Center of Education Reform (Consoletti, 2012). Michigan charters however, which receives 27.7 percent less funding than TPS's, consistently rank 5th in the nation. Because each state has the freedom to determine their charter school system, laws, and approaches to funding, there are many potential paths. Such differences are important to consider when comparing charters across state lines, as the success in Arizona may not equate to the problems in Illinois.

Best Practices from the Literature:

This literature review provides an overview of the common research methods used in identifying the relationships between charter schools' academic achievement. The variation between methodologies used was nearly as great as each studies' findings. Most conform to similar control variables and analysis models. Fixed-effects analysis seems to be the most widely accepted assessment, but an interest in an econometric analysis is starting to grow. Other methods like lottery-based testing, while a relatively popular assessment, has inherent bias. In some cases, like Hoxby and Rockhoff (2005), these findings did not produce statistical significance. While findings also differ, most studies suggest a common theme: charter schools offer little difference to public schools in terms of academic achievement, especially over the long-term. This statement is far from a consensus, and further analysis is bound to occur. These findings may also be completely dependent upon the charter laws passed in each state. With completely different regulations in terms of funding, regulations, development goals, and establishment requirements, each charter school could influence beyond what is tested.

From this review of literature, I learned some important best practices to use in this study. Based on the results in the literature, this study uses fixed-effects analysis to examine academic achievement. While Chapter 3 discusses specifics about data and methodology, this study also ensures to use the most current data available, to avoid using data where charter schools were still in an infancy phase. Finally, this study recognizes the benefit of using student-level panel data, and examining student switchers as an explanatory variable, but cannot use them, and is discussed in greater detail in Chapter 3.

CHAPTER III: Data and Methodology

This chapter considers the collective best practices identified in the literature review, and presents this study's data parameters and methodology. This study uses school-level panel data to examine charter school academic achievement through fixed-effects analysis. The first section operationalizes the data, provides data parameters, identifies dependent and explanatory variables, and examines potential limitations. The second section outlines the methodology used and identifies possible limitations, providing a clear understanding of findings.

Datasets and Potential Limitations:

Under the *Public Schools Accountability Act of 1999*, the California Department of Education (CDE) began collecting Academic Performance Index (API) data to measure academic performance and growth in California schools (California Department of Education, 2017). However, approval to institute Common Core standards in 2012, and combined efforts of the CDE and the State Board of Education (SBE) to launch a new school accountability system, suspended continued tracking of API data. Therefore, the last API report was issued in 2013, and last year of base data was recorded in 2012.

In March 2017, the CDE and SBE launched the new school accountability system, and there first dataset is now publicly available on the CDE website. However, as this study examines charter school academic performance through fixed-effects regression and panel data, this new accountability system will not be applicable for some time.

Although the API datasets are outdated, they are still extremely valuable, especially when viewed longitudinally. The following sub-sections identify data parameters, and operationalize variables. Academic achievement, identified through API scores in these data, is our dependent variable. For simplicity, this study groups explanatory variables into three categories: socioeconomic factors, demographic factors, and school-based factors. The table below provides summary statistics for variables used in this study.

Table 1: Summary Statistics for All Variables

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
CHARTER	11376	0.0704114	0.2558503	0	1
API Score	11347	816.2717	75.02494	410	998
% Black	11373	6.517014	10.77101	0	98
% Native American	11373	0.9391541	3.889182	0	100
% Asian	11373	7.98558	13.23385	0	97
% Filipino	11373	2.270729	4.200119	0	65
% Hispanic	11373	50.23916	29.9772	0	100
% Pacific Islander	11373	0.5171019	1.091727	0	23
% White	11373	28.44192	26.28159	0	100
% Meals	11373	60.61655	30.82563	0	100
% Migrant Ed Program	11373	1.477007	4.116737	0	82
% English Learners	11373	27.81755	20.99837	0	100
% Disability	11373	11.39989	8.845368	0	100
% Not HS Graduate	11373	18.91445	17.67124	0	100
% HS Graduate	11373	24.54023	12.93169	0	100
% Some College	11373	24.13831	11.10393	0	100
% College Graduate	11373	19.21085	13.06496	0	100
% Graduate School	11373	12.54119	14.68209	0	100
% Tested	11376	0.9965607	0.0203478	0	1

Examining Data Parameters:

This study uses API datasets from the base years 2011 and 2012. These datasets track school-level data, measuring 150 variables for over ten thousand California schools (units of observation). To create a more manageable and meaningful analysis, this study focuses on elementary schools by reducing the datasets, 2011 base has 5,983 elementary schools, while 2012 base has 5,792. To make this data comparable, I paired all elementary schools by ID code and removed any non-matching schools. Between the two years, the final number of observations is 11,347, equating to 5,688 elementary schools. Of these, 400 are elementary charters schools, which is seven percent of the total number of elementary schools, and roughly half of the number of charter schools reportedly in California between 2011 and 2012. This provides a reliable sample size for analysis.

Operationalizing Variables:

The API datasets provides 150 data fields. Fortunately, collection and formatting remained identical throughout the CDE's use of API data, so data is complete for these fields. Although a fruitful resource, many of these fields are unnecessary or irrelevant to this study. This section identifies the variables used in this study, separating them into three categories: socioeconomic, demographic, and school characteristics. Appendix B provides a list of all the explanatory values, and their expected effect on academic achievement.

Socioeconomic factors examine education, income, and employment of an individual or groups to conceptualize a social class or economic standing in society. These socioeconomic factors, including their family's household income, their parent's level of education, and their family background, may influence a student's ability to achieve academically. Examining such variables identifies societal inequities, making them important factors to control.

Although API data does not provide actual student household income information, other variables provide indirect indicators. Parent education level is an indicator for income level, as research shows that higher levels of education are often correlated with higher income (Baum and Payea, 2005). Free and reduced school lunches are another indicator used to determine household income of the student. Finally, special programs such as the Migrant Education Program (MEP), as well as percent of English learners are also used as socioeconomic indicators. Migrant and English learner students are more likely to come from a low-income family and have less parental support with school. This could have adverse effects on their academic achievement and are important to control. When modeled, socioeconomic factors look like this:

Socioeconomic Factors = f(Parent education level by percentage [not a high school grad, high school grad, college graduate, graduate school], percent student eligible for free/reduced school lunch, percent English learners, percent Migrant Education Program)

Demographic factors consider differences in population characteristics, such as race, age, gender, and geographic location in order gain a greater understanding of societal structure. However, the dataset has some limitations when controlling for demographic factors. Student gender was not recorded, limiting a potential observation. The study also does not distinguish between schools in urban or non-urban environments. Zimmer and Buddin (2006) and Angrist et al (2012) suggest that urban charter schools see more significant gains than non-urban charters, which would have been interesting to test further. Unfortunately, API datasets do not represent this information.

One important factor I did control for is race. Although race can often have a spurious relationship to the dependent variable, as other variables are more strongly correlated, it is an important factor to control for nonetheless. All studies discussed in the literature review also ensured to place control variables for race, especially White, Hispanic, and African American. This study controls for race categorically by African American, Native American, Asian, Filipino, Hispanic or Latino, Native Hawaiian/Pacific Islander, and White. The API datasets also include “multiple races,” however I omitted this variable because it is not clearly definable, and detracts focus from the other categories and overall message. I also include the percentage of students with disabilities in demographic factors. Unfortunately, the API dataset did not specify whether these were mental or physical disabilities, or whether these were students that needed special conditions while taking the test. When modeled, demographic factors look like this:

Demographic Factors= f(Race by percent [African American, Native American, Asian, Filipino, Hispanic or Latino, Native Hawaiian/Pacific Islander, White], percent student with disabilities)

This final category examines school characteristics that may cause variance with academic performance. Charter schools, although our key explanatory variable, is a school characteristic, and placed here for categorical correctness. In the dataset, the charter schools field categorized as “D” for direct-funded charters, “Y” for indirect-funded charters, or left “blank” for not a charter. While we previously discussed performance indications between charters that examine direct-funded versus local-funded, this study does not examine these differences. To properly code the charter field, I created a dummy variable, where 1 represents charters (comprised of direct and indirect-funded charters), and all non-charters equal 0.

Finally, I control for percent of students tested as it may affect academic performance. Actively involved parents may withdraw students who feel their children will underperform. Involved parents are usually better educated and white. If those parents remove children from testing, it may indirectly increase test scores for white students. To create the variable “Percent Tested,” I divided the data field “Tested” by the “Enrolled” data field to gain a percentage of student’s present on the first day of testing. The model form of school characteristics looks like this:

Demographic Factors= f(Race by percent [African American, Native American, Asian, Filipino, Hispanic or Latino, Native Hawaiian/Pacific Islander, White], percent student with disabilities)

Methodological Approach:

Examining Study Limitations Around Fixed-Effects:

As seen in the literature review, fixed-effects analysis provides a relatively accurate interpretation of school performance between charter schools and the traditional public model. With simple regression, we cannot control for unobserved heterogeneities, allowing the chance for bias in the resulting estimates. Fixed-effects analysis is beneficial because it controls for these unobservable variables (Bifulco and Ladd, 2006). The literature offers some best practices when using fixed-effects analysis to examine academic achievement.

Using student-level data and switcher students is prevalent across multiple studies. Baude *et al* (2014), Booker *et al* (2006), Bifulco and Ladd (2006), Garcia *et al* (2008), Sass (2006), Zimmer and Buddin (2006), and Zimmer *et al* (2011) use student-level data and "switcher" students as key indicators in their fixed-effects models. As discussed in the literature review, examining student switchers provides clearer understanding of the direct effects of achievement in a charter school and a TPS on the same student. Student-level data is necessary to measure individual switcher and stayers as it tracks achievement by the student, rather than the school. While effective at measuring within-student variation, switcher data has some limitations. Sass (2006) shows that observations often note performance drops on the first year of a student switching to a TPS or charter school. In some cases, this may result from poor adjustment, bad teachers or other unobserved variables. However, using multiple years of longitudinal data after a switch occurs helps reduce drop variation.

Unfortunately, the data used in in this study is school-level data, and does not track switcher students. Some studies suggest that examining switchers is the only way to control for fixed-effects, as the parameters to this model identify within-student variation (Sass 2006, Bifulco and Ladd 2006). However, this is not accurate. While a best practice, lacking switcher data does not bar the use of fixed effects analysis. Instead of examining the individual effects school type has on achievement, this study looks at differences on a school-level. While switchers are an ideal control because they identify provide comparisons on the same observation, they are not necessary. Fixed-effects still achieves this research goal instead by examining general, school-level differences between API scores of charters and TPSs. Drawing conclusions on student achievement through this study must be done with caution, so as not to extrapolate implications.

Fixed-Effects Model:

Regression analysis is a powerful tool that helps us understand if correlations exist between different, and sometimes seemingly unrelated, variables. With a simple linear regression, one variable is compared to a dependent variable to try and determine any correlations. In the real world, such relationships rarely exist, so most regression is multivariate, or using many explanatory variables to try and understand relationships. However, there are always unobservable variables, or heterogeneities. Consider a student that does not show up for class. He may have been sick, or his car broke down, or he slept through his alarm, or maybe he is in the emergency room. However, there are unobserved variables here, as the student possible just skipped class. By not accounting for these unobserved heterogeneities, the relationship between student and class will have bias in its estimates.

Fixed-effects analysis is powerful because it controls for heterogeneity. Fixed-effects assigns a coefficient to each unit of observation (in our case School ID), which adds significantly to the regressions predictive power. While this is generally beneficial, it has potential drawbacks. These individual coefficients also allow each school to be different, but does not identify what drives those differences. This level of specificity without a clear understanding suggests an inflated R-squared. R-squared tells us how close data are to the fitted regression line, so the higher in value or percent, the more the model explains variation. It would also lead to extremely long regression results, as each of the 11,347 units of observation in this study would receive an individually-assigned coefficient.

This study controls for this by using fixed-effects with a “within estimator.” This tool calculates the within mean of all schools, and subtracts for the value of all variables. Because “School ID” remains constant over time (school G with sill be school G in 2011 and 2012), it allows a point to test against. Those individual coefficients for school drop, and R-squared is not as easily inflated.

In addition to using within estimators, I use a linear fixed-effects regression (lin-lin), and a fixed-effects regression where the dependent variable (API Scores) runs as a logarithm (log-lin). In linear regression, a line of best fit falls between points of observation. This can be explained by interpreting the regression coefficients of each model. To do so, ask: Given some change in X, how much is Y expected to change? The following model explains linear (lin-lin) regression:

$$Y_t = \beta_1 X_t + \beta_n X_{nt} + \boldsymbol{\varepsilon}$$

Here, Y is the dependent variable (API Scores), X is the explanatory variable (Charters, Percent African American, etc.), β is the coefficient for that explanatory variable, and **ε** is the error term (where "robust" controls for heteroskedasticity). To interpret the regression coefficient, if X changes by 1 unit, the expectation is Y changes by β. This produces a line.

However, real-world relationships are not linear, so the log-lin model corrects for that by creating a curved line of best fit to better understand the relationships between variables, making a stronger regression. The following model explains log-lin regression:

$$\ln(Y_t) = \beta_1 X_t + \beta_n X_{nt} + \boldsymbol{\varepsilon}$$

The model is similar to the linear model except the dependent variable is run as a logarithm. Interpreting β is different, however. Here this relationship is ultimately curved and not linear. Interpreting the coefficient, if X changes by 1 unit, the expectation is Y changes by β x 100 percent. For example, if X equals percent student with disabilities, increasing X by one unit would increase API Scores by 100 percent times the β of X. With both models, this interpretation only works for statistically significant coefficients.

With a better understanding of these models, I add this study's variables to see the resulting fixed effects regression model. This model only reflects the linear model, however changing API Scores to ln(API Scores) re-interprets this model into log-lin form:

$$\mathbf{API\ Scores_{2011,2012} = \beta_1(Charter\ Schools[D])_{2011} + \beta_2(Percent\ African\ American)_{2011} + \beta_3(Percent\ Native\ American)_{2011} + \beta_4(Percent\ Asian)_{2011} + \beta_5(Percent\ Filipino)_{2011} + \beta_6(Percent\ Hispanic)_{2011} + \beta_7(Percent\ Pacific\ Islander)_{2011} + \beta_8(Percent\ White)_{2011} + \beta_9(Percent\ Disabilities)_{2011} + \beta_{10}(Percent\ Free\ or\ Reduced\ Meals)_{2011} + \beta_{11}(Percent\ Migrant\ Ed\ Program)_{2011} + \beta_{12}(Percent\ English\ Learner)_{2011} + \beta_{13}(Percent\ Parent\ Not\ HS\ Grad)_{2011} + \beta_{14}(Percent\ Parent\ HS\ Grad)_{2011}\ \beta_{15}\ (Percent\ Parent\ College\ Graduate)_{2011} + \beta_{16}(Percent\ Parent\ Graduate\ School)_{2011} + \beta_{17}(Percent\ Tested)_{2011}\ \beta_1(Charter\ Schools[D])_{2012} + \beta_2(Percent\ African\ American)_{2012} + \beta_3(Percent\ Native\ American)_{2012} + \beta_4(Percent\ Asian)_{2012} + \beta_5(Percent\ Filipino)_{2012} + \beta_6(Percent\ Hispanic)_{2012} + \beta_7(Percent\ Pacific\ Islander)_{2012} + \beta_8(Percent\ White)_{2012} + \beta_9(Percent\ Disabilities)_{2012} + \beta_{10}(Percent\ Free\ or\ Reduced\ Meals)_{2012} + \beta_{11}(Percent\ Migrant\ Ed\ Program)_{2012} + \beta_{12}(Percent\ English\ Learner)_{2012} + \beta_{13}(Percent\ Parent\ Not\ HS\ Grad)_{2012} + \beta_{14}(Percent\ Parent\ HS\ Grad)_{2012} + \beta_{15}\ (Percent\ Parent\ College\ Graduate)_{2012} + \beta_{16}(Percent\ Parent\ Graduate\ School)_{2012} + \beta_{17}(Percent\ Tested)_{2012} + \varepsilon}$$

Addressing Multicollinearity:

Before running the fixed-effects regression models, I tested the variables for multicollinearity. Multicollinearity exists when one variable is highly correlated with one or more variables. This is problematic as variables that are highly correlated, those with coefficients of a sufficient positive magnitude, may have an adverse effect on the regression estimates. For example, we may assume that the racial characteristic Hispanics may be highly correlated with students in English Learner classes. While we could remove highly correlated variables, doing so would likely detract from the study. Additionally, it is important to remember that correlation does not mean causation. I choose to leave any highly correlated variables in the study, and recognize the multicollinearity may exist.

To test multicollinearity, I first ran a variance inflation factor (VIF) test. Specifically designed to check this problem, if the test reports a value higher than 10, multicollinearity exists. If above five, it is a likely reason p-values are statistically insignificant. In other words, the detection of possible multicollinearity through VIF and correlations is only an issue if the suspect variables are not statistically significant. However, there are some limitations to running a VIF test; namely that is does not work with fixed-effects analysis. Instead I run an ordinary least squares (OLS) regression (See Table 3, Chapter 3) with the same variables used in our fixed-effects models, then run the VIF test on that.

Table 2: VIF Test

Variable	VIF
% Hispanic	34.92
% White	26.95
% Not High School Graduate	9.14
% Asian	7.68
% Meals	7.12
% Black	5.58
% Graduate School	5.52
% College Graduate	4.98
% English Learners	4.57
% High School Graduate	4.48
% Some College	3.26
% Filipino	1.95
% Native American	1.66
% Migrant Ed Program	1.27
% Pacific Islander	1.18
% Disability	1.12
% Tested	1.11
CHARTER	1.09
Mean VIF	**6.87**

Looking at the VIF test (See Table 2), we see high scores, and a mean VIF of 6.87. Hispanics and Whites are the most concerning variable, having VIF scores of nearly 35 and 27, respectively. Parents without a high school education, or those with a college degree of better, Asians, Blacks, and students receiving free or reduced cost lunches all have VIFs of five or above. This test suggests nearly half the variables used are susceptible to multicollinearity, which may account for potentially statistically insignificant p-values.

While VIFs are high, this may be a result from running VIF with panel data for fixed-effects analysis. Stata warned that VIF testing on OLS with this dataset would likely produce very high scores, which it did. Because of this, I ran a second test for multicollinearity using a pairwise correlation comparison with the dependent and all explanatory variables. Pairwise correlations are useful because, unlike VIF testing which just provides a score, this table shows how all variables are related.

Here, multicollinearity becomes a problem when correlations are around 0.7 to 0.8. All variables with a star are statistically significant. The table (available in Appendix C) confirms multicollinearity exists in this study. Parent college graduates and above show high correlations with API scores; Hispanics are highly correlated with parents who did not graduate high school, with attending EL classes, and with receiving free or reduced cost meals; transversely, students receiving free lunches are highly correlated as enrolled in EL classes, and parents that have an education of high school or below.

Testing and Correcting for Heteroskedasticity:

After identifying multicollinearity, a final test will check for the presence of heteroskedasticity. When a regression has heteroskedasticity, it predicts the explanatory variables statistical significance incorrectly. It may suggest that a variable has greater significance than it does. To test this, I ran the Breusch-Pagan test on our OLS regression. The test produces two values: a chi-squared, and a p-value to determine statistical significance. If chi-squared is large, then heteroskedasticity exists. The test produced a p-value of 0.0000 and a chi-squared of 3610.91. I can therefore say with 99.9999% confidence that heteroskedasticity exists. Fortunately, correcting for heteroskedasticity is simple. To do so, I use a robust standard error when running the fixed-effects models.

CHAPTER IV: Resulting Implications and Conclusions

Using API datasets from 2011 and 2012, and running two different fixed-effects regression models, I estimated the effect charter schools have on academic achievement. This chapter looks at both the linear fixed-effects and log-lin fixed effects regression, as well as an OLS regression model primarily used to determine test and control for multicollinearity and heteroskedasticity. This chapter presents analysis of these results, and interprets the explanatory variables effects on API scores.

This thesis contributes to a growing work of literature, providing insight on the research question: do charter schools perform as well as traditional public schools in terms of academic achievement? Dozens of studies have asked this question, and many with differing results. This question is not asked in vain, but to add to that body of work, and enhance our collective understanding of California's education system. To do so, this study applies these regression findings and analysis from past literature to promote a discussion of potential education policy. This chapter asks: what implications can policy-makers apply from this study, and what take-aways bring value to better serve this study's key stakeholders: California's children.

Examining Preliminary Findings:

This study used OLS regression not as a primary model to examine charter school achievement, but as a useful and necessary tool to control for confounding effects.

Neither the VIF test for multicollinearity nor the Breusch-Pagan test for heteroskedasticity run on the fixed-effects regression model, and OLS regression is a reliable linear model. While not our key test, I present findings of this preliminary measure. These initial findings help by starting to identify certain trends in the data, making comparisons to past studies more holistic.

In this regression, all variables are statistically significant, meaning the p-value assigned to each variable is less than 0.05. The R-squared is nearly 0.68, meaning that the line of best fit fits with 68 percent of variation. This study's key explanatory variable, charter schools, has a large negative coefficient (-16.367), at first suggesting charter schools perform worse than traditional public-school models.

Looking at demographic factors, the percentage of African American, Native American, and Pacific Islander students have negative relationships to API Score, our measure for academic achievement. While most studies do not account for Native American or Pacific Islanders, African Americans make up explanatory variables in nearly every study in this literature review. Results for African American academic performance is mixed however. Many studies (Bettinger 2004, Zimmer and Buddin 2006, Booker *et al*. 2004, Bifulco and Ladd 2006, and Garcia *et al.* 2008) present similar findings that African Americans see significant, negative achievement gains, often in both charters and traditional schools. Conversely, Hispanics, Asians, Whites, and Filipinos all see positive correlations.

Table 3: OLS Regression			
API Score	**Coefficient**	**Standard Error**	**P>t**
CHARTER	-16.36691	1.628051	0.000
% Black	-0.502747	0.0875971	0.000
% Native American	-1.02459	0.1359268	0.000
% Asian	1.055658	0.0834604	0.000
% Filipino	0.4819281	0.132428	0.000
% Hispanic	0.6177815	0.0786222	0.000
% Pacific Islander	-1.696042	0.3968605	0.000
% White	0.1873743	0.0788198	0.017
% Meals	-0.6326007	0.0345215	0.000
% Migrant Ed Program	-1.529799	0.1088951	0.000
% English Learners	-0.5180176	0.0406116	0.000
% Disability	-1.184568	0.0476963	0.000
% Not HS Graduate	-0.9025714	0.0682118	0.000
% HS Graduate	-0.8506303	0.0653588	0.000
% Some College	-0.4773086	0.0648585	0.000
% College Graduate	0.5497687	0.0681474	0.000
% Graduate School	0.5252332	0.0638481	0.000
% Tested	324.5865	44.40446	0.000
Number of observations	11347	**R-squared**	**0.6798**
***Significant at 90% Confidence**		**Adj. R-squared**	**0.6793**

An important distinction to note for socioeconomic factors is parent education. Here education seems to directly influence API scores, as the coefficients for parents with no high school diploma to parents with graduate degrees gradually becomes positive. These findings could suggest that students with more educated parents attain higher academic achievement. However, these are preliminary findings. This study presents is main findings in the following section.

Examining Fixed Effects Analysis:

Lin-Lin Regression Findings:

Our first two fixed-effects tests is the linear fixed-effects model. When testing for multicollinearity, I chose to recognize it exists, but keep the variables in the model. After testing for heteroskedasticity in the OLS model, we also found it existed. To control for this, I ran this regression using a robust standard error. Table 4, below the findings of this model.

First, note the overall R-squared dropped to 0.051, which is not a terrible score. What is more surprising is how few variables remain statistically significant. The most noticeable of the statistically significant is the key explanatory variable, charter schools. With a statistically significant p-value at 90 percent confidence, its magnitude (or coefficient) is 11.19. While seemingly high, this is an absolute score in relation to API scores, the mean of which is 816. This should not downplay the finding that this model shows charter schools have a positive effect on academic achievement.

Table 4: Lin-Lin n Fixed-Effects Regression			
API Score	**Coefficient**	**Robust Standard Error**	**P>t**
CHARTER	11.19088	5.729412	0.051
% Black	-0.579292	0.3981488	0.146
% Native American	0.0921036	0.448663	0.837
% Asian	0.7585057	0.2142256	0
% Filipino	0.5952441	0.2329195	0.011
% Hispanic	0.2605545	0.1777464	0.143
% Pacific Islander	0.3052139	0.5912032	0.606
% White	0.118882	0.1168167	0.309
% Meals	0.0975719	0.0531372	0.066
% Migrant Ed Program	-0.329389	0.2003851	0.1
% English Learners	-0.541031	0.0954274	0
% Disability	-0.768494	0.1750514	0
% Not HS Graduate	-0.057189	0.1511221	0.705
% HS Graduate	-0.106167	0.1528842	0.487
% Some College	0.1162187	0.1538959	0.45
% College Graduate	0.1780658	0.1579259	0.26
% Graduate School	0.3846725	0.1621629	0.018
% Tested	-148.0668	68.65264	0.031
Number of observations	**11347**	**Overall R-squared:**	
***Significant at 90% Confidence**		**0.538**	

Looking at demographic factors, Asians and Filipinos saw significant correlations with API scores, albeit with small magnitudes of 0.759 and 0.6 respectively. Both White and Hispanic students are no longer statistically significant, although still show positive correlations to API scores. Students with disabilities and those in EL classes saw statistically significant, negative correlations to achievement, with small magnitudes of -

0.768 and -0.541 respectively. These findings suggest that students with certain educational barriers will not perform as well.

With socioeconomic factors, we again notice that as education levels increase, so does the coefficient. Unlike the OLS regression findings however, here only parents who went to graduate school see a statistical significance. This may suggest more about the parent rather than anything else however. Highly educated parents are likely to be more driven, and more involved with their child's education. While these findings also present important insight, we wait to draw conclusions or implications until the log-lin model.

Log-Lin Regression Findings:

A great advantage of the log-lin model over the lin-lin model is that is provides greater control over variable interactions. The Log-ling model better interprets relationships with the coefficients, ultimately by a curved line that better fits variation. We would expect then to have a higher R-Squared than in the linear fixed-effects regression. Yet the regression results in Table 5 show nearly the same R-squared. Here, the overall is 0.52, and is actually lower than the linear model. However, when converting for linear to logarithmic, the R-squared shifts from an absolute score, to a percentage. Therefore, while still low, the logarithmic regression fits 52 percent of variance within it "curve of best fit."

Table 5: Log-Lin Fixed-Effects Regression			
API Score	**Coefficient**	**Robust Standard Error**	**P>t**
CHARTER	0.0146505	0.007348	0.046
% Black	-0.0006659	0.0005497	0.226
% Native American	6.33E-05	0.0006534	0.923
% Asian	0.0008845	0.000281	0.002
% Filipino	0.0007287	0.0003036	0.016
% Hispanic	0.0003688	0.0002358	0.118
% Pacific Islander	0.0004453	0.0007651	0.561
% White	0.0001518	0.0001522	0.319
% Meals	0.0001143	0.000071	0.107
% Migrant Ed Program	-0.0004586	0.0002845	0.107
% English Learners	-0.0006916	0.0001238	0
% Disability	-0.0009192	0.0002314	0
% Not HS Graduate	-0.0000562	0.0001989	0.778
% HS Graduate	-0.0001131	0.0002003	0.573
% Some College	0.0001735	0.0002044	0.396
% College Graduate	0.0002499	0.0002042	0.221
% Graduate School	0.0004594	0.0002037	0.024
% Tested	-0.2110198	0.0962743	0.028
Number of observations	**11347**	**Overall R-squared:**	
***Significant at 90% Confidence**		**0.5153**	

When examining variables statistical significance, we find the same explanatory variables remain significant, and with relatively similar magnitudes. The one variable that saw a drastic shift in its coefficient was charter schools. While still statistically significant, the magnitude shifted from over 11 to 0.015. In terms of academic achievement, charter schools and traditional public schools perform at roughly the same level. There is no noticeable difference in academic achievement gain between charters and the traditional public model. Students in EL classes and with disabilities still have a statistically significant p-values, but their magnitude shrank down to -0.001 for both. This is a nearly negligible and suggests that students with learning barrier only have a slight effect on a schools' API score.

An interesting result is the relationship between API scores and percent of school tested. In both models, we see statistically significant results, but with negative coefficients. As discussed in Chapter 3, we controlled for percent tested because we thought it might bolster results for students with educated parents, as they may be more involved in school, or not want their child tested. Looking at pairwise correlations however, we infer the opposite. Percent of students tested has statistically significant, negative correlations, and generally got more negative with increased education. However, the log-linear model results show a coefficient of -0.211. This is difficult to assess, but might mean that those tested had a slightly negative effect on API Scores.

This study's findings show interesting, and statistically significant results. Most notable, charter schools perform nearly as well as traditional public schools when examining achievement. While unable to measure achievement through switcher students, or run student-level data, this study produced statistically significant findings on charter school academic achievement.

Discussion of Policy Implications:

This thesis is interested in providing California educators, parents, and policy-makers with a better understanding of charter school performance. The fixed-effects regressions used in this study produced many significant findings that address this goal, and many findings that lacked in statistical significance altogether. However, sometimes an insignificant finding sheds light on something else. This section discusses these findings, and effect they could have on California education policy. First, I compare the findings to previous literature in the field to identify similarities and differences, and better interpret my findings. If this study found similar results to most studies, it would provide further legitimacy to my findings. From there, I draw policy implications to guide policy-makers on this increasingly popular, but still controversial issue. I then look at California's current efforts of educational reform, and provide recommendations.

Drawing from Past Literature:

Past literature greatly influenced the regression models I used for this study, what variables to choose, and how to operationalize my data. Therefore, it is fitting that I compare my findings with studies form my literature review. This section will examine the major findings of this study, and see how closely they relate to other findings. This section is structured based upon my explanatory variables categories. First, I will examine school characteristics, which will focus on charter school achievement. Then I will look at demographic factors, and the similarity and differences in those past studies. Finally, I will look at socioeconomic factors, specifically parent-level education.

This study shows a statistically significant correlation (0.15) between charter schools and academic achievement, and answers our main research question by confirming charter schools perform as well as traditional public schools. This finding is in line with much of the other research in this field. Booker et al. (2004), Hoxby and Rockhoff (2005), Zimmer and Buddin (2006), Sass (2006), Garcia et al (2008), Dobbie and Fryer (2009), Abdulkadiroglu et al (2011), Zimmer (2011), Rorrer and Ni (2012), Angrist et al. (2012), and Baude et al. (2014) all found some degree of academic achievement gains for charter schools. With statistically significant results, this study adds to this growing body of work.

While significant, the limited dataset prevented me from looking at more detailed look at differences between charters and traditional public schools. One such pattern seen in multiple studies (Sass 2006, Rorrer and Ni 2012) shows that charters perform worse that TPSs in their first year of operation, but by their third to fifth year, perform at or above TPS achievement levels. Another pattern in some studies (Booker et al. 2004, and Garcia et al. 2008, was the significant negative effect students had from leaving a TPS for a charter. However, academic achievement sees gains above previous TPS score in the following years. Finally, Angrist et al. (2012) and Zimmer (2011), and Dobbie and Fryer (2009) examined urban schools, finding charters do a better job improving achievement than traditional schools.

Demographic factors are also critical to understanding, both because of the importance that all children succeed academically, and because of the political and long-term policy effects if minority students falling behind academically. In the log-lin regression results, only statistically significant results of Asian and Filipino students show positive effects on API scores. Looking at summary statistics in Table 1 (See Page 23), Asians and Filipinos make up only ten percent of California students, but have the most significant, positive effect. This may be due to cultural differences placing as heavy emphasis on education, or some other unobservable factor.

While black students did not show statistical significance in this regression, the OLS regression did show a significant, negative effect on API scores. Unlike Asian, Filipino, Pacific Islander and first nation students which most studies do not examine, nearly every study examines academic achievement for African Americans. Many studies (Bettinger 2004, Zimmer and Buddin 2006, Booker *et al*. 2004, Bifulco and Ladd 2006, and Garcia *et al.* 2008) present similar findings that African Americans see significant, negative achievement gains, often in both charters and traditional schools. While not significant in our final analysis, an overwhelming number of studies finding similar concerns suggests it deserves further attention.

Another recurring trend seen throughout my results related to socioeconomic factor. Parents with graduate level education show a significant positive effect on API scores. What's just as interesting is in every regression achievement negatively effects non-high school graduate parents, but that negative relationship gets more positive with each increased level of achievement. While only graduate school variable holds significance, it does suggest that parents with higher education will likely take a more active role in their children's education, ultimately leading to better performance. No other studies examine parent education level as a factor. This hardly suggests this is a groundbreaking study, and is more likely studies either found another variable to replace it or could not control for it.

This study adds to the growing body of literature that shows charter schools perform as well as traditional public schools when academic achievement is a goal. The findings in this paper and related comparisons of previous literature contribute to the policy implications specified in the following section.

Charter Schools and California Lawmakers:

While a significant body of research exists on charter school achievement, and lawmakers are likely familiar with some of their findings, very few studies exist on California schools. Zimmer (2011) examined two large urban centers in southern California, San Diego and Los Angeles, but I did not come across a single published statewide study of California charters during my research. With that said, this study may provide a more targeted assessment of charter schools than some policy-makers have seen.

The results of this study suggest charter schools are a benefit to students in California. No results in this study suggest that charter schools will have an adverse effect on a student's academic achievement, and charter schools perform just as well, and perhaps slightly better than traditional public schools. As a first recommendation, I suggest charters continue remaining a school choice for parents and their children. With the growing popularity and acceptance of charter schools, I imagine policy-makers would approve of this recommendation.

Looking back on demographic factors, African American achievement lags behind other races. While the final regression results did not show statistical significance for all demographic variables, past literature suggest is a real problem. With a history of racial segregation and isolation, African Americans have had a hard time closing the achievement gap. However, other studies suggest that charter schools may just be a solution, or at least one of many. Angirst *et al.'s* (2012) study shows urban charter schools help black students succeed academically, and often where traditional school models do not. This may be a result of the very nature of charter schools: they allow teachers to innovate to reach the most underserved communities with unorthodox, yet effective teaching methods. Therefore, my second recommendation is to continue supporting efforts to reduce the disparity gap between blacks and other minorities, and increase support for charter schools in high-density urban areas where underserved communities live.

Finally, and although not a direct implication from the regression results, I address as a reminder the importance of reducing funding disparities between charters and traditional public schools. In Chapter 1, I discuss the LCFF and the few issues with continued funding disparity, especially for students with disabilities. The final regression does show a statistically significant (although very minute) negative relationship between students with disabilities and API scores. While it might be easy to suggest that students with learning barrier will always fall behind the achievement gap, it is important to remember that these students take an altered test, and are still falling behind. However, that funding disparity caused by the LFCC may have a potentially negative impact on these children's ability to higher academic achievement. My final recommendation is for California law-makers to review the LFCC and ensure that the same regulations are placed on both charter schools and TPS, and charters receive the same amount of funding for students with disabilities.

Conclusion:

Since the inception of charter schools in the early 1990s, this new approach to learning inspired parents, policy-makers and researchers. Parents were excited for new opportunities for their children's education, and to potentially have a bigger voice in their child's school. Policy-makers were passionate about educational reform, and the chance to spur innovation inside the classroom. And researchers dedicated themselves to understanding the effectiveness of this new approach to learning, and ensure they were providing children with opportunities for success. This paper added to that growing body of research on charter school academic achievement, and contributed to the small list of California-based studies. This paper asked, do California charter schools perform as well traditional public schools?

This study reviewed an extensive body of literature to better understand the best practices for examining charter school achievement, and built a model suitable to answer the research question. Using a fixed-effects regression model and longitudinal data, and controlling for potentially confounding multicollinearity and heteroskedasticity, this study produced statistically significant results showing charter schools perform as well as traditional public schools.

California was the second state in the nation to create legislation to allow for charters in 1992. When they first opened, charter schools were a point of major contention, and to this day many people still do not completely understand what a charter school is. However, over time the number of charters has grown steadily in California, and popularity of charters continues to increase. Along with that support by law-makers and a growing acceptance within educational circles, charter schools are very likely here to stay.

With that, it is important for policy-makers to recognize and address some potential issues within the system. African American students are behind academically, and urban charter schools may help reduce that academic achievement gap. Students with disabilities too are struggling, which may result from funding disparities inherent in California's LFCC. This paper urges policy-makers to examine these points, and ensure the most vulnerable in our society are not left behind.

This paper understands the importance of charter schools in California, both as institutions to help students reach their academic potential, and encourage traditional public schools to evolve and grow. As charter school popularity continues to grow, and more charter schools open every year, charter schools will likely become less controversial. Until then, it's important that researchers continue to understand the effects of these institutions, if not for the sake of charter schools themselves, but for the academic achievement of California's most important resource: its children.

APPENDIX A: Literature Review Table

Author/ Date	**Location of Study**	**Parameters/ Unit of Analysis**	**Methodology and main test models**	**Findings**
Positive Effect on Charters/ Charters Show Similar Achievement to TPS				
Booker ***et al.*** (2004)	TX	Tracks school achievement from 1996-2002.	Fixed-effects analysis. Tracked achievement over multiple years of “switchers” and “stayers.”	Charter schools show statistically significant effects on academic achievement, with magnitudes 0.109 in math and 1.33 in reading. However, significant negative effect of student transition from TPS to CS (-2.42), but positive effect with transition from CS to TPS (3.48).
Hoxby and Rockhoff (2005)	Chicago, IL	Elementary students (K-5 only)	Measuring achievement through random-effects analysis via “lottery testing.”	Lottery has positive effect on charter school academic achievement. Results are statistically insignificant, but show positive

Author/ Date	Location of Study	Parameters/ Unit of Analysis	Methodology and main test models	Findings
				magnitudes of 1.57 for math and 3.41 for reading.
Zimmer and Buddin (2006)	Los Angeles/ San Diego, CA	Student and school-level data on elementary and secondary school students from 1997-2002.	Examining achievement through fixed-effects and random-effects analysis, and controlling for student switchers.	Results are statistically significant and mixed, showing charters perform -0.38 percentile points worse than TPS in reading, but 0.27 percentile points higher in math. Authors suggest school type has no major effect on academic achievement.
Sass (2006)	FL	Student level data from 1997-2003.	Examines academic achievement of charter schools through value-added, fixed-effects analysis.	Charters perform worse than TPSs in their first year of operation (-2.51), but show higher achievement than TPSs by their fifth year in operation (1.66). Both findings are statistically

Author/ Date	Location of Study	Parameters/ Unit of Analysis	Methodology and main test models	Findings
				significant.
Garcia ***et al.*** (2008)	AZ	Student-level data for Elementary students from 2002-2003.	Used progressive Ordinary Least Squares (OLS) regression.	Charter schools show statistically significant effects on academic achievement in math (17.67) and reading (18.18). Significant, negative effect for transition from TPS to charters (-11.42), while positive effect with transition from charters to TPS (2.18).
Dobbie and Fryer (2009)	Harlem Children's Zone, NY	Student-level data from 2003-2009.	Measured achievement on minority students using random-effects analysis.	Students attending charters saw a statistically significant increase in academic achievement in both reading (0.48) and math (0.42).
Abdulkadiroglu ***et al.*** (2011)	Boston, MA	Student-level data from 2001-2009.	Achievement through lottery system in charters	Lottery-based charter schools show

Author/ Date	Location of Study	Parameters/ Unit of Analysis	Methodology and main test models	Findings
		Examined middle and high schools.	and pilot schools (unionized charters).	statistically significant increases in scores when compared to pilot schools. Charter student achievement increases .4 standard deviations/year in math and .2 in English.
Zimmer ***et al.*** (2011)	5 states; 2 metropolitan cities.	Multiple datasets of student-level with a range of years. All are panel data.	Examines academic achievement through fixed-effects analysis, controlling for switcher students.	Results vary greatly by state and cities examined. Author state that overall, charter school achievement nearly indistinguishable from students in TPSs. Statistically significant results show charter schools perform better than TPSs in Denver (0.17) and Milwaukee (0.05), and perform worse

Author/ Date	Location of Study	Parameters/ Unit of Analysis	Methodology and main test models	Findings
				than TPSs in Ohio (-0.18) and Texas (-0.12).
Rorrer and Ni (2012)	UT	Student-level data on elementary students from 2004-2009.	Achievement through fixed-effects analysis and model matching.	Results are statistically significant, showing new charters perform worse than TPS (-0.127), after three years in operation, charters start seeing positive achievement gains (0.108).
Angrist ***et al.*** (2012)	MA	Student-level and school-level data from 2001-2011.	Achievement through lottery-system in charter schools, and differences in urban and non-urban areas. Random-effects analysis.	On average, charter schools improve academic achievement (0.213) when compared to TPSs. Urban charter schools saw achievement gains (0.321), while non-urban charters saw reduced achievement (-0.123) when compared to TPSs. All

Author/ Date	Location of Study	Parameters/ Unit of Analysis	Methodology and main test models	Findings
				results are statistically significant.
Baude ***et al.*** (2014)	TX	Student and school level data from 2001-2011.	Examines academic achievement of charters adhering to “No Excuses” policy through fixed-effects analysis.	Charter schools adhering to “No Excuses” policy saw statistically significant achievement gains (0.064) over charters that did not.
Negative Effect on Charters/ Charters Perform Worse than TPS				
Bettinger (2004)	MI	Student and school-level data for elementary schools from 1996-1999.	Fixed-effects analysis. Examined effects of CS on TPS, and TPS w/in 5 miles of CS.	Charter schools do not improve test scores as well as TPSs. Charters show a statistically significant yet small magnitude of -0.01 for math scores and -0.013 for reading.
Bifulco and Ladd (2006)	NC	Student-level data of elementary students from 1996-2000.	Fixed effects analysis, examining “switcher” students.	Charter schools show statistically significant negative effects on academic achievement. Average charter schools show -0.16 magnitudes

Author/ Date	Location of Study	Parameters/ Unit of Analysis	Methodology and main test models	Findings
				in math and -0.095 in reading.
Findings Did Not Specifically Target Achievement Between Charters and TPS				
Holmes ***et al.*** (2003)	NC	Student and school level data between 1996-2000, and mapping software to identify distance between charters and TPSs.	Examines achievement gains for TPSs by charter school proximity through fixed effects analysis.	TPS schools see statistically significant achievement gains (0.01) with charter schools in a 10-kilometer proximity. Approximate one percent achievement increases when TPS must compete with charter.

APPENDIX B: Explanatory Variable Descriptions and Expected Effects

Explanatory Variables: Description and Expected Effects		
Variable	Description	Effect
Socioeconomic Factors		
Parent Education Level	Represented by percent	Reference
Not High School Graduate	Did not graduate high school	-
High School Graduate	Did graduate high school	-
College Graduate	Graduated from college	+
Graduate School	Earned post college degree	+
Free/ reduced lunch	Student eligible for school lunch	-
English learner	Non-native English speaker	-
Migrant Education Program	Student in Migrant Education Program	-
Demographic Factors		
Breakdown of Race	Represented by percent	Reference
African American	Student is African American	-
Native American	Student is Native American	?
Asian	Student is Asian	+
Filipino	Student is Filipino	+
Hispanic or Latino	Student is Hispanic or Latino	-
Native Hawaiian/Pacific Islander	Student is Native Hawaiian/Pacific Islander	+
White	Student is Caucasian	+
Student with Disabilities	Percent of students with Disabilities	_
School Characteristics		
Charter	Dummy Variable: 1= charter, 0= TPS	-
Students tested	Percent of students tested	?

APPENDIX C: Pairwise Correlations

APIScore CHARTER	CHARTER	% Black	% Native American	% Asian	% Filipino
APIScore	1				
CHARTER	0.0194*	1			
% Black	-0.2171*	0.0953*	1		
% Native American	_0.1152*	0.0136	-0.0503*	1	
% Asian	0.4072*	-0.0838*	-0.0636*	-0.0770*	1
% Filipino	0.1446* -	0.0683*	0.0504*	-0.0624*	0.2030*
% Hispanic	-0.5679* -	0.0942*	-0.1121*	-0.1587*	- 0.3906*
% PacIslnd	-0.0714*	-0.0431	0.2037*	-0.0249*	0.0526*
% White	0.4905*	0.1108*	-0.2566*	0.1028*	- 0.0647*
% Meals	-0.7470*	-0.1025*	0.1804*	0.0345*	- 0.3309*
% Migrant Ed Program	-0.2857*	-0.0667*	-0.1404*	-0.0198*	- 0.1389*
% English Learners	-0.5286*	-0.1218	-0.0963*	-0.1498*	- 0.0871*
% Disability	-0.1873*	-0.0982*	0.0678*	0.0484*	- 0.0639*
% Not HS Graduate	-0.6192*	-0.1019*	-0.0205*	-0.0526*	- 0.2813*
% HS Graduate	-0.6314*	-0.1282*	0.1239*	0.0918*	- 0.2566*
% Some College	-0.0426*	0.0597*	0.1985*	0.1356*	- 0.2262*
% College Graduate	0.6917*	0.1018*	-0.0927*	-0.0639*	0.3174*
% Grad School	0.6841*	0.0912*	-0.1451*	-0.0619*	0.3825*
% Tested	0.0256*	-0.0943*	-0.0011	-0.0553*	0.0276*

% Hispanic	% Pacific Islander	% White	% Meals	% Migrant Ed Program	% English Learners
1					
-0.1549*	1				
0.2419*	-0.0721*	1			
-0.1136*	-0.7771*	-0.1033*	1		
-0.1440*	0.7774*	0.0392*	-0.7207*	1	
-0.1080*	0.3496*	-0.0860*	-0.2215*	0.2793*	1
-0.0509*	0.7838*	0.0204*	-0.7257*	0.6956*	0.3775*
-0.0033	-0.0264*	0.0193*	0.0276*	0.0408*	-0.0699*
-0.2058*	0.8008*	-0.0480*	-0.6620*	0.7621*	0.4152*
-0.0731*	0.5767*	0.0830*	-0.5411*	0.7538*	0.1346*
0.1037*	-0.2150*	0.1113*	0.2195*	-0.0330*	-0.1742*
0.2530*	-0.7096*	-0.0015	0.6104*	-0.8230*	-0.2928*
0.0123	-0.6299*	-0.0908*	0.5547*	-0.7834*	-0.2097*
0.0250*	0.1048*	0.0073	-0.1227*	0.0840*	0.0334*

% Disability	% Not HS Graduate	% HS Graduate	% Some College	% College Graduate	% Grad School	% Tested
1						
-0.0456*	1					
0.8048*	-0.0251*	1				
0.5001*	0.0678*	0.4648*	1			
-0.4058*	0.0717*	-0.4118*	0.0328*	1		
-0.6256*	-0.0438*	-0.7541*	-0.7150*	0.0749*	1	
-0.5293*	-0.0627*	-0.5820*	-0.7416*	-0.2558*	0.6583*	1
0.0954*	-0.1983*	0.0807*	0.0624*	-0.0479*	-0.0645*	-0.0602*

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