8-13-2019

Three Essays On The Role Of Student And Teacher Non-Cognitive And Cognitive Skills In Determining Student Success

Carycruz M. Bueno
Wesleyan University

ABSTRACT

THREE ESSAYS ON THE ROLE OF STUDENT AND TEACHER NON-COGNITIVE AND COGNITIVE SKILLS IN DETERMINING STUDENT SUCCESS

BY

CARYCRUZ MIRIAM BUENO

August 2019
Committee Chair: Dr. Tim Sass
Major Department: Economics

This dissertation's essays exploit longitudinal data sets to provide evidence on education economics topics of school choice, social-emotional learning curriculum, and teacher hiring.

Chapter 1 estimates the causal effect of full-time virtual school attendance on student outcomes. I use a longitudinal data set composed of individual-level information on all public-school students and teachers throughout Georgia from 2007 to 2016 and implement individual fixed effect and semi-parametric cell analysis to investigate how attending virtual schools influences student outcomes. I find that attending a virtual school leads to a reduction in English Language Arts, Mathematics, Science, and Social Studies achievement test scores for students in elementary and middle school. I also find that ever attending a virtual school is associated with a 10-percentage point reduction in the probability of ever graduating from high school.

Chapter 2 examines the impact of Social-Emotional Learning (SEL) curriculum on student achievement over a three-year period in an urban district. I use a longitudinal data set composed of individual-level information of students and teacher. I implement a staggered difference-in-difference approach to estimate the causal effect of implementing SEL program on student outcomes. I find that the program does not impact attendance, discipline, nor test scores across the elementary and middle school grades. For high school students, the program leads to a reduction of the number of incidents, an increase in attendance, and no statistical impact on end-of-course exams nor on graduation.

Chapter 3 evaluates the predictive power of the non-cognitive traits measured in TeacherInsight™ (TI) testing tool in comparison to other measures of prospective teachers' abilities, like educational credentials, and certifications. I implement regression analysis to evaluate the relationship between teachers' non-cognitive skills (TI score), value-added test score, and observational score. I find that the Teacher Insight Score does not do a good job at predicting which teachers will be effective as measured by the teacher's value-added score. In contrast, the Teacher Insight Score and the observational score have a positive relationship. More specifically, a one-point increase in Teacher Insight score is associated with a .04 increase in teacher observation score.

THREE ESSAYS ON THE ROLE OF STUDENT AND TEACHER NON-COGNITIVE AND COGNITIVE SKILLS IN DETERMINING STUDENT SUCCESS

BY

CARYCRUZ MIRIAM BUENO

A Dissertation Submitted in Partial Fulfillment
of the Requirements for the Degree
of
Doctor of Philosophy

in the

Economics Department - Andrew Young School of Policy Studies
of
Georgia State University

GEORGIA STATE UNIVERSITY
August 2019

Acceptance

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University

Dissertation Chair:	Dr. Tim Sass
Committee:	Dr. C. Kevin Fortner
	Dr. Barry Hirsch
	Dr. Tom Mroz

Electronic Version Approved:

Sally Wallace, Dean
Andrew Young School of Policy Studies
Georgia State University
August 2019

Dedication

I dedicate my dissertation to my family. To my mother, Miriam, for giving me the gift of life and moving in with me to help me raise my son, allowing me to finish my dissertation. To my father, Julio, his enthusiasm and encouragement have always pushed me to pursue my dreams. To my grandmother, Cruz Maria, who followed her dreams and migrated to the United States, her sacrifice is an essential part of my success today. To my sister, Dr. Cruz Caridad Bueno, my first mentor, your constant encouragement, example, and endless belief in what I can accomplish are my light and pushes me to keep working hard in search of solutions that plague society. To my brother, Julio, thank you for your support, always looking after me, and pushing me to be the best in my trade. To my Irish Twin brother, Ernesto, thank you for your love, happiness, and encouragement; you keep me excited about learning. To my husband, Tony, I couldn't have completed my PhD. with out your support, you saw me through the worse nights of studying, crying, and failing but you never doubted that I would be able to contribute to the profession in a meaningful way. To my son, Indigo, you inspire me every day to work hard for my dreams; you taught me unconditional love, to celebrate the small accomplishments, and that even in the toughest times one can find moments of true happiness.

Acknowledgements

I am grateful to my family, friends, and mentors who have invested time, guidance, emotional support, and endless encouragement for me to complete this dissertation and my doctorate. To Dr. Sass, I am beyond thankful for your guidance since my first semester at Georgia State University, developing my research skills, giving me feedback, providing learning opportunities, and mentorship. I couldn't have asked for a more supportive advisor. To my committee members, Kevin, Barry, and Tom, thank you for your support and constructive input. To my other mentors, Dr. Jon Smith, Dr. Dan Kriesman, Dr. Lisa Cook, Dr. Marie Mora, Dr. Hamilton and others thank you for your support, input, and creating opportunities for me. I am also grateful for the financial support of National Science Foundation, the American Economics Association Mentoring Program, Georgia Policy Labs, American Society of Hispanic Economists, and Georgia State University.

Table of Contents

List of Figures

List of Tables

Introduction

This dissertation exploits longitudinal data sets to provide evidence on education economics topics of school choice, social-emotional learning, and teacher hiring.

Chapter 1 estimates the causal effect of full-time virtual school attendance on student outcomes with important implications for school choice. Despite the increasing demand for K-12 virtual schools over the past decade little is known about the impact of full-time virtual schools on students' cognitive and non-cognitive outcomes and the existing evidence is mixed. I use a longitudinal data set composed of individual-level information on all public-school students and teachers throughout Georgia from 2007 to 2016 to investigate how attending virtual schools influences student outcomes. I implement a variety of econometric specifications to account for the issue of potential self-selection into virtual schools. I find that attending a virtual school leads to a reduction of 0.1 to 0.4 standard deviations in English Language Arts, Mathematics, Science, and Social Studies achievement test scores for students in elementary and middle school. I also find that ever attending a virtual school is associated with a 10-percentage point reduction in the probability of ever graduating from high school. This is early evidence that full-time virtual schools as a type of school choice could be harmful to students' learning.

Chapter 2 examines the impact of implementing a Social Emotional Learning (SEL) curriculum on student achievement and non-cognitive outcomes, like attendance, behavior, and dropout rate over a three-year period in an urban district.There is a growing recognition among economists of the importance of, non-cognitive skills–including social-emotional skills have been studied to explain the difference in future labor outcomes. I use a longitudinal data set composed of individual-level information of students and teachers. I implement a staggered difference-in-difference approach to estimate the causal effect of implementing SEL program on student outcomes. I find that the program does not impact attendance, discipline, nor test scores across elementary and middle school students. For high school students, the program leads to a reduction of number of incidents, an increase in attendance, and no statistical impact on end-of-course exams nor on graduation.

Chapter 3 evaluates how a teacher's pre-service non-cognitive skills can predict how successful they will be in improving student's cognitive and non-cognitive skills and whether information on these characteristics can improve the selection of teachers relative to selection on pre-service credentials alone. In particular, I examine the predictive power of the non-cognitive traits measured in TeacherInsightTM (TI) testing tool in comparison to other measures of prospective teachers' abilities, like certifications. I implement regression analysis to evaluate the relationship between teachers' non-cognitive skills (TI score), value-added test score, and observational score. I find that The Teacher Insight score does not do a good job a predicting which teachers will be effective as measured by the teacher's value-added score. In contrast, the Teacher Insight Score and the classroom observational score have a positive relationship. More specifically, a one-point increase in Teacher Insight score is associated with a .04 increase in teacher observation score.

The remainder of this dissertation is organized around the three chapters, including the background, existing literature, data, methods, results, and conclusions for each.

1 Bricks and Mortar vs. Computers and Modems: The Impacts of Enrollment in K-12 Virtual Schools

1.1 Introduction

Full-time virtual schools offer a new school paradigm for accumulating human capital from the traditional brick-and-mortar school setting. It is unclear if society's investments in these schools are producing positive returns. Full-time kindergarten through 12^{th} (K-12) grade virtual schools offer students education without having to attend a physical school. Virtual schools began in the United States in the 1990s (Barbour and Reeves, 2009), and they are one of the fastest-growing types of school choice. In the fall of 2010, there were an estimated 200,000 students enrolled in virtual schools (Watson et al., 2010). In comparison, in the 2013-14 school year, there were over 288,000 students enrolled in either a blended or a full-time virtual school in the United States (Miron and Gulosino, 2016). The popularity of virtual schools has grown for multiple reasons, such as, scheduling flexibility, parent dissatisfaction with their local school options, homeschool parents seeking educational resources, increased accessibility of computers and tablets, students being unsuccessful in the traditional school system, demand for individualized plans and pace, and desire for enhanced course offerings. Virtual schools can be full- or part-time depending on if all of the classes are virtual or if virtual classes supplement the brick-and-mortar school's courses. The relative effectiveness of virtual schools to brick-and-mortar schools is unclear and given their growth, it is essential to understand their impacts on the students they serve.

This paper measures the impact of attending a full-time virtual school on students' cognitive and non-cognitive outcomes-including test scores, graduation, attendance, and discipline. The main challenge in accurately measuring the impact is that students and families self-select into virtual schools. Self-selection into virtual schools is problematic for finding causal estimates because unobserved student characteristics could confound the real full-time virtual school effect and the students who self-select into virtual schools would perform the same regardless of virtual school attendance. To address this problem, I use novel longitudinal data, Georgia's Academic and Workforce Analysis and Research Data System (GA•AWARDS), and implement panel and quasi-experimental econometric approaches to estimate causal effects. Specifically, I use a student-fixed-effects approach, which relies on students who switch between virtual and brick-and-mortar schools for identification. This method yields causal estimates of the impact of virtual school enrollment so long as student switching between school types is uncorrelated with unobserved factors that affect student outcomes. I address the potential problems of this strategy in section 6. Second, I use a semi-parametric cell analysis to compare the outcomes for students who were in the same 4^{th} grade school and cohort and are the same gender and race/ethnicity but had different amounts of full-time virtual school enrollment after fourth grade. This approach has been shown to produce treatment effect estimates that are similar to those derived from random assignment enrollment lotteries (Angrist et al., 2013; Dobbie and Fryer, 2013; Deming, 2014).

Although there is an increased demand for virtual schools by parents and their children, the evidence of their success compared to brick-and-mortar is mixed. Some studies have shown that virtual schools have performed better or about the same as traditional schools when it comes to both academic and non-academic achievement outcomes of students (Chingos and Schwerdt, 2014; U.S. Department of Education, 2009; Rittner, 2012)). Other reports, however, find evidence that virtual schools do significantly worse than brick-and-mortar schools as measured by student's standardized test scores, completion rates, and on-time graduation (Center for Research on Education Outcomes, 2012, 2015; Barth et al., 2012; Hubbard and Mitchell, 2011; Miron et al., 2012) . With the exception of Chingos and Schwerdt (2014) and Center for Research on Education Outcomes (2015), most of the research has been lacking causal methods of evaluating the performance of virtual schools.

This paper contributes to the literature by establishing a causal link between student performance and virtual school attendance. Previous papers, such as Chingos and Schwerdt (2014) and future Institution of Education Sciences (IES) grant work by Jacob and Loeb (2015) are only analyzing a single institution, the Florida Virtual School, which is a part-time virtual school where students also take classes in brick-and-mortar schools. However, my research looks at multiple full-time virtual schools. Also, unlike previous work, the data I employ provides a more complete record of students' K-12 educational history, permitting me to utilize panel methods. Thus, this study advances the discussion regarding the impacts of virtual school attendance on student outcomes by providing causal evidence using richer longitudinal data on multiple virtual schools spanning 2007 to 2016.

I find that attending a full-time virtual school leads to a statistically significant reduction of between 0.1 and 0.4 standard deviations, in English Language Arts (ELA), Mathematics, Science, and Social Studies for students in elementary and middle school. This reduction is equivalent to approximately a loss of one to two school years of learning (Center for Research on Education Outcomes, 2015). This impact is large relative to other educational programs and policies studied in the education economics literature. For example, Angrist (2014) find that "no-excuse" charter schools, which emphasize high expectations for students academically and behaviorally, have an impact of 0.1 standard deviations in ELA. Also, the results in this paper are in the same negative direction found in the Center for Research on Education Outcomes (2015) report. For non-cognitive outcomes, I find that ever attending a virtual school is associated with a 10-percentage point reduction in ever graduating high school.

The rest of the paper is structured as follows. Section 1.2 provides background information about the full-time virtual schools in Georgia. Section 1.3 presents prior research. Section 1.4 describes the data. Section 1.5 and 1.6 explain the theoretical foundation and econometric methods that I use. Section 1.7 presents the results. Section 1.8 discusses the policy implications of these findings and concludes.

1.2 Background

In Georgia, schools can be chartered by local school districts and by the State Charter Schools Commission (SCSC). Students in Georgia can take virtual classes either through a part-time program or a full-time virtual state charter school. There are eight fully accredited, district-run, virtual part-time programs, whose primary focus is to supplement the education of the students in their district by offering online classes.[1] Besides the eight district-run virtual programs, there is one statewide virtual education program, Georgia Virtual School,[2] which supplements students' education regardless of whether they are in public schools, private schools, or are being home-schooled. In 2014-15, the Georgia Virtual School served 30,000 students taking one or more courses. While these part-time and full-time virtual schools serve many students in Georgia, the majority of Georgia students taking full-time online classes do so through charter schools under the authority of the SCSC.

During the period of this study there were three full-time virtual state charter schools in Georgia: Georgia Cyber Academy (GCA), Georgia Connections Academy, and Graduation Achievement Charter (formerly Provost Academy)[3]. As all charter schools in Georgia, the full-time virtual schools are overseen by nonprofit governing boards. The board holds the charter or contract and can contract with companies such as K12 Inc., Pearson Inc., or EdisonLearning Inc. to provide services to the school. As full-time virtual schools, students attend these schools remotely five times a week via an off-site computer. The teachers at virtual schools face the same

[1]The eight district-run virtual programs are Fulton Virtual, Atlanta Virtual Academy, Cobb Virtual, Dekalb Virtual, Forsyth iAchieve Virtual Academy, Gwinnett Online Campus, Henry County Impact Academy, and Rockdale Virtual Campus. Georgia Virtual School (GVS) is a Georgia Department of Education's Office of Technology Services program serving 6-12th graders statewide. GVS serves as an educational supplement for public, private and home school students seeking additional courses or remedial classes. Information on GVS is taken from http://www.gavirtualschool.org/.

[2]This institution is comparable to Florida Virtual School as studied by Chingos and Schwerdt (2014)

[3]Graduation Achievement Charter closed SY 2017-2018 due to poor academic performance

certification requirements as brick-and-mortar charter teachers in Georgia. Teachers communicate regularly with their students via virtual class, online, phone, e-mail, and face-to-face meetings. These schools offer aid to their qualifying students in the form of loaner computers and internet subsidies as these two things could be barriers to entry into virtual schools. This setting allows for time flexibility for students and their families.

Table 1a presents enrollment by school type throughout the years of the panel: 2007 to 2016. Virtual schools enter the public school market during in the 2009-2010 school year. By 2016, enrollment increased to over 21,000 students. Although there has been a large increase in demand, and Georgia has one of the largest full-time, virtual charter school enrollments in the United States, full-time virtual school students still represent a small portion of the total student population. More specifically, in 2015-2016, all full-time virtual charter students represented a little over one percent of the entire Georgia student population (1.8 million students) attending public schools.

The first and the largest full-time virtual state charter school, Georgia Cyber Academy (GCA), was created in 2009. GCA's board contracts management to the for-profit education company K12 Inc. In table 1b the yearly enrollment of each charter school is reported. Georgia Cyber Academy had 13,837 total students enrolled in kindergarten through 12^{th} grade in 2016. Unlike other virtual schools, which typically serve high school students (Barth et al., 2012), only 35 percent of GCA's students are in high school. Before the 2014-2015 school year, GCA was part of the Odyssey School (a brick-and-mortar state charter school) and thus school-level statistics for that period include both students enrolled in online and traditional classrooms, however, Odyssey students were a small portion of the GCA population. The second virtual school, Georgia Connection Academy, opened in the fall of 2011 with an initial enrollment of 863 students, serving grades kindergarten through 12^{th} grade. Georgia Connection Academy's board contracts with Connections Education owned by the for-profit company Pearson Inc. for management. As shown in table 1b, enrollment increased almost five-fold to 4,241 by the 2014-2015 school year. The third virtual school, Graduation Achievement Charter High School, only serves high school students. Graduation Achievement's board first contracted with EdisonLearning for management , but later switched to Edgenuity Inc. Although Graduation Achievement's student population has fluctuated since its first year of operation, 2013-2014, in school year 2016 2,386 students were enrolled.

A seen in Table 1.2, sixty-six percent of full-time virtual school students between 2010-2016 came from a Georgia district, brick-and-mortar school. The second largest group is students coming from home-schooling. About four percent of first-time virtual students are in kindergarten or first grade (i.e. they have never previously attended school). As seen in Table 1.3, students come from various school districts across the state of Georgia. Table 5a presents summary statistics for the number of years students attend full-time virtual schools. On average, students attend virtual schools in Georgia for two years and their attendance ranges from one to seven years.[4] Table 5b gives a count of how many years students attend virtual schools. From those who attend virtual school, the majority, 32,399 students, only

[4]Note that the data are right censored and I only have data through 2016 school year

attend virtual school for one year. Table 5c provides information for the subset of students who attend a virtual school for a single year. Eighty-four percent of these students go to a virtual school one year and then go back to a brick-and–mortar school. Ten percent only attended a Georgia public schools one year and left to attend a non-public school in Georgia, thus leaving the sample. Lastly, five percent are recorded as attending for one year because they were only enrolled during the last year in the panel, 2016 (i.e. they are right censored, and it is unknown if they will continue to attend a virtual school in the future).

1.3 Prior Studies

Online education promises reduced costs and increased access to education for students. In its different forms, online education has been increasingly studied in the past decade. Full-time virtual schools offer a different experience than blended learning in brick-and-mortar(e.g., Rouse (2004) and Heinrich et al. (2018)), part-time virtual school (e.g., Chingos and Schwerdt (2014)), and online college courses (e.g., Goodman et al. (2018)). I restrict my review to the studies that examine full-time virtual schools.

Over the past three years, the SCSC and the Governor's Office of Student Achievement (GOSA) have published reports on the performance of state-authorized charter schools (Sass, 2016). The report gives descriptive information about the 15 SCSC schools such as student demographics, date of opening, grades and counties served, and types of curriculum, highlighting the diversity among the state-sponsored charter schools. Sass (2016) relies primarily on a value-added model approach to evaluate each school's performance, where both student demographics, school-level demographics, and prior test scores are used as controls to assess the school's average contribution to student achievement each year. Results from a second method, the student growth percentile (SGP) model, are also presented in the annual reports. The SGP approach compares students who had the same previous test scores, ranking them according to their standing in the distribution of current-year test scores. Unlike value-added, the student growth model does not explicitly take into account the students' characteristics such as race, gender, and school lunch status. Sass (2016) finds that although all three state-chartered virtual schools have strengths, on average they are performing below the state average in multiple subjects and grade levels. Sass (2016) gives a general evaluation of these charter schools' academic performance but does not address a number of important issues such as: (1) the characteristics of students attending virtual schools; (2) the non-academic outcomes for virtual school students, such as attendance, discipline, and graduation, and (3) the heterogeneous impact attending a virtual school has on outcomes across different student sub-groups. Addressing these additional questions provides a more comprehensive picture of these virtual school's performance.

To date, Center for Research on Education Outcomes (2015) is the most comprehensive report on virtual schools, studying 158 virtual charter schools in 17 states and the District Columbia. All the schools in the report are full-time virtual schools, i.e. the student's primary school. Their main findings compare average test achievement of students in virtual schools to those in traditional brick-and-mortar and find that overall virtual schools do worse than traditional schools. They also look at subgroup– race, economic status, English language learner, and special education– performance, and, in general, still find the full-time virtual school students perform worse than their traditional school comparison. In addition to a national evaluation, Center for Research on Education Outcomes (2015) presents findings for each state, finding that Georgia virtual charter schools did significantly better than brick-and-mortar traditional public schools in reading but performed significantly worse in mathematics. Despite their broad coverage, neither Center for Research on Education Outcomes (2015) nor the State Charter School Commission report addresses the impact of virtual school attendance on non-academic student outcomes (e.g., behavior, attendance, drop-out, and graduation). These prior studies did not have detailed data on non-test-score outcomes. By exploiting the rich individual-level longitudinal data in Georgia, I can go beyond previous work in other ways, including analyses of the types of students that attend virtual schools, how they are different from non-virtual-school students, and the ways in which virtual schools differ from brick-and-mortar schools, including the characteristics of teachers who work at virtual schools.

1.4 Data

To evaluate the performance of Georgia's virtual state charters, I utilize individual-level information on students and teachers in both full-time virtual charter schools and brick-and-mortar public schools (both charter and traditional) throughout Georgia. The data come from the state's longitudinal database, Georgia's Academic and Workforce Analysis and Research Data System (GA•AWARDS). GA•AWARDS includes data from the educational agencies spanning K-20 as well as Georgia's Department of Labor. [5]

GA•AWARDS includes teachers' demographics, pre-service credentials, years of experience, certification, and unemployment insurance records from the Department of Labor from 2006/07 through 2015/16. Student-level data include demographics, grade level, course enrollment, course grades, standardized test scores across four subjects (ELA, math, science, and social studies), attendance, discipline, educational attainment, and program participation (special education, English language learner, free or reduced-price lunch, gifted, and homeless).

Table 1a shows enrollment by year and school type in Georgia. Annual public school enrollment in Georgia is approximately 1.8 million students. Although Georgia Cyber Academy opened in school year 2009-2010, they were part of a brick-and-mortar school, the Odyssey School, until 2014-15. During this time the Georgia Department of Education (GaDOE) did not differentiate between students attending the brick-and-mortar program and the virtual program.[6] Table 1.6 gives some basic demographic information of the students in Georgia split out by virtual school attendance versus non-virtual school attendance during the 2016 school year.

[5]Educational agencies include Bright from the Start: Department of Early Care and Learning, Georgia Department of Education, State Charter Schools Commission, Georgia Student Finance Commission, University System of Georgia, Technical College System of Georgia, Georgia Independent College Association. Georgia Professional Standards Commission, and Governor's Office of Student Achievement

[6]From 2010-2014 students who have their school as Odyssey, the brick and mortar associated with Cyber are coded as attending Georgia Cyber as most of the students enrolled attended Georgia Cyber

Full-time virtual schools have a slightly higher proportion of females, a smaller fraction of Hispanic students, lower average state test scores, and lower attendance rates.

1.5 Conceptual Framework

Selection into Virtual Schools

A major impediment to generating causal estimates of the impact of attending a full-time virtual school on student outcomes is that students self-select into virtual schools. If unmeasured factors that determine the type of schools that students select also affect student outcomes, the estimated effects of attending a virtual school will be biased. For example, if the student's parents get a divorce and this shock leads the student to both go to a virtual school and have decreased performance, we would be overestimating the effect of attending a virtual school on student outcomes, by attributing the effect solely to the student's attendance at a virtual school when in reality the impact is at least partially due to the parents' divorce. Hence modeling the selection into a virtual school is an important task.

There is a small literature that formally models the choice between charters and traditional public schools (e.g., Walters (2017); Ferreyra and Kosenok (2015); Mehta (2017)).[7] This prior work on charter school choice is not directly applicable to the virtual school selection problem due to several factors that distinguish full-time virtual charter schools from brick-and-mortar charter schools, that are utilized to

[7] Other studies focus on the supply side of the market, modeling the entry of charter schools. See (Glomm et al., 2005; Singleton, 2017)

model selection for traditional charters. Because virtual schools face little to no capacity constraints, potential students do not face any of the costs associated with applying for entry and attending admission lotteries that applicants to oversubscribed brick-and-mortar charter schools incur. Similarly, without over-subscription, application data are not available to identify student/family preferences. Second, given there is no spatially defined sub-statewide market area for virtual schools, general equilibrium effects are extremely difficult to uncover. Third, peer effects in virtual schools are hard to characterize, much less identify, as students do not necessarily participate simultaneously and do not have face-to-face interactions with one another.

While extant charter school choice models are not directly applicable to the decision to enroll in a virtual school, I utilize Walters' general framework as a starting point. I model school type selection as a family maximizing their expected utility over different school options in the face of information costs. In reality, families face a variety of schooling options, including private schools, traditional public schools, public charter schools, homeschooling, and virtual charter schools.[8] To simplify the model, I ignore the private school and homeschooling options and focus on choices among public school alternatives. I also do not distinguish between traditional and charter brick-and-mortar schools.[9] I assume that brick-and-mortar charters are close

[8]Due to the tuition cost, one could argue that private schools are not a viable option for many families and thus their choice set is limited to public schools. Although there are some cities and states where vouchers have made this a viable option. While homeschooling involves no tuition cost, the homeschooling sector is still quite small. As I show in the empirical analysis, most of the movement in and out of virtual is within public schools

[9]This assumption is reasonable if the choice between traditional public schools and full-time virtual charter schools is independent of the availability of local brick-and-mortar charter schools. I argue that differences between virtual and brick-and-mortar learning environments are far greater

substitutes to brick-and-mortar traditional schools and argue that families are primarily choosing on the margin of the type of instructional setting (virtual versus brick-and-mortar) rather than charter status. I further assume that there is a single virtual charter school. These assumptions simplify the problem to a binary choice between enrolling in a public brick-and-mortar school and a public full-time virtual school. Families choose the school setting that yields the highest expected utility.

Families select a virtual school in year t if the expected utility they receive is higher than the expected utility from a brick-and-mortar school. The uncertainty in the utility associated with each choice is due to imperfect information on school quality, the “fit” of the learning environment with a child’s educational needs, and the parental time costs associated with supporting their child in each type of school.

As in Walters (2017), family preferences for schools depend in part on expected academic achievement. The expected test score, Y_{ij}, for student i in school j, is given by:

$$Y_{ij} = y_j(X_i, S_{it}, \epsilon_i), \tag{1.1}$$

where X_i are student demographics, S_{it} are school quality, and ϵ_i is unobserved academic ability.

In addition to student achievement, families may consider a variety of school characteristics, including distance to the school (which equals zero in the case of a virtual school), school schedule, non-academic peer interactions, costs of school

that the differences between traditional and charter brick-and-mortar schools and thus having the option of brick-and-mortar charter schools in the model would not radically alter the conclusions one can derive.

materials (notebooks, computers, internet access, etc.), availability of extra-curricular activities, and time cost associated with supporting their child's education, and unobserved heterogeneity. The utility for attending the virtual school, v, is

$$U_{iv} = u(Y_{iv}, X_i, S_{vt}, Int_{ivt}, TC_{ivt}, \omega_{iv}), \tag{1.2}$$

where X_i is a vector of observable student demographic which determines the student/family's preferences, S_t is a vector of characteristics of the virtual school–other than test scores. Int_{it} is internet accessibility, and TC_{ivt} is the expected time costs parents must invest to assist their student in the virtual school. Last, ω_{iv} is unobserved heterogeneity of students' preference for virtual schools as well as unobserved heterogeneity about the school. Distance is excluded from the utility function since there are no travel costs to attend a virtual school. Likewise, Peer characteristics are excluded since it is assumed that peer interactions in the virtual environment are negligible.

The utility associated with attending a brick-and-mortar school,b, is

$$U_{ib} = u(Y_{ib}, X_i, S_{bt}, P_{bt}, D_{ibt}, TC_{ibt}, \omega_{ib}), \tag{1.3}$$

where P_{bt} is a vector of peer characteristics at the brick-and-mortar school, D_{bt} is the distance to the brick and mortar school that reflects the travel costs of attendance. Internet access is excluded, based on the assumption that instruction occurs at the brick-and-mortar school site and at-home internet access is therefore not essential. The difference in utility between the virtual and brick-and-mortar schools equals:

$$U_{iv} - U_{ib} = u(Y_{iv}(X_i, S_{it}\epsilon_i), X_i, S_{vt}, Int_{ivt}, TC_{ivt}, \omega_{iv}) - u(Y_{ib}(X_i, S_{it}\epsilon_i), X_i, S_{bt}, P_{bt}, D_{ibt}, TC_{ibt}, \omega_{ib})$$

$$= \mathrm{u}_j(X_i, S_{vt}, S_{bt}, Int_{ivt}, P_{bt}, D_{ibt}, TC_{ivt}, TC_{ibt}, \Omega_i) \quad (1.4)$$

where Ω_i captures the effects of both academic ability and the unobserved preferences for school characteristics. Families choose a virtual school in year t if u_j is positive.

Student's who expect a higher achievement at a virtual school are more likely to attend a virtual school. The relationship between student demographics and selection into virtual school is unclear. It could be that certain students of different race, special education status, and social-economic background select differently into virtual school. The more negative the environment or the lower school quality in the student's local school, the more likely the student would choose to attend a full-time virtual school. Independent of school quality, peers at local schools could impact the choice of selecting into virtual schools. The worst the peers at the local school–for example, more bullies–the more likely a student is to attend a virtual school. I predict that the relationship of distance to local brick-and-mortar and selection into virtual school is positive. In other words, the further away your local school the more likely you gain utility from going to a virtual school. There are some costs to attending a virtual school: students need a home where there is a computer[10], good internet connection or broadband, time costs to find out about these schools, and time parents spend with the children to ensure they are doing the work. The higher

[10]Full-time virtual schools provide a loaner computer if the family does not own a computer. But the families who do not own a computer have the cost of applying for financial aid to receive the computer.

these costs are, the less likely a student has a home with these resources available to him making it less likely they will attend a virtual school. Finally, there are unobserved reasons why the student wants to attend the virtual school that are not visible to the researcher. All these reasons lead me to the following predictions:

1. Students with worse prior performance are more likely to attend a virtual school.

2. Student's who prefer a flexible schedule are more likely to attend a virtual school.

3. Students with worse local schools are more likely to attend a virtual school.

4. Student's with worse peers at their local school are more likely to attend a virtual school.

5. Student's with longer commutes to local school are more likely to attend a virtual school.

6. Students with better home resources (i.e. lower costs) are more likely to attend a virtual school.

Performance

To evaluate student performance, I look at the impact of virtual schools on student performance as an input to the education production function.[11]

[11] One could also ask what do virtual schools do to the effectiveness or performance of traditional brick and mortar. The question is out of the scope of this paper and almost impossible to answer as the market is statewide and the impact on any one school is small as virtual school students come from many different schools, as opposed to a handful of schools or one area.

The education production function measures student achievement as a function of the individual, family, peer, and school inputs (Hanushek, 1979). In its most general form, achievement of student i in time period t is $A_{it} = f(I_i, F_i, P_i, S_i)$, where A_{it} represents student outcomes which can be cognitive (i.e. test scores) and non-cognitive (i.e. attendance, graduation, and behavior). Student outcome is a function of four vectors: student i individual abilities, I_i, their family background characteristics over their lifetime, F_i, the peer effects, P_i, and cumulative school inputs, S_i. Building on this previous work, we can see that virtual schools would mainly impact student achievement through the school input and non-peer input.

Full-time virtual schools could lead to either a positive or negative effect on student achievement. First, if virtual schools offer an individualized learning experience and students receive targeted education, this will lead to positive academic outcomes. On the other hand, virtual schools do not offer in-person contact, and if students need this to learn and master the material, student achievement should suffer. These positive and negative mechanisms could be working simultaneously, and this research will help answer which is stronger on average. Another input where virtual school attendance could impact student achievement is through peer composition, P_i. As students leave traditional schools (where their peers could have a direct negative or positive impact on their achievement) for virtual schools, (where they do not directly have peer influence) the relationship of peer effect and student achievement would be the inverse. For example, if in the traditional schools, the student's peers have a positive effect on them such as working together in pairs, now at a virtual school where students have to work more independently, their academic achievement could be negatively impacted. The opposite could be true. For example, if a student is being bullied and does not do well because of this negative peer effect, changing from that setting to a virtual school could lead to positive academic achievement for the student.

1.6 Estimation Framework

Selection into Virtual Schools

It is important to understand the correlates of virtual school attendance for two reasons. First, policymakers who must decide on funding for virtual schools will want to know who these schools are serving. Second, given that selection into virtual schools is non-random, understanding the determinants of virtual school attendance allows for the creation of instruments that could be used in a two-stage-least-squares strategy to combat selection bias in the estimation of the impacts of virtual schools on student outcomes. Recall from equation 1.4 above, the choice between virtual and brick-and-mortar schools will depend on the expected achievement level in each school type, Y_{iv} and Y_{ib}, student/family characteristics, (X_i), school characteristics (other than their effect through test scores), S_{vt} and S_{bt}, peer characteristics at the brick and mortar school that may affect non-academic outcomes (e.g., bullying), P_{bt}, distance to the brick and mortar school, D_{bt}, availability of internet access, Int_{ivt}, and the parental time costs of supporting their child in a virtual school (TC_{ivt}) as compared to a brick-and-mortar school (TC_{ibt}).

Currently, I focus on the descriptive analysis to characterize students who attend virtual schools. In particular, I only consider student/family characteristics and estimate:

$$VirtualSch_{igt} = \alpha_0 + \alpha_1 \mathbf{X}_i + \alpha_2 \mathbf{A}_{it-1} + \epsilon_{igt}, \tag{1.5}$$

where VirtualSch is an indicator variable if the student attended a virtual school or not in year t. X_i is a vector of student demographics, A_{it-1} is a vector of student outcomes from the previous year, and ϵ_{igt} is the normally-distributed error term.

Performance

I employ a value-added framework, where current achievement, A_{it} , is a function of student characteristics and the prior-year test score, A_{it-1} (which serves as a sufficient statistic for all prior educational inputs). I begin with a naïve ordinary least squares (OLS) estimation of :

$$A_{it} = \alpha_0 + \alpha_1 X_i + \alpha_2 VirtualSch_{igt} + \alpha_3 A_{it-1} + \epsilon_{igt}, \tag{1.6}$$

where A_{it} is the outcome variable for individual student i at the end of their t^{th} school year. X_i is a vector of student demographics such as race/ethnicity, sex, lunch status, special education status, and limited English proficiency (LEP) eligibility. A_{it-1} is the student's prior year achievement which captures both innate ability, family characteristics and prior schooling inputs (Sass et al., 2014). $VirtualSch$ is an indicator variable if the student attended a virtual school or not.[12] Lastly, ϵ_{igt} is the

[12]In addition to the binary definition of attending a virtual school, I will also present results where Virtual is defined as the number of years student has attended a virtual up to year t when the outcome is measured

normally-distributed error term. The coefficient of interest is α_2 which captures the relationship between attending a virtual school and achievement. Given the non-random selection into virtual schools discussed above, OLS estimates of equation 1.6 are likely to be biased.

As noted in the conceptual model, unmeasured attributes of students and their families are likely to influence both student achievement (equation 1.1) and affect the preferences of school attributes which determine the choice of school type (equations 1.2 and 1.3). This would lead to biased estimates in the naïve OLS estimation. To control for unmeasured time-invariant student/family characteristics, I estimate an individual fixed effects model, where the student's performance at a virtual school is compared to their own performance at a brick-and-mortar school.

I estimate:

$$A_{it} = \alpha_0 + \alpha_1 VirtualSch_{igt} + \delta_i + \epsilon_{igt}, \tag{1.7}$$

$$A_{it} = \alpha_0 + \alpha_1 VirtualSch_{igt} + \alpha_2 A_{it-1} + \delta_i + \epsilon_{igt}, \tag{1.8}$$

where δ_i is the individual or student fixed effect. As Imberman (2011) explains, it is important to estimate fixed effects models of student achievement with and without lagged achievement so as to bound the impact of charter attendance on achievement. The drawbacks of student fixed effects are that identification relies on those students who switched between school types which might not be a representative of the population. Second, these students self-select to enter virtual schools and can also self-select to leave the school. Third, individual fixed effects does not take into account selection due to time-varying factors or shocks that are correlated with the dependent and independent variable; it is possible that switchers experienced a dip in their academic achievement which motivated them to change schools and they will naturally bounce back from the dip, i.e., the classic "Ashenfelter Dip" issue.

Lastly, following the semi-parametric matching methods in Dobbie and Fryer (2016), I match virtual students to non-virtual students at a cell level where a cell consists of 4^{th}-grade school, gender, race, and cohort. Although this method does not completely deal with the bias of students who self-select into virtual charter schools, it does control for differences along these four dimensions, as well as unmeasured characteristics associated with the neighborhood in which a student attended an elementary school. Furthermore, prior work (e.g., Angrist et al. (2016, 2013) have shown this method produces results that are similar to those from experimental studies (i.e. studies based on randomized enrollment lotteries). I estimate:

$$A_{it} = \alpha_0 + \sum_m \alpha_2 VirtualSch_{itv} + \alpha_3 A_{it-1} + \sigma_{cell} + \epsilon_{it}, \tag{1.9}$$

where VirtualSch is the number of years a student i has attended school v by year t (Dobbie and Fryer, 2016) and α_2 measures the effect of attending a virtual charter school, v. σ_{cell} is a cell fixed effect. As in Dobbie and Fryer (2016), I cluster standard errors at the matched cell level as this takes into account correlation of errors among observationally equivalent students who attended the same elementary school.

1.7 Results

Predicting attendance into Virtual school

Table 8a presents the estimates for selection into virtual schools outlined in equation 1.5. Column one only includes prior English Language Arts (ELA) test score as a regressor on attending a virtual school this year. Alone, prior ELA score does not seem to predict if a student will attend a virtual school the following year. The second column includes only the prior mathematics test score as a predictor. This estimate tells us that a one-standard-deviation increase in prior-year mathematics test score is associated with a decrease of 0.1 percentage points in the likelihood of attending a virtual school that year. In other words, a student with a better math score last year is less likely to go to a virtual school this year. Column 3 and 4 have the student's last year percent of attendance and number of disciplinary incidents respectively. The last column includes prior year ELA score, mathematics score, disciplinary incidents and attendance, as well as student demographics. Here we see a negative selection into virtual schools, based on prior math performance and FRL status but not based on prior attendance nor prior number of incidents.

One issue with this selection into virtual school is that students previous school could have been at a virtual or a non-virtual school, hence some of the estimate is picking up the impact from already being at a virtual school. To disentangle this issue, the results presented in Table 8b are based on a sample that limits the analysis to students who in the previous year attended a non-virtual school and predicts if the student attends a virtual school or not the next year. As in table 8a, we see a similar relationship in column 5.

Ordinary Least Squares

Estimates from ordinary least squares, estimation of equation 1.6, are presented in Table 9a. Table 9a shows that, conditional on same-subject lagged test scores and demographics, attending a virtual school is associated with lower test scores across all four subjects. More specifically, 9a says attending a virtual school is associated with a statistically significant reduction of 0.011 standard deviations in ELA, 0.169 standard deviations in mathematics, 0.107 standard deviations in science, and 0.190 standard deviations in social studies. These last three estimates are large decreases in test scores. Except for Sass (2016), Social Studies and Science scores have never been analyzed in the context of full-time virtual schools. These associations suggest that students who attend full-time virtual schools are faring worse than their counterparts in science and social studies in addition to the two more frequently researched subjects, mathematics and ELA.

When I limit the population to those who in the previous year attended a non-virtual school in Table 9b, we see the impact is stronger, indicating coming directly from a non-virtual school to a virtual school has a larger impact on students, or that the first transition year is the hardest. In particular, it shows that attending a virtual school and controlling for the student's previous non-virtual school test score and demographics is associated with a reduction of 0.06 standard deviations in

ELA, 0.26 standard deviations in mathematics, 0.21 standard deviations in science, and 0.34 standard deviations in social studies

Table 1.10 restricts the population to only charter school students in order to see if this is a virtual school or a charter school effect. We see similar results to table 9a, where students who attend full-time virtual charter school do between 0.18 and 0.03 standard deviations worse than charter brick-and-mortar students across the four subjects. These results are suggestive evidence that the relationship is not coming from a charter school effect, but are a virtual school effect. These results are associations, and do not directly deal with the issue of selection into virtual schools, which the next models address.

Student Fixed Effects

One way to mitigate selection is by implementing individual fixed effects, hence controlling for time invariant characteristics. Identification relies on the students who switch between school setting and unbiasedness requires that the reason for the switch is not correlated with the outcome. As stated earlier, I present estimates for individual fixed effects both with and without the prior-year score. These two numbers serve as a bound of the impact of virtual school on student test scores. Table 1.11 shows that when controlling for time-invariant characteristics, students who attend a virtual school perform worse than the OLS regression suggests. For each subject, I present the estimates from individual fixed effects without a test lag first and in the following column, controlling for same-subject-lagged test score. Specifically, attending a virtual school leads to a reduction of 0.12 standard deviations in ELA, 0.31 standard deviations in mathematics, 0.27 standard deviations in science, 0.4 standard deviations in social studies. To put these number in context, an experienced teacher with ten or more years of experience has been shown to increase student's reading test scores by about 0.17 standard deviations Rockoff (2004), this would mean these students would need more than 2 years with an experienced teacher just to come back from the negative effects of attending a virtual school.

One issue with individual fixed effects is time-varying shocks impacting the outcome cannot be controlled for. One way to test this is by looking at test score trends pre and post entry into a virtual school. Figures 1.3 through 1.6 present regression coefficients plotted on the y axis for the time periods before and after student's first year in a virtual school across different populations of student who have ever attended a full-time virtual school and enter a full-time virtual school in grades 3 through 8. Figure 1.3 presents students who have ever attended a virtual school and upon entry never exited a virtual school. For both ELA and Math students experience a slight dip before entering a virtual school. During the first year they attend a virtual school they suffer a further dip– more so in math– and slightly improve after being at a virtual school for three years. Figure 1.4 tells the same story even though the population excludes those who only attended a virtual school for one year. Figure 1.5 shows the trend for students who attend a virtual school for only one year and return to a brick-and-mortar. They had a more dramatic decline in both test scores before entering a virtual school, but once they return back to brick-and-mortar school they experience a recovery back to their previous performance. I cannot rule out that this impact is due to selection of students who choose to leave. Similarly, Figure 1.6 where students attend a virtual school for two years and return to a brick-and-mortar school experience a dip and a recovery once they return.

Given the drastic difference between students who only attend one year versus those who attend more than one year and remain at a virtual school, I perform sub-sample analysis for these two groups. Table 1.13 shows that the students who attend a full-time virtual school one year only and return back to brick-and-mortar do between 0.16 to .44 standard deviations worse than their non-virtual years across the four subjects. Those who attend a full-time virtual school for at least two years and do not exit do .079 to .364 of a standard deviation worse than while in a virtual school in comparison to their performance in brick-and-mortar school. These are two different samples and can not be directly compared two each other due to the selection that might be occurring in which families select to only attend one year versus staying at a full-time virtual school.

One way previous papers, such as Imberman (2011), have dealt with the Ashenfelter dip problem is by implementing an interrupted panel. As Imberman (2011) did, I drop the year before entering a virtual school and use the average of two year gain as the lagged score. One draw back of not using the direct lagged score is that I lose sample size. Table 11b presents the interrupted panel estimates of attending a virtual school on student test scores. I find attending a virtual school leads to a reduction of 0.12 to 0.08 standard deviations in ELA, 0.3 to 0.2 standard deviations in mathematics, 0.3 to 0.14 standard deviations in science, 0.4 to 0.19 standard deviations in social studies.

Another way to evaluate if the results are driven by selection of students is to evaluate if students who transition into full-time virtual schools in non-typical transition years do worse than those who transition in normal transition grades. Table 1.12 compares full-time virtual school effects for students who enter a virtual school for the first time at “normal” transition point (K, 6 and 9) versus atypical entry grades. Students who switch at non-transition grades are probably more likely to be switching for some unanticipated reason, like major disciplinary problems. To test this I estimate the main individual-fixed-effects with an additional interaction term, attending a virtual school year t by if the student made first transition into a full-time virtual school at an “atypical” grade. As hypothesized, the interaction term shows that students who transition during atypical grades do between 0.03 to 0.07 standard deviations worse than students who transition during typical grade levels.

Table 1.14 through 1.17 presents heterogeneous effects across demographics, if previously home-schooled, and grade level. Table 1.14 shows the impacts of four different sub-samples, females only, males only, ever FRL, and Non-white students. Both females and males fare worse while attending a full-time virtual school. In the males samples, boys do 0.15 standard deviations worse in ELA in comparison to when they were in a brick-and-mortar. Students who have ever been on free or reduced lunch (FRL), as well as non white students also do 0.1 to 0.4 of standard deviation worse while in a full-time virtual school. Table 1.15 and 1.16 look into heterogeneous effects across grade level, it could be the case that these impacts are being driven by either elementary or middle school students. Table 1.15 shows the individual fixed effects for students in 4^{th} and 5^{th} grade. I find attending a virtual school leads to a reduction of 0.16 standard deviations in ELA, 0.32 standard deviations in mathematics, 0.31 standard deviations in science, 0.32 standard deviations in social studies. Middle school students sample are slightly better than elementary students but the negative impact remains. Table 1.16 shows that attending a virtual school leads to a reduction of 0.05 standard deviations in ELA, 0.24 standard deviations in mathematics, 0.27 standard deviations in science, 0.36 standard deviations in social studies for students in middle schools grades 6 through 8. Table 1.17 limits the sample to students who have ever previously attended homeschool, in this population we still see attending a full-time virtual leads to a reduction of 0.1 to 0.4 standard deviations. Figures 1.7 and 1.8 plots the distribution of mean difference in students normed ELA and Math test scores in brick and mortar schools vis-à-vis virtual schools. This gives us a virtual school impact, not controlling for other factors, for each student that switches.

Semi-Parametric Cell Model

Ideally to measure the causal impact of attending a full-time virtual school on student outcome I would randomize which students attend a virtual school. Since this and over subscription are virtually impossible the next best method which comes close to causal estimates is semi-parametric cell analysis(Angrist et al., 2013), where full-time virtual school students are compared to non-virtual school students who were in their same 4^{th} grade school, gender, race, and cohort. In Table 1.18, the impact of attending a virtual school is statistically different from zero across the four subjects. The impact is between .02 to .2 standard deviation decline in test scores in comparison to someone who went to the same brick and mortar school with the student in 4^{th} grade and have the same sex and race.

Linear Probability Model -Graduation and Attendance

Table 1.19 presents the results for the relationship of attending a virtual school and graduating high school. The first column defines the independent variables as ever attending a full-time virtual school in Georgia, I find that it is associated with a 10-percentage point reduction in ever graduating high school. In the second column, I find that an additional year of attending a virtual school is associated with a 2.6-percentage point decline in ever graduating high school, or about a 3.6 percent reduction relative to the average graduation rate of 73 percent. Table 1.20 demonstrates results of the relationship of virtual school attendance and percent of attendance in a school year. Across the three definitions of virtual school: total number of years virtual, ever virtual, and years of virtual enrollment by year t, all indicate zero relationship. In other words attending a virtual school is associated with no worse attendance. I caution against putting too much weight on this last result as attendance is measured differently at full-time virtual schools.

1.8 Conclusion

One of the most debated education issues today is school choice, and the fastest growing option are virtual schools. The debate centers around if parents should have more choices over which school their student attends, and if these new options are better for students than the existing alternatives. In particular, with full-time virtual schools it is unclear if the impact they will have on students is overall positive, due to their individualized structure, or negative, due to the lack of in-person instruction, depending on which of these two forces are stronger.

In this paper, I study the impact of attending a virtual school on test scores and other student outcomes. I find that attending a virtual school leads to negative impact on student test scores in the order of 0.1 to 0.4 standard deviations across four subjects- English, Mathematics, Science, and Social Studies- where the magnitudes depends on the model implemented. This is robust to implementing an interrupted panel method to mitigate the "Ashenfelter dip" students experience prior to enrolling in a virtual school and a semi-parametric cell analysis that has been shown to produce results similar to those from experimental studies. I also perform sub-sample analysis and find that those who attend a virtual school for one year and return to brick-and-mortar school perform worse than what we expect them to do in comparison to how they perform in non-virtual schools. These negative impacts also hold in the sub sample analysis, across previously attending home school, gender, frl status, and race. I also find that elementary students are doing slightly worse than middle school students. Furthermore, for high school students, attending a virtual school is also associated with a reduction in graduation rate of about 2 to 10 percentage points. These impacts are large and economically significant. These results further support the Center for Research on Education Outcomes (2015) report's conclusion that full-time virtual schools on average have a negative impact on students.

Given these results and the money invested in these schools, it seems that full-time virtual school as a school choice is not a positive option for the average parent and their children. Given the little research done on full-time virtual schools, this is evidence that virtual schools as a type of school choice could be harmful to students' learning, students' future economic opportunities, and sub-optimal use of taxpayer money in the state of Georgia. When parents apply to these schools more information about student performance should be given to parents so they can choose the school setting that maximizes their expected utility given their personal situation. For some particular students this setting still could be beneficial, especially if the alternative for the student is dropping out or other negative outcomes such as committing a crime. Also, if full-time virtual charter schools are not reaching their accountability targets, these schools should be closed.[13] Furthermore, this paper only studies Georgia full-time virtual schools; more research should be done to see if these results apply to other states as well. Likewise, more research needs to be done on long-run outcomes such as college enrollment and persistence, as well as labor force participation.

[13] The State Charter School Commission closed Graduation Achievement Charter during this study as they were not reaching academic goals

1.9 Figures and Tables

Table 1a: Number of Students Enrolled in Georgia per Year by School Type

School Year	Non-Virtual Schools Enrollment	Virtual Schools Enrollment	Total Enrollment
2007	1708156	0	1708156
2008	1722093	0	1722093
2009	1724994	0	1724994
2010	1728364	6418	1734782
2011	1735161	6738	1741899
2012	1737150	12208	1749358
2013	1748500	15230	1763730
2014	1766868	19272	1786140
2015	1786754	20845	1807599
2016	1801315	21058	1822373
	(98.84)	(1.16)	(100.00)
Total	17459355	101769	17561124

Notes:Numbers in parentheses are percentages for school year 2016.

Table 1.3: Previous District for First-Time Full-time Virtual School Students from 2010-2016

District Name	Relative Percent
Appling County	0.95
Atkinson County	1.62
Atlanta Public Schools	2.62
Bacon County	1.63
Baker County	0.51
Baldwin County	2.51
Banks County	2.85

Table 1.3: Previous District for First-Time Full-time Virtual School Students from 2010-2016

District Name	Relative Percent
Barrow County	2.24
Bartow County	2.95
Ben Hill County	2.09
Berrien County	1.96
Bibb County	3.01
Bleckley County	1.49
Brantley County	2.40
Bremen City	1.30
Brooks County	2.99
Bryan County	2.76
Buford City	0.94
Bulloch County	1.36
Burke County	2.10
Butts County	2.78
Calhoun City	0.92
Calhoun County	0.72
Camden County	2.56
Candler County	1.71
Carroll County	2.81
Carrollton City	1.02

Table 1.3: Previous District for First-Time Full-time Virtual School Students from 2010-2016

District Name	Relative Percent
Cartersville City	1.99
Catoosa County	1.27
Charlton County	3.52
Chatham County	3.47
Chattahoochee County	2.40
Chattooga County	2.05
Cherokee County	2.81
Chickamauga City	0.87
Clarke County	1.50
Clay County	0.00
Clayton County	3.26
Clinch County	1.03
Cobb County	2.00
Coffee County	1.59
Colquitt County	1.69
Columbia County	3.20
Commerce City	1.63
Cook County	1.14
Coweta County	3.61
Crawford County	4.54

Table 1.3: Previous District for First-Time Full-time Virtual School Students from 2010-2016

District Name	Relative Percent
Crisp County	1.23
Dade County	1.98
Dalton City	0.49
Dawson County	2.38
Decatur City	0.99
Decatur County	1.23
DeKalb County	2.83
Dodge County	1.00
Dooly County	1.65
Dougherty County	1.91
Douglas County	2.76
Dublin City	1.50
Early County	0.84
Echols County	0.98
Effingham County	2.82
Elbert County	1.76
Emanuel County	1.83
Evans County	1.10
Fannin County	2.81
Fayette County	2.47

Table 1.3: Previous District for First-Time Full-time Virtual School Students from 2010-2016

District Name	Relative Percent
Floyd County	1.77
Forsyth County	1.41
Franklin County	1.88
Fulton County	2.27
Gainesville City	0.57
Gilmer County	3.50
Glascock County	4.02
Glynn County	1.70
Gordon County	1.62
Grady County	0.74
Greene County	1.91
Gwinnett County	1.81
Habersham County	1.67
Hall County	1.37
Hancock County	0.74
Haralson County	2.15
Harris County	1.27
Hart County	2.24
Heard County	1.89
Henry County	2.81

Table 1.3: Previous District for First-Time Full-time Virtual School Students from 2010-2016

District Name	Relative Percent
Houston County	2.24
Irwin County	1.61
Jackson County	2.41
Jasper County	3.69
Jeff Davis County	1.16
Jefferson City	2.07
Jefferson County	1.28
Jenkins County	1.58
Johnson County	2.04
Jones County	2.74
Lamar County	2.57
Lanier County	3.56
Laurens County	2.01
Lee County	2.50
Liberty County	2.53
Lincoln County	1.87
Long County	2.62
Lowndes County	1.46
Lumpkin County	2.61
Macon County	1.35

Table 1.3: Previous District for First-Time Full-time Virtual School Students from 2010-2016

District Name	Relative Percent
Madison County	2.18
Marietta City	3.65
Marion County	2.36
McDuffie County	1.54
McIntosh County	1.64
Meriwether County	2.65
Miller County	1.42
Mitchell County	0.89
Monroe County	1.66
Montgomery County	9.61
Morgan County	1.92
Murray County	1.75
Muscogee County	1.78
Newton County	3.54
Oconee County	1.73
Oglethorpe County	2.39
Paulding County	3.42
Peach County	2.99
Pelham City	1.47
Pickens County	3.26

Table 1.3: Previous District for First-Time Full-time Virtual School Students from 2010-2016

District Name	Relative Percent
Pierce County	1.68
Pike County	2.79
Polk County	2.58
Pulaski County	1.76
Putnam County	2.75
Quitman County	2.24
Rabun County	1.09
Randolph County	1.24
Richmond County	3.24
Rockdale County	3.17
Rome City	1.13
Schley County	1.63
Screven County	2.31
Seminole County	1.75
Social Circle City	2.31
Spalding County	3.17
State Charter Schools	2.96
Stephens County	2.08
Stewart County	0.66
Sumter County	1.46

Table 1.3: Previous District for First-Time Full-time Virtual School Students from 2010-2016

District Name	Relative Percent
Talbot County	2.43
Taliaferro County	1.34
Tattnall County	2.20
Taylor County	3.21
Telfair County	0.72
Terrell County	1.34
Thomas County	1.01
Thomaston-Upson County	1.89
Thomasville City	0.90
Tift County	1.51
Toombs County	2.34
Towns County	3.36
Treutlen County	2.03
Trion City	0.79
Troup County	1.53
Turner County	0.55
Twiggs County	4.78
Union County	2.24
Valdosta City	1.31
Vidalia City	1.35

Table 1.3: Previous District for First-Time Full-time Virtual School Students from 2010-2016

District Name	Relative Percent
Walker County	1.73
Walton County	3.11
Ware County	2.21
Warren County	2.22
Washington County	1.69
Wayne County	2.29
Webster County	3.69
Wheeler County	1.33
White County	2.97
Whitfield County	1.17
Wilcox County	2.30
Wilkes County	1.34
Wilkinson County	3.82
Worth County	3.30

Figure 1.1: Grade Level of Initial Enrollment in Georgia Full-Time Virtual Schools, 2010-2016

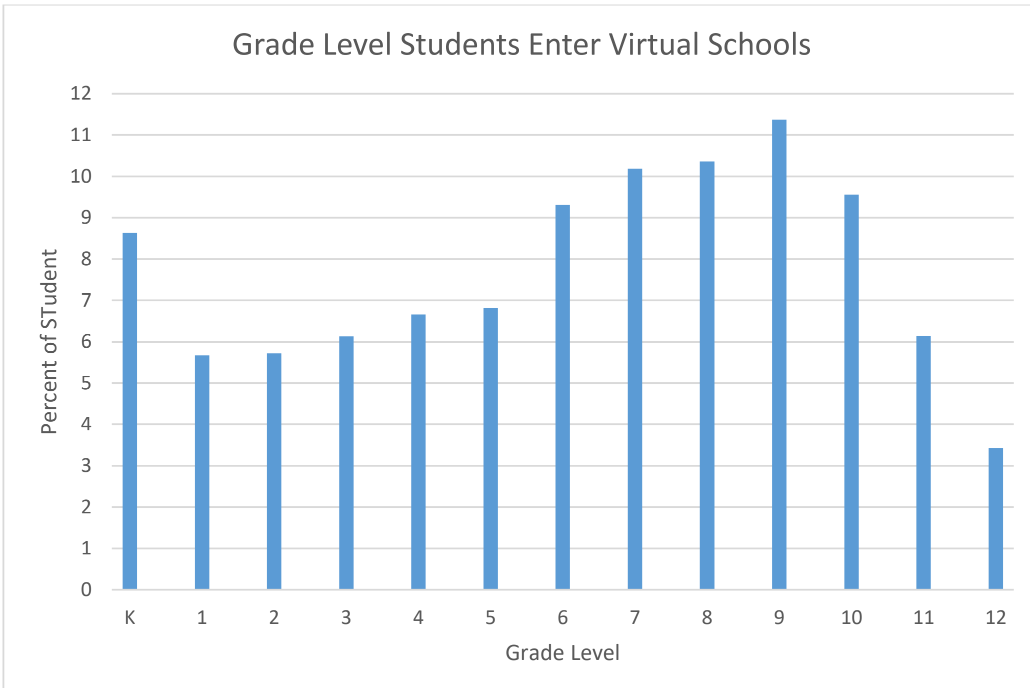


Figure 1.2: Grade Level at Which First-Time Georgia Virtual School Students Exit A Full-Time Virtual School, 2010-2016

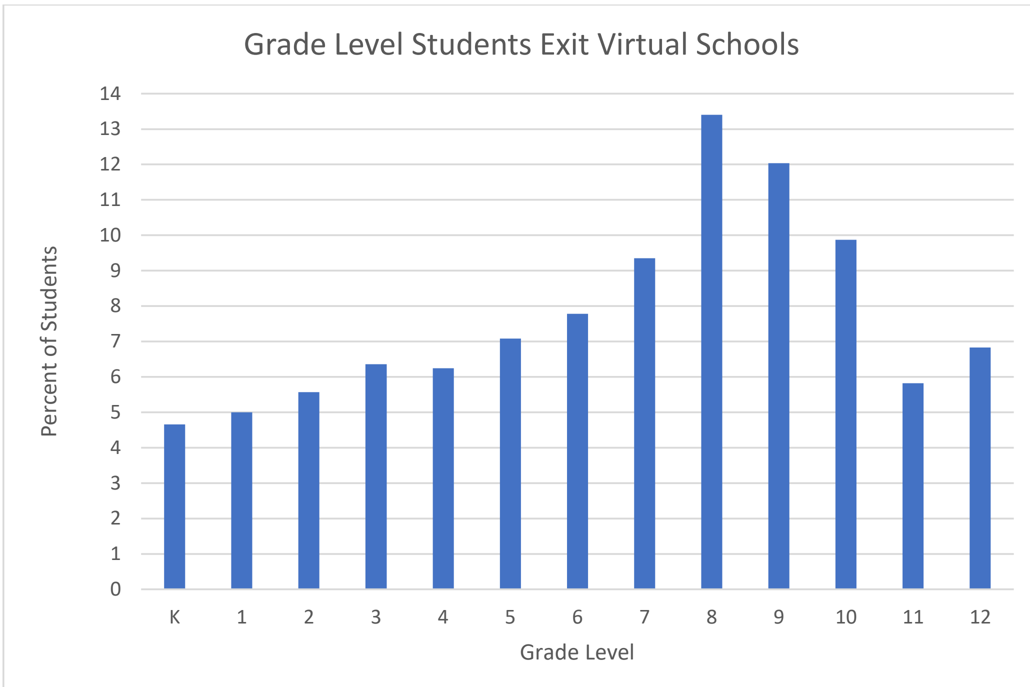
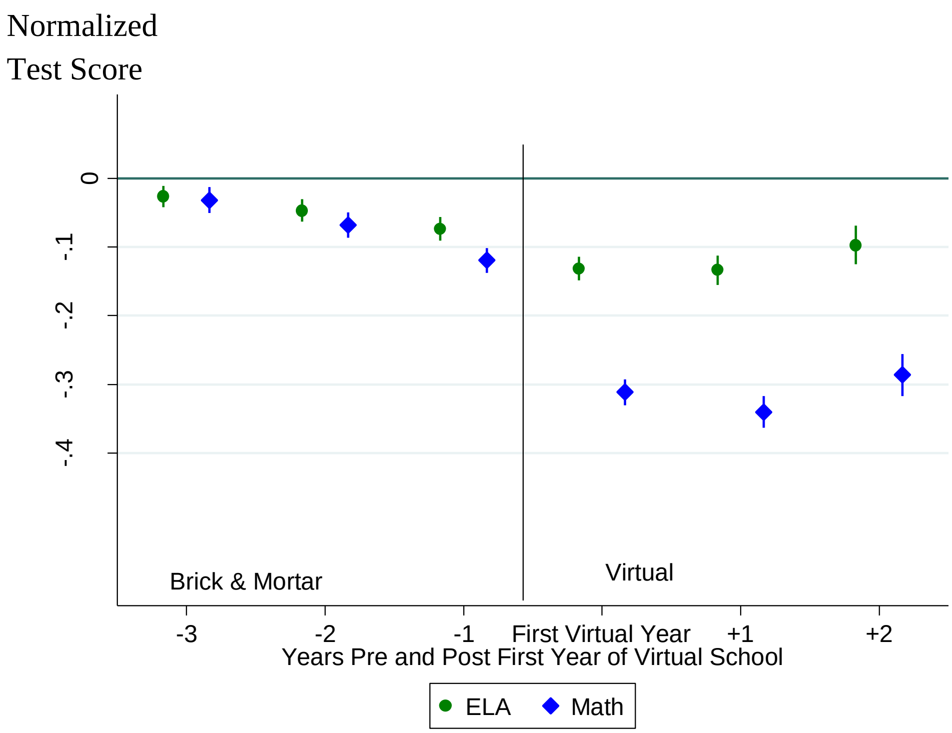
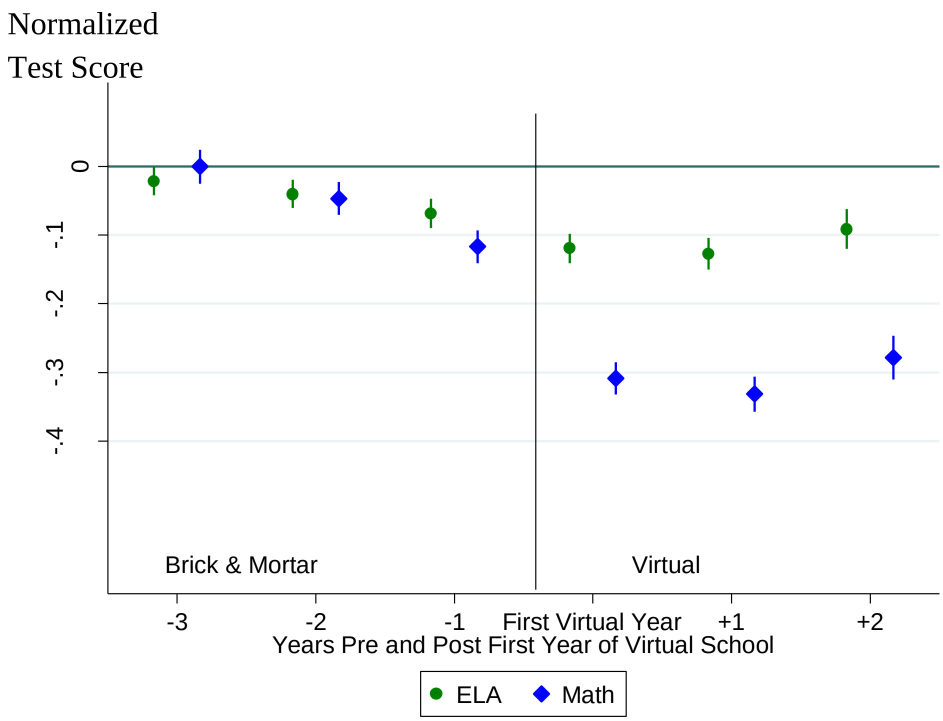


Figure 1.3: Student Test Scores by School Type for Students who Transition between Brick and Mortar and Virtual School, attend a Virtual School and do not Exit, and Enter a Virtual School in grades 3-8 for School Years 2007-2016.



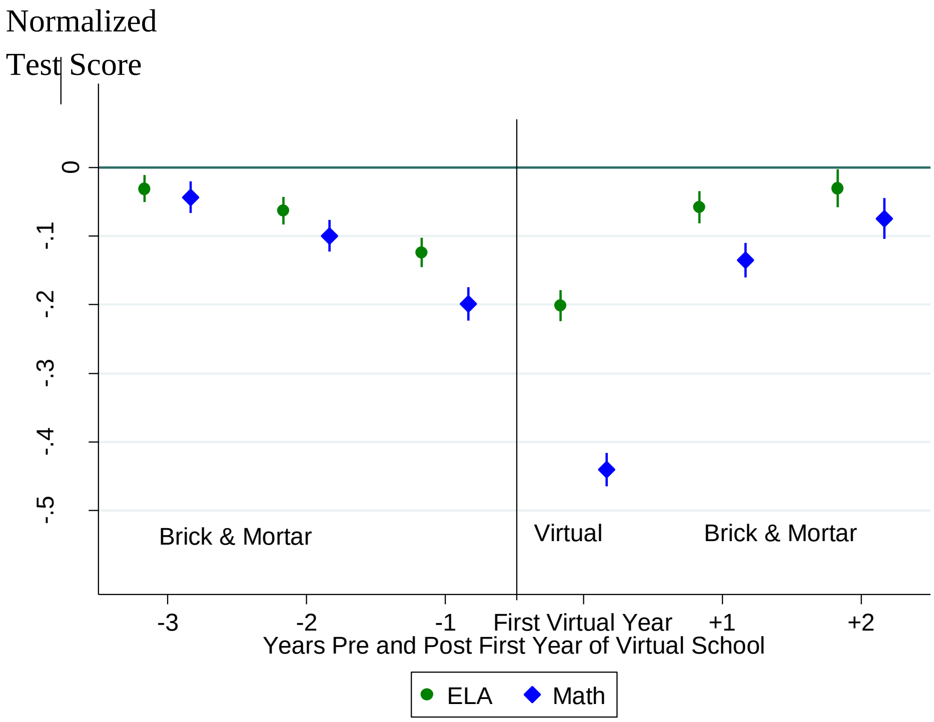
Notes: Coefficients of indicator variables are plotted on the graph, where the variable equals one if they were x years before or after entering a virtual school. Vertical band represent +/- 1.96 confidence intervals. The sample is limited to students who enter a virtual school in grades 3 through 8. English Language Arts has 55,691 Student-Year observations and Mathematics has 55,250 Student-Year observations

Figure 1.4: Student Test Scores By School Type For Students Who Transition Between Brick And Mortar And Virtual School, Attend A Virtual School For More Than One Year And Do Not Exit, And Enter A Virtual School In Grades 3-8 For School Years 2007-2016.



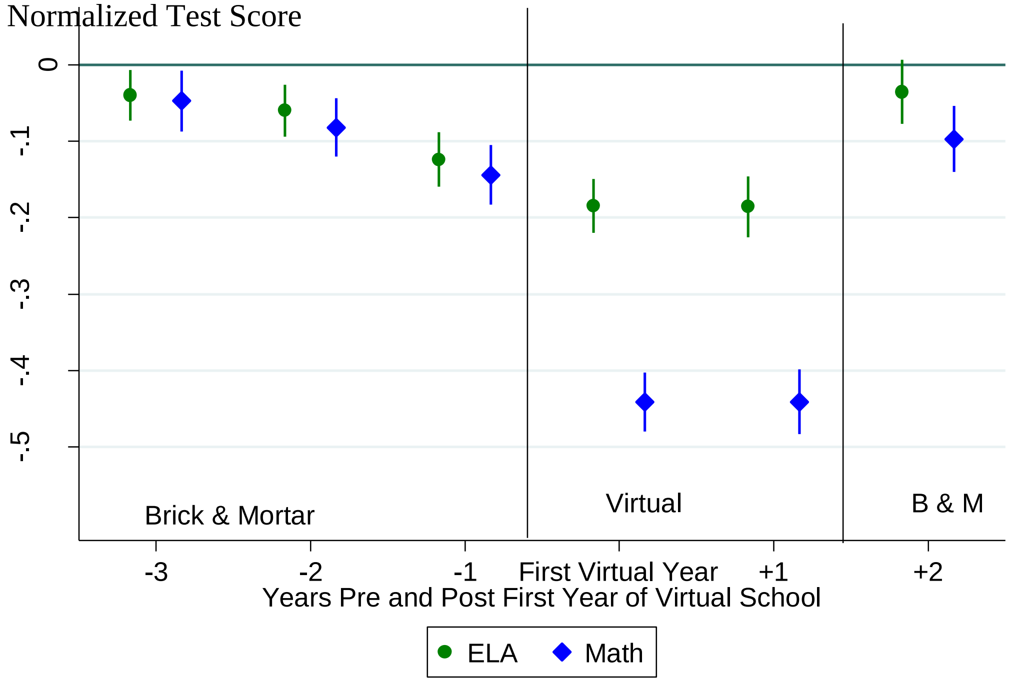
Notes: Coefficients of indicator variables are plotted on the graph, where the variable equals one if they were x years before or after entering a virtual school. Vertical band represent +/- 1.96 confidence intervals. The sample is limited to students who enter a virtual school in grades 3 through 8. English Language Arts has 33,976 Student-Year observations and Mathematics has 33685 Student-Year observations

Figure 1.5: Student Test Scores By School Type For Students Who Transition Between Brick And Mortar And Virtual School, Attend A Virtual School For One Year And Exit, And Enter A Virtual School In Grades 3-8 For School Years 2007-2016.



Notes: Coefficients of indicator variables are plotted on the graph, where the variable equals one if they were x years before or after entering a virtual school. Vertical band represent +/- 1.96 confidence intervals. The sample is limited to students who enter a virtual school in grades 3 through 8. English Language Arts has 32,541 Student-Year observations and Mathematics has 32,286 Student-Year observations

Figure 1.6: Student Test Scores By School Type For Students Who Transition Between Brick And Mortar And Virtual School, Attend A Virtual School For Two Years And Exit, And Enter A Virtual School In Grades 3-8 For School Years 2007-2016



Notes: Coefficients of indicator variables are plotted on the graph, where the variable equals one if they were x years before or after entering a virtual school. Vertical band represent +/- 1.96 confidence intervals. The sample is limited to students who enter a virtual school in grades 3 through 8. English Language Arts has 11,728 Student-Year observations and Mathematics has 11,649 Student-Year observations

Table 1b: Number of Students Enrolled in Georgia per Year by Virtual School

	Virtual Schools Enrollment	Georgia Cyber Academy	Georgia Conn. Academy	Grad. Ach. Academy
2007	0	0	0	0
2008	0	0	0	0
2009	0	0	0	0
2010	6418	6418	0	0
2011	6738	6738	0	0
2012	12208	11345	863	0
2013	15230	11782	2269	1179
2014	19272	13506	3571	2195
2015	20845	13837	4241	2767
2016	21058	14530	4142	2386
Total	101769	78156	15086	8527

Notes:Enrollment is separated out by the three full-time virtual schools in Georgia.

Table 1.2: Previous school type for first-time virtual school students from 2010-2016

Reason for Entering	First Time Virtual	Percent
Re-enter Other	16	0.03
GA District	36232	64.68
Homeschool	8574	15.31
Other	10	0.02
Never Attend	3887	6.94
Out State	1948	3.48
Private	3075	5.49
Re-enter After Withdrawal	77	0.14
Unknown	2195	3.92
Total	56014	100

Notes: Table reports entry code for the first time a student enters a full-time virtual school. If a student did not have an entry code they were coded as unknown. The category Other includes: Illness, Incarcerated, School Choice, and Within the School System

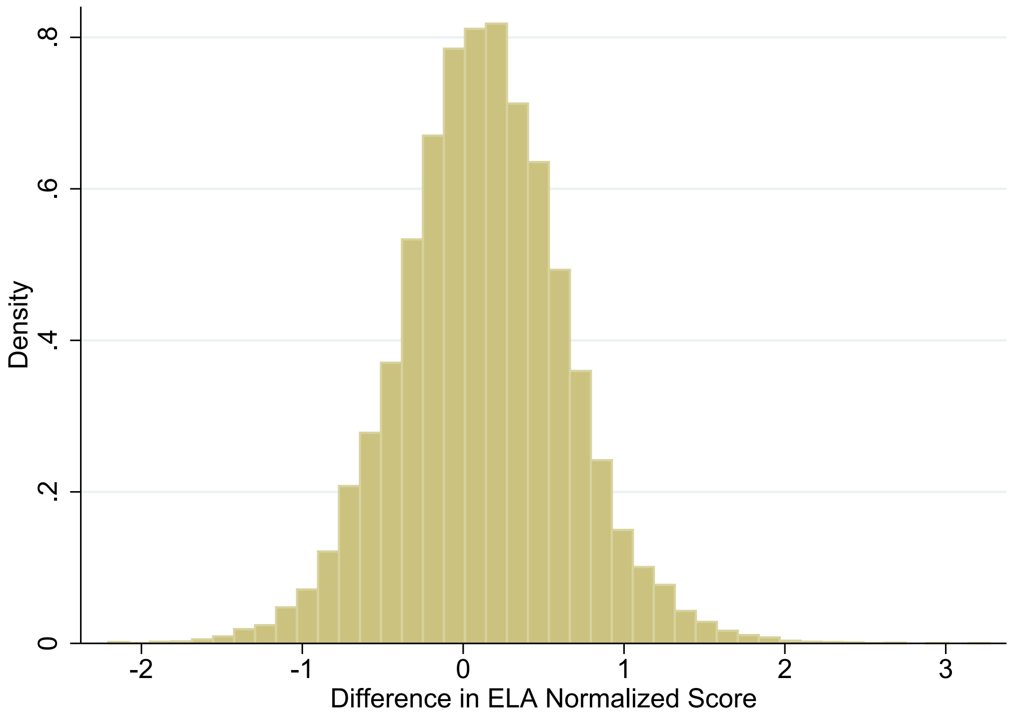


Figure 1.7: Distribution of Mean Difference in Switchers Normed English Language Arts Test Scores in Brick-and-Mortar Schools vis-à-vis Full-time Virtual Schools In Grades 3-8

Table 1.4: Percentage Attrition by Year for Each Virtual School from 2010-2016 – Excluding 5th grade and 8th grade transitions

School Year	Georgia Cyber Academy	Georgia Conn. Academy	Grad. Ach. Academy
2010	33.34		
2011	25.81		
2012	33.16	50.51	
2013	28.67	44.95	27.29
2014	33.75	42.79	19.66
2015	27.92	34.67	20.60
Total	63,626	10,944	6,141

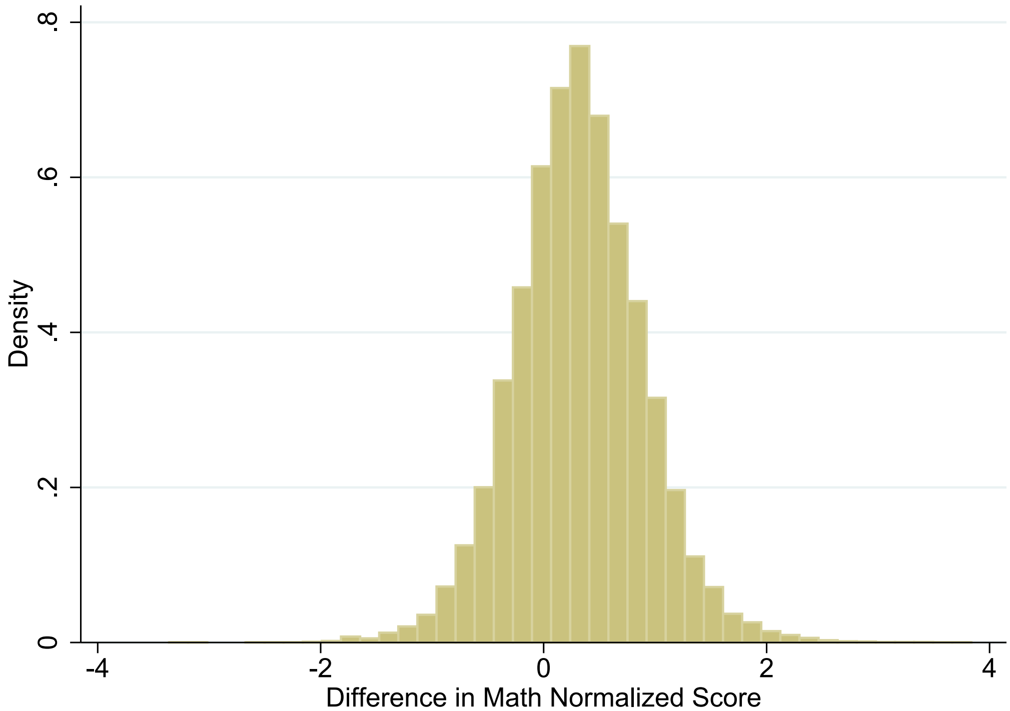


Figure 1.8: Distribution of Mean Difference in Switchers Normed Mathematics Test Scores in Brick-and-Mortar Schools vis-à-vis Full-time Virtual Schools In Grades 3-8

Table 5a: Summary Statistics of Years Students Attend Virtual Schools from 2010-2016

Years Student's Attend Virtual School	Mean
Mean	1.82
SD	1.27
Min	1.00
Max	7.00
Observations	56014

Table 5b: Number of Years Students Attend Virtual Schools at the Student Observation Level

Number of Years	Student Observations
0	3482386
1	32399
2	12080
3	5774
4	2875
5	1533
6	748
7	605
Total	3,538,400

Table 5c: Breakdown of Students Who Attend Full-time Virtual School for One Year

Classification of One Year in a Full-time Virtual School	Count	Percent
Enter and Exit a Virtual School	27,333	84.4%
One Year in the Ga. Public School Sys.	3,344	10.3%
During the Last Available Year of the Panel-2016	1,722	5.3%
Total	32399	100%

Table 1.6: Means of Characteristics of Students School Year: 2016

	All Students Mean	Non-Virtual Students Mean	Virtual Students Mean	Difference
Female	0.50	0.49	0.52	0.03***
Black	0.37	0.37	0.37	0.00
White	0.50	0.49	0.50	0.02***
Native American	0.031	0.033	0.0038	-0.03***
Asian	0.039	0.038	0.016	-0.02***
Pacific Islander	0.002	0.002	0.0010	0.00*
Multi-racial	0.045	0.047	0.074	0.03***
Hispanic	0.14	0.15	0.067	-0.08***
Ever SPED	0.16	0.16	0.17	0.01***
Ever LEP	0.023	0.023	0.0013	-0.02***
Ever Migrant	0.0054	0.0056	0.00062	0.00***
Ever Homeless	0.065	0.066	0.069	0.00
Ever Free or Red. Lunch	0.67	0.68	0.83	0.15***
Percent Present	87.9	88.1	78.9	-9.11***
ELA Norm Score	0.005	0.007	-0.13	-0.13***
Math Norm Score	0.003	0.007	-0.36	- 0.36***
Science Norm Score	0.00051	0.0021	-0.16	- 0.16***
Social Std. Norm Score	0.001	0.004	-0.40	- 0.40***
Observations	2135827	1801274	21058	1822332

Table 6b: Mean of Characteristics of Students who Attend a Charter School in 2016 by School Type

	Charter B-M	Charter Virtual	
	mean	mean	Difference
Female	0.49	0.52	0.03***
Black	0.38	0.37	-0.01**
White	0.48	0.50	0.02***
Native American	0.03	0.00	-0.03***
Asian	0.04	0.02	-0.02***
Pacific Islander	0.00	0.00	0.00
Multi-racial	0.05	0.07	0.03***
Hispanic	0.16	0.07	-0.09***
Ever SPED	0.14	0.17	0.04***
Ever LEP	0.03	0.00	-0.02***
Ever Migrant	0.00	0.00	0.00***
Ever Homeless	0.05	0.07	0.02***
Ever Free or Red. Lunch	0.62	0.83	0.21***
Percent Present	88.0	78.9	-9.01***
ELA Norm Score	0.07	-0.13	-0.20***
Math Norm Score	-0.01	-0.36	-0.34***
Science Norm Score	-0.02	-0.16	- 0.14***
Social Std. Norm Score	-0.01	-0.40	- 0.39***
Observations	95002	21058	116060

Table 1.7: Means of Characteristics of Students School Year 2016 by Full-Time Virtual School

	Non-Virtual Mean	Georgia Cyber Mean	Georgia Conn. Mean	Grad. Ach. Mean
Female	0.49	0.52	0.55	0.48
Black	0.37	0.33	0.33	0.64
White	0.49	0.54	0.54	0.24
Native American	0.03	0.00	0.00	0.02
Asian	0.04	0.02	0.02	0.00
Pacific Islander	0.00	0.00	0.00	0.00
Multi-racial	0.05	0.08	0.07	0.04
Hispanic	0.15	0.06	0.07	0.08
Ever SPED	0.16	0.17	0.16	0.20
LEP	0.08	0.00	0.00	0.01
Ever LEP	0.02	0.00	0.00	0.00
Ever Migrant	0.01	0.00	0.00	0.00
Ever Homeless	0.07	0.06	0.05	0.14
Ever Free or Red Lunch	0.68	0.87	0.67	0.85
LEP	0.08	0.00	0.00	0.01
Free or Red. Lunch	0.48	0.67	0.44	0.08
Percent Present	88.05	82.31	78.04	60.05
ELA Norm Score	0.01	-0.18	0.09	.
Math Norm Score	0.01	-0.37	-0.30	.
Science Norm Score	0.00	-0.19	-0.03	.
Social Std. Norm Score	0.00	-0.43	-0.28	.
Observations	1801274	14530	4142	2386

Table 8a: : Linear Probability Model: Predictors of Virtual School Attendance 2009-2016

	(1)	(2)	(3)	(4)	(5)
Lagged ELA Score	-0.000				0.001***
	(0.000)				(0.000)
Lagged Math Score		-0.001***			-0.001***
		(0.000)			(0.000)
Lagged Percent Present			-0.000***		-0.000***
			(0.000)		(0.000)
Lagged Number of Incidents				0.000***	0.000***
				(0.000)	(0.000)
Female					-0.000*
					(0.000)
Black					-0.003***
					(0.000)
Asian					-0.002***
					(0.001)
Hispanic					-0.004***
					(0.000)
Ever SPED					0.000**
					(0.000)
Ever LEP					-0.004
					(0.004)
Ever Migrant					-0.002*
					(0.001)
Ever Homeless					-0.002***
					(0.000)
Ever Free or Red. Lunch					0.001***
					(0.000)
Year FE	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓
Previous School FE	✓	✓	✓	✓	✓
Observations	6383006	6369027	9607692	1133293	924805

Notes:* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Standard errors in parentheses. Virtual school is defined as 1 if student attended a virtual school that year.

Table 8b: Linear Probability Model: Predictors of Virtual School Attendance Conditional on not Attending a Virtual School the Previous Year. 2009-2016

	(1)	(2)	(3)	(4)	(5)
Lagged ELA Score	-0.000**				0.001***
	(0.000)				(0.000)
Lagged Math Score		-0.000***			-0.001***
		(0.000)			(0.000)
Lagged Percent Present			-0.000***		-0.000***
			(0.000)		(0.000)
Lagged Number of Incidents				0.000***	0.000***
				(0.000)	(0.000)
Female					0.000
					(0.000)
Black					-0.002***
					(0.000)
Asian					-0.002***
					(0.000)
Hispanic					-0.003***
					(0.000)
Ever SPED					0.000***
					(0.000)
Ever LEP					-0.002***
					(0.001)
Ever Migrant					-0.001***
					(0.000)
Ever Homeless					-0.002***
					(0.000)
Ever Free or Red. Lunch					0.003***
					(0.000)
Year FE	✓	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓	✓
Previous School FE	✓	✓	✓	✓	✓
Observations	6358931	6345053	9566844	1132714	6325097

Notes:* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Standard errors in parentheses. Virtual school is defined as 1 if student attended a virtual school that year. Sample is limited to those who in the previous year were not in a virtual school and virtual equals to one if they attended a virtual school that year.

Table 9a: Ordinary Least Square Estimates of the Effect of Virtual School Attendance on Normalized End-of-Grade Achievement Test Scores, Grades 4-8, School Years 2010-2016

	ELA	Mathematics	Science	Social Studies
Virtual	-0.011***	-0.169***	-0.107***	-0.190***
	(0.003)	(0.003)	(0.003)	(0.003)
ELA Lagged	0.770**			
	(0.0003)			
Math Lagged		0.713**		
		(0.0003)		
Science Lagged			0.719**	
			(0.0003)	
Social Studies				0.717**
				(0.0003)
Year FE	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓
Observations	6355086	6303140	5397484	4610350

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Notes: Standard errors in parentheses. Virtual school is defined as 1 if student attended a virtual school that year. Demographics include race, Hispanic, sex, special education eligibility, ever free and reduced lunch, ever homeless and ever migrant. Science and social studies samples are smaller because the state stopped giving theses exams in all grades.

Table 9b: Ordinary Least Square Estimates of the Effect of Virtual School Attendance on Test Score Grades 4-8 and Conditional on Not Attending a Virtual School the Previous Year.Years

	ELA	Mathematics	Science	Social Studies
Virtual	-0.061*** (0.004)	-0.266*** (0.005)	-0.208*** (0.005)	-0.348*** (0.005)
ELA Lagged	0.767** (0.0003)			
Math Lagged		0.702** (0.0003)		
Science Lagged			0.718** (0.0003)	
Social Studies				0.717** (0.0003)
Year FE	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓
Observations	6326573	6244083	5358227	4572734

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Notes: Standard errors in parentheses. Sample is limited to those who in the previous year were not in a virtual school. Virtual school is defined as 1 if student attended a virtual school that year. Demographics include race, Hispanic, sex, special education eligibility, ever free and reduced lunch, ever homeless and ever migrant. Science and social studies samples are smaller because the state stopped giving theses exams in all grades.

Table 1.10: Ordinary Least Square Estimates of the Effect of Virtual School Attendance on Test Score Grades 4-8 and Conditional on Students Attending a Charter School Scores, Grades 4-8, School Years 2010-2016

	ELA	Mathematics	Science	Social Studies
Virtual	-0.028***	-0.165***	-0.084***	-0.177***
	(0.003)	(0.004)	(0.004)	(0.004)
ELA Lagged	0.763**			
	(0.001)			
Math Lagged		0.714**		
		(0.001)		
Science Lagged			0.717**	
			(0.001)	
Social Studies				0.715**
				(0.001)
Year FE	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓
Observations	297621	295828	254095	227753

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Notes: Standard errors in parentheses. Virtual school is defined as 1 if student attended a virtual school that year. Demographics include race, Hispanic, sex, special education eligibility, ever free and reduced lunch, ever homeless and ever migrant. Science and social studies samples are smaller because the state stopped giving theses exams in all grades.

Table 1.11: Student Fixed Effects Model Estimates of the Effect of Virtual School Attendance on Test Score Grades 4-8. School Years 2010-2016

	ELA		Math		Science		Social Studies	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Virtual	-0.119***	-0.116***	-0.309***	-0.307***	-0.265***	-0.271***	-0.396***	-0.400***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ELA Lagged		-0.030***						
		(0.000)						
Math Lagged				-0.037***				
				(0.000)				
Science Lagged						-0.126***		
						(0.000)		
Social Std. Lagged								-0.063***
								(0.000)
Observations	8538404	6351128	8466631	6268306	7519158	5381632	7039285	4596128

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Notes: Standard errors in parentheses. Virtual school is defined as 1 if student attended a virtual school that year. Demographics include race, Hispanic, sex, special education eligibility, ever free and reduced lunch, ever homeless and ever migrant. Science and social studies samples are smaller because the state stopped giving theses exams in all grades.

Table 11b: Interrupted Panel Student Fixed Effects Model Estimates of the Effect of Virtual School Attendance on Test Score Grades 4-8. School Years 2010-2016

	ELA		Math		Science		Social Studies	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Virtual	-0.139***	-0.079***	-0.345***	-0.197***	-0.299***	-0.143***	-0.426***	-0.186***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
ELA 2 Year Avg. Gain		0.961***						
		(0.001)						
Math 2 Year Avg. Gain				-0.928***				
				(0.001)				
Science 2 Year Avg. Gain						0.966***		
						(0.001)		
Social Std. 2 Year Avg. Gain d								-0.963***
								(0.001)
Observations	8523317	4590145	8488905	4537333	7521251	3678212	7042552	3252875

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Notes: Standard errors in parentheses. The year before students enter a virtual school is dropped. The lagged score is an average gain over two years, specifically it is the norm score in year t minus norm score in year t-2 divided by 2. Virtual school is defined as 1 if student attended a virtual school that year. Demographics include race, Hispanic, sex, special education eligibility, ever free and reduced lunch, ever homeless and ever migrant. Science and social studies samples are smaller because the state stopped giving theses exams in all grades.

Table 1.12: Virtual Schools and Test Score Outcome student Fixed Effects for Students who Enter a Full-time Virtual School in a Atypical Grade

	(1) ELA	(2) Math	(3) Science	(4) Social Studies
Virtual	-0.093***	-0.260***	-0.222***	-0.441***
	(0.007)	(0.008)	(0.008)	(0.008)
Atypical Grade * Virtual	-0.033***	-0.072***	-0.060***	0.056***
	(0.008)	(0.009)	(0.009)	(0.009)
Constant	0.005***	0.017***	0.002***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	8544363	8509731	7540775	7060835

Table 1.13: Student Fixed Effects Model Estimates of the Effect of Virtual School Attendance on Test Score Grades 4-8, School Years 2010-2016

	ELA	Mathematics	Science	Social Studies
One Year and Exit	-0.167***	-0.367***	-0.332***	-0.444***
	(0.007)	(0.008)	(0.009)	(0.009)
Two Plus Never Exit	-0.079***	-0.277***	-0.213***	-0.364***
	(0.005)	(0.006)	(0.005)	(0.007)
Observations	48783	48444	42002	40379
Observations	62163	61772	54821	51628

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Notes: Standard errors in parentheses. Virtual school is defined as 1 if student attended a virtual school that year. Science and social studies samples are smaller because the state stopped giving theses exams in all grades.

Table 1.14: Sub-sample Analysis of Student Fixed Effects Model Estimates of the Effect of Virtual School Attendance on Test Score Grades 4-8, School Years 2010-2016

	ELA	Mathematics	Science	Social Studies
Female	-0.087***	-0.305***	-0.278***	-0.405***
	(0.005)	(0.005)	(0.005)	(0.005)
Male	-0.150***	-0.324***	-0.258***	-0.393***
	(0.005)	(0.005)	(0.006)	(0.006)
Ever FRL	-0.121***	-0.319***	-0.273***	-0.402***
	(0.003)	(0.003)	(0.005)	(0.004)
Non-White	-0.095***	-0.261***	-0.223***	-0.356***
	(0.005)	(0.005)	(0.006)	(0.006)
Observations	4200434	4184935	3700684	3467688
Observations	4342950	4323818	3839160	3592236
Observations	6114599	6091236	5395140	5060702
Observations	4310336	4294181	3815159	3572701

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Notes: Standard errors in parentheses. Virtual school is defined as 1 if student attended a virtual school that year. Prior year test score is not included. Science and social studies samples are smaller because the state stopped giving theses exams in all grades.

Table 1.15: Student Fixed Effects Model Estimates of the Effect of Virtual School Attendance on Test Score Elementary Grades 4-5. Years 2010-2016

	ELA		Math		Science		Social Studies	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Virtual	-0.155***	-0.156***	-0.328***	-0.323***	-0.312***	-0.305***	-0.321***	-0.317***
	(0.010)	(0.009)	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)
ELA Lagged		-0.441***						
		(0.001)						
Math Lagged				-0.383***				
				(0.001)				
Science Lagged						-0.410***		
						(0.001)		
Social Std. Lagged								-0.379***
								(0.000)
Observations	2518540	2166281	2512907	2143836	2538624	2173490	2529964	2164159

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Notes: Standard errors in parentheses. Virtual school is defined as 1 if student attended a virtual school that year. Science and social studies samples are smaller because the state stopped giving theses exams in all grades.

Table 1.16: Student Fixed Effects Model Estimates of the Effect of Virtual School Attendance on Test Score Middle Grades 6-8. Years 2010-2016

	ELA		Math		Science		Social Studies	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Virtual	-0.050***	-0.0594***	-0.230***	-0.244***	-0.223***	-0.232***	-0.361***	-0.359***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
ELA Lagged		-0.273***						
		(0.001)						
Math Lagged				-0.231***				
				(0.001)				
Science Lagged						-0.268***		
						(0.001)		
Social Std. Lagged								-0.254***
								(0.000)
Observations	3717074	3200862	3684888	3146992	3707999	3187422	3241132	2411426

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Notes: Standard errors in parentheses. Virtual school is defined as 1 if student attended a virtual school that year. Science and social studies samples are smaller because the state stopped giving theses exams in all grades.

Table 1.17: Virtual Schools and Test Score Outcome Individual Fixed Effects Limited Sample to Students Who Have Ever Been Home-schooled

	(1)	(2)	(3)	(4)
	ELA	Math	Science	Social Studies
Virtual	-0.124***	-0.344***	-0.297***	-0.424***
	(0.006)	(0.007)	(0.008)	(0.008)
Observations	178098	176803	154936	145465

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Standard errors in parentheses. Virtual school is defined as 1 if student attended a virtual school that year. Demographics include race, Hispanic, sex, special education eligibility, ever free and reduced lunch, ever homeless and ever migrant. Science and social studies samples are smaller because the state stopped giving theses exams in all grades.

Table 1.18: Cell Analysis Model of the Effect of Virtual School Attendance on Test Score Grades 5-8, School Years 2010-2016

	ELA	Mathematics	Science	Social Studies
Virtual	-0.0234***	-0.183***	-0.129***	-0.238***
	(0.005)	(0.006)	(0.006)	(0.007)
ELA Lagged	0.759**			
	(0.0001)			
Math Lagged		0.698**		
		(0.001)		
Science Lagged			0.714**	
			(0.001)	
Social Studies				0.716**
				(0.001)
Year FE	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓
Observations	6176875	6095220	5237106	4470491

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Notes: Standard errors in parentheses. Virtual school is defined as 1 if student attended a virtual school that year. Demographics include race, Hispanic, sex, special education eligibility, ever free and reduced lunch, ever homeless and ever migrant. Science and social studies samples are smaller because the state stopped giving theses exams in all grades.

Table 1.19: Probit Model Estimates of the Effect of Virtual School Attendance on Graduation– Conditional on Being In High School at least Four Years.

	Graduation	
Ever Virtual	-0.104***	
	(0.002)	
Number Years Virtual		-0.026***
		(0.001)
Demographics	✓	✓
Year FE	✓	✓
Grade FE	✓	✓
Observations	611854	611854

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Notes: Standard errors in parentheses. Virtual school is defined as 1 if student attended a virtual school that year. Demographics include race, Hispanic, sex, special education eligibility, ever free and reduced lunch, ever homeless and ever migrant. Science and social studies samples are smaller because the state stopped giving theses exams in all grades.

Table 1.20: Probit Model Estimates of the Effect of Virtual School Attendance on Daily Attendance

	Daily Attendance		
Ever Virtual	-0.000***		
	(0.0000)		
Total Number Years Virtual		-0.000***	
		(0.000)	
Number Years Virtual by Year t			-0.000***
			(0.000)
Lagged Percent Present	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Demographics	✓	✓	✓
Year FE	✓	✓	✓
Grade FE	✓	✓	✓
Observations	13956517	13956517	13956517

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Notes: Standard errors in parentheses. Virtual school is defined as 1 if student attended a virtual school that year. Demographics include race, Hispanic, sex, special education eligibility, ever free and reduced lunch, ever homeless and ever migrant. Science and social studies samples are smaller because the state stopped giving theses exams in all grades.

2 Does Social-Emotional Learning Curriculum Improve Cognitive and Non-cognitive Skills?

2.1 Introduction

In labor economics, it is well documented that intelligence or cognitive ability leads to better labor outcomes (e.g., Neal and Johnson (1996) and Bowles et al. (2001)). Although cognitive ability can explain some of the variation between labor outcomes, there remain unexplained differences between people with similar intelligence but with different labor outcomes. More recently in economics, non-cognitive ability has been studied to explain the difference in future labor outcomes (e.g., Heckman and Rubinstein (2001) Heckman et al. (2013)). Although relatively new in economics, the study of non-cognitive ability, such as conscientiousness, perseverance, locus of control, grit, etc., has been studied for decades in psychology (e.g., James (1907) ; Cox (1926); Duckworth et al. (2007). While there is a growing literature on the study of non-cognitive abilities, it is unclear whether these skills can be taught and how they determine later student outcomes.

The charter school literature has shown that charter schools have positive long-term impacts on students despite little or no influence on test scores, which suggests that there may be imparting non-cognitive skills. For example, Sass et al. (2016) find that in Florida, students who attend a charter high school are more likely to graduate from high school, enter and persist in college, graduate from college, and receive higher earnings. Hence, charter schools could be imparting non-cognitive skills that improve long-term student outcomes. This leads to a larger question: can schools impart social-emotional skills that impact cognitive and non-cognitive skills? School leaders, teachers, and researchers have raised the concern that during the No Child Left Behind Accountability era, too much focus was placed on academic performance in the core subjects and not enough on the holistic student, including their social-emotional skills. Social-Emotional Learning (SEL) is a framework that teaches students to "acquire and effectively apply the knowledge, attitudes, and skills necessary to understand and manage emotions, set and achieve positive goals, feel and show empathy for others, establish and maintain positive relationships, and make responsible decisions" (CASEL, 2016). Recently, there has been an increase in interest and implementation of social-emotional learning programs in classes, schools, and districts (Greenberg et al., 2003). Given the growth of SEL, it is essential to study the impacts on students' outcomes.

The purpose of this paper is to estimate the impact of implementing SEL curriculum on student non-cognitive outcomes—attendance, discipline, school climate, and high school graduation—and cognitive outcomes—end of grade test scores and end-of-course test scores. I exploit the fact that the district implemented the curriculum over three years, and use a staggered difference-in-difference model to arrive at causal impact estimates.

Although scholars have studied the effect of SEL on student's health and academic outcomes, most of them only study short-term programs (Durlak et al., 2011). Studies on SEL programs date back to soon after its origins in 1994 (CASEL, 2016). Durlak et al. (2011) is a meta-analysis of 213 studies that evaluate SEL's impact on students. They find that students who received SEL intervention were more likely to have enhanced attitudes, positive social behaviors, fewer behavioral problems, and improved academic outcomes. Most related to this paper, Wang et al. (2016) study the effect of social-emotional learning on dropout rates and learning anxiety in China. Implementing a randomized control trial, they find that in the short-run, SEL programs are effective at lowering the dropout rate and learning anxiety, but in the long term, these effects fade out. We do not know if these findings apply to the U.S. in the short run, or if they would also fade-out over time.

Schools counselors are the staff members that most interact with students who have behavioral problems and suffer from emotional distress. Hence, they usually form a vital part of the success of Social-Emotional Programs. Reducing the counselor-student ratio leads to a reduction of disciplinary incidents and recurrence of negative behavior (Carrell and Carrell, 2006). Reback (2010) finds that the increased presence of mental services leads to a decrease in reports of students misbehavior and fewer teachers reporting that class time was obstructed due to student behavior. Many schools and districts are interested in integrating SEL into their curriculum to bring about long-term systemic changes, not just short-term SEL programs. As Durlak et al. (2011) note, most studies included in their meta-analysis were small scale and less than a year in duration. Unlike other studies, this study will look at the impact of an SEL program on student achievement and non-cognitive outcomes, like attendance, behavior, and graduation over three years in an urban district. Additionally, this paper will directly contribute to school and district leaders' decision on whether to implement SEL or continue to implement the program at their school.

I find that the program does not impact attendance or number of disciplinary incidents across the elementary nor middle school. For high school students, the program leads to a reduction in the number of incidents and an increase in attendance. For elementary and middle school students, I find no evidence that SEL implementation impacts test scores across four subjects: English, Mathematics, Science, and Social Studies. For high school, I find no evidence that the end-of-course exams nor graduation are impacted by SEL implementation.

The rest of the paper is structured as follows. Section 2.2 provides background information and describes the data. Section 2.3 explains the econometric methods that are utilized. Section 2.4 presents the results. Section 2.5 discusses the policy implications of these findings and concludes.

2.2 Background and Data

SEL program implementation exists in many forms. The leading researchers in the area have come to a consensus on the essential features for effective SEL programs. Durlak et al. (2011) state that these qualities are (1) a sequenced step-by-step training approach, (2) use of active forms of learning, (3) devoting sufficient time to skill development, and (4) having explicit learning goals, these qualities are referenced in the literature by the acronym SAFE. The first feature is important as it sets a standard of what skills students need to learn and how to apply these skills to their daily lives. Also, allowing for the program to be active learning instead of passive allows students to interact with the material and implement what they learn. Finally, having explicit and enough exposure to the program is crucial for students to be able to focus on the skills at hand as well as enough time to assimilate the information.

For the past couple years, the district I study has actively been looking for solutions to the violence many of its students' face. Among anti-violence interventions [1] the district has started, one intervention is implementing a social emotional learning curriculum in all its schools and teaches its students these skills. During the 2015-2016 school year the district rolled out a school-wide SEL interventions to twenty-five of its schools. These first schools were not selected randomly, but there were no set criteria for how these schools were selected either. The district is structured in clusters, where elementary schools feed into certain middle schools and in turn these middle feed into a high school. In the first year, two clusters and all middle schools implemented the SEL program. In its second year, 2016-2017, all but five of the remaining schools implemented SEL in their school [2]. The final five elementary schools implement SEL during year three, 2017-2018. Charter schools[3] in the district did not participate in the district-wide initiative but they could implement the program at their school without any direct support from the SEL team. Each school has an SEL team composed of administrators, counselors,

[1] Starting school year 2016-2017, the district implemented its own internal police force, to promote a safe environment for their students which aligns with their SEL program.

[2] These six schools were not randomly assigned to start in year three.

[3] Although charter schools are public schools serving students in the district their autonomy allows them to decide what interventions to implement at their school

and teachers. The team is supported by one of the eight district SEL coaches. A coach has works with between 5 and 11 schools, depending on the number of failing schools [4] they support.

The district selected two SEL curriculums- Second Step for elementary and middle school, and School-Connect® for high school- to be implemented in all schools within the three-year roll out period. At the elementary and middle school level, students receive Second Step SEL curriculm during homeroom, which is about 20 min a day for five days a week. Second Step is a structured curriculum with lessons plans, activities, songs, multi-media, and games in the effort to reduce teacher prep time. The Second Step curriculum is structured to align with district standards and engage students at their current age level. For high school students, they receive SEL instruction through the School-Connect® curriculum during advisory. School-Connect® is one of the top providers of SEL curriculm for high schools providing 80-lesson multimedia curriculum. The curriculum directly aligns to the five competencies CASEL identified as crucial part of SEL skills[5]. One feature that drew the district to School-Connect® was the amount of flexibility it offers to high schools; hence this allowed each school to decide the intensity of the intervention [6]. The intensity varies by the number of hours of explicit instruction,

[4] A school is characterized as failing if it has scored below a 69 on the state's College and Career Ready Performance Index for three consecutive years. Had the amendment passed, these same schools had the potential to be taken over by the state under the Opportunity School District before the November 2016

[5] On School-Connect website they explain: "The program consists of four modules based on CASEL's Social and Emotional Learning (SEL) Competencies identified by researchers as critical to success in school, the workplace, and life in general: social awareness, self-awareness, self-management, relationship skills, and responsible decision making."

[6] The level of intensity then becomes endogenous to other school characteristics but given that the level of interventions have been recorded I will control for this in my economic models

the number of days, intensity of monitoring, the number of members on the SEL team, and teacher/coach training. In addition to the explicit curriculum, schools strive for students to be exposed to SEL throughout the day and take the lessons home to have a full integration of SEL in the students' life.

I use data from a large urban district in the U.S. south. The district has over 90 schools (including charter and non-traditional schools) and serves over 50,000 students a year. This urban district offers a new setting to understand the importance of SEL skills, and its impact on students who live in cities. This district has a high proportion of students in poverty, a large population of minorities, and lower achieving students which in turn contribute to the achievement gap.

The data consists of student-level longitudinal data from 2009/10 through 2015/2017 for grades K-12. It includes demographics, program participation (such as special education, lunch status), enrollment, attendance, behavioral incidents, criterion-referenced state-wide tests for grades 3-12 and graduation data. The criterion-referenced state-wide end-of-grade exam tests four to five different subjects : Reading, English Language Arts, Mathematics, Science, and Social Studies. At the high school level, state-wide end-of-course exams are given, which include subjects such as American Literature, algebra, physical sciences, economics, among others. The district has also collected SEL data such as: the intensity of the intervention, student surveys, and SEL team's monthly evaluation of their progress on their goals.

Table 2.1 presents the summary statistics of all elementary students in the district throughout school years 2012-13 to 2017-18, as well as statistics broken out by if the school implemented SEL curriculm in 2016, or not, and whether they were a charter school. The demographic variables are used as controls in the econometric models. Looking across the tables the demographics look similar except charters have slightly fewer Latino/s students, less Black, and less students receiving free or reduced lunch than the non-charter schools. The non-cognitive outcomes, attendance and number of disciplinary incidents are measured over the school year. In particular, number of incidents, is the total number of disciplinary incidents a student has in a school year, which ranges from disruption in class to more serious infractions such as drug use. There are a lot of students who never have a disciplinary incident in the district. Table 2.2 presents the t-test difference in means between students who implemented in the first year versus in the second or third year. compares two averages (means) and indicates if they are signficantly different from each other. Table 2.3 and Table 2.4 provide similar summary statistics for middle schools and high schools.

2.3 Econometric Methods

To evaluate the effect of the SEL program on student outcomes I exploit the fact that the district rolled out the program over three school years. More specifically, I implement a staggered difference-in-differences model. The counter factual is that the district would have continued educating their students without implementing this program.

To estimate the impact of SEL curriculum on attendance and behavior, I estimate the following equation:

$$A_{it} = \beta_0 + \beta_1 SEL_{mt} + \beta_2 X_i + \delta_m + \sigma_g + \gamma_t + \epsilon_{it}, \tag{2.1}$$

To estimate the impact of SEL curriculum on graduation, I estimate:

$$Prob[D_{it}] = \Phi[\beta_1 SEL_{mt} + \beta_2 X_i + \delta_m + \beta_3 8^{th} GradeTest_{it-4}] + \gamma_t + \epsilon_{it}, \tag{2.2}$$

where D_{it} equals one if student i graduated high school at the end of their t^{th} school year. X_{it} is a vector of student demographics such as gender, free or reduced lunch status (frl), special education, and race. δ_m is a school fixed effect controlling for all time invariant characteristics of the school. $8^{th} GradeTest_{it-4}$ is the student's 8th grade test score prior year achievement which captures both innate ability, family characteristics and prior schooling inputs. SEL is an indicator variable equal to one if student i's school implemented SEL curriculum that year. Lastly, ϵ_{it} is the normally distributed error term. β_1 is the coefficient of interest which measures the impact of implementing SEL curriculum on the outcome of interest.

To estimate the impact of SEL curriculum on student test scores I estimate:

$$\lambda_{it} = \beta_0 + \beta_1 SEL_{mt} + \beta_2 X_i + \delta_m + \gamma_t + \beta_3 \lambda_{it-1} + \epsilon_{it}, \tag{2.3}$$

where λ_{it} is the student achievement measured by the state test for a student i at the end of their t^{th} school year. X_{it} is a vector of student demographics such as gender, FRL status, special education status, and race. δ_m is a school fixed effect controlling for all time invariant characteristics of the school. λ_{it-1} is the student's prior year achievement which captures both innate ability, family characteristics and prior schooling inputs. SEL is an indicator variable equal to one if student i's school implemented SEL curriculum that year.Lastly, ϵ_{it} is the normally distributed error term. β_1 is the coefficient of interest which measures the impact of implementing SEL curriculum on the outcome of interest.

2.4 Results

Non-Cognitive Outcomes

Table 2.6 and 2.7 provide the staggered difference-in-difference results of the impact of SEL on non-cognitive outcomes for all students in the district. These results allow us to glean the impact of SEL program implementation on attendance and number of disciplinary incidents. Whether we include or exclude charter students in the sample the impact of SEL implementation on non-cognitive outcomes are not statistically different from zero. Table 2.8 presents the impact of implementing an SEL curriculum on the number of incidents of cheating, fighting, class disruption, skipping, and bullying. These types of incidents should be the most impacted by SEL skills acquisition, but none of these types of incidents are statistically different from zero.

Table 2.9 through 2.13 presents sub-sample analysis for elementary and middle school students as combining all students might confound the differential effects across grade levels. When we exclude charter school students, both these grade levels attendance has declined but the estimate is not statically different from zero. The number of disciplinary incidents increased in elementary schools and declined in middle school, although these are also not statistically different from zero. Table 2.11 and Table 2.14 breakout the types of disciplinary incidents for elementary and middle school students respectively. For both grade levels, I do not find statistically significant impact of SEL implementation on interpersonal behavioral incidents.

Tables 2.15 and 2.16 provide results for high school students. When I exclude charter schools, whom did not explicitly implement the SEL program with the SEL team support I find that attendance increased by 1.8 percentage points. The impact of SEL on attendance and discipline is significant at the five percent level and provides evidence that this program increases attendance and number of discipline incidents for high school students. Table 2.17 provides the estimates of the impact of SEL on different types of disciplinary incidents. The fourth column in Table 2.17 shows that implementing an SEL curriculum lead to a reduction in the number of skipping incidents.

Test Score Outcomes and Graduation

Table 2.18 presents the results of the impact of implementing SEL program on test scores across four subjects for elementary and middle school students. Although, Mathematics and Science test scores decline while ELA and Social Studies improve, none of the four tests are statistically different from zero. Given the differences in elementary and middle school student's I break out these test score outcomes by elementary in Table 2.19 and middle school in Table 2.20. In table 2.19 presents evidence that SEL had a positive impact on elementary students ELA scores by .04 standard deviation. For middle school students, we do not see any statistically significant impact.

Tables 2.21 - 2.24 report the end-of-course exams for high school students aggregated to the high school level where the outcome is the average normed test score for that school that year and the prior year's averaged normalized score is used as a control. For the math tests, I find a negative relationship between SEL implementation and math test scores but it is not statistically different from zero. The English, science, and social studies end-of-course exams have a positive relationship but its not statistically different from zero.

2.5 Conclusion

We know that non-cognitive ability is valued in the labor market. School and district leaders have implemented SEL curriculum to teach students these important skills across the United States. Given the growth of SEL, it is essential to study the impacts on students' outcomes.

In this paper I estimate the impact of implementing SEL curriculum on student non-cognitive outcomes—attendance, discipline, and high school graduation—and cognitive outcomes—end of grade test scores and end of course test scores. I exploit the fact that the district implemented the curriculum over a three-year period, and use a staggered difference-in-difference model to arrive at causal impact estimates. I find that the program does not impact attendance or discipline across elementary nor middle school. For high school students, the program leads to a reduction in the number of incidents and increase in attendance. For elementary and middle school students, I find no evidence that SEL implementation impacts test scores across four subjects: English, Mathematics, Science, and Social Studies. For high school, I find no evidence that end-of-course scores is impacted by SEL implementation. Using both linear probability model and probit, I find no impact of SEL on graduation.

In the short-run, implementing SEL curriculum has had the most impact on high school students, specifically in reducing the number of discipline behaviors, increasing attendance, and improving performance on end-of-course test, analytic geometry. To further evaluate the impact of SEL programs it would help to have outcomes more aligned with the SEL skills, so researchers can directly evaluate if these skills are improving. This is only the first three years of the program, more years of data and long-term outcomes, such as college completion and labor force participation, are important to evaluate to get a better picture of the impact of explicitly teaching students non-cognitive skills.

2.6 Figures and Tables

Table 2.1: Means of Characteristics of Elementary School Students School Years 2013-2018

	All	Implemented 2016	Not Implemented 2016	Charter
	Mean	Mean	Mean	Mean
Demographics				
Female	0.49	0.48	0.48	0.49
Asian	0.02	0.002	0.02	0.01
Black	0.73	0.96	0.67	0.74
Hispanic	0.05	0.03	0.07	0.02
White	0.17	0.002	0.21	0.19
LEP	0.028	0.02	0.04	0.01
Special Edu.	0.09	0.09	0.09	0.07
Free or Reduced Lunch	0.68	0.88	0.65	0.60
Outcomes				
Percent Attendance	95.2	94.3	95.2	96.2
Number Incident	2.13	1.87	2.24	1.78
Ela norm	-0.19	-0.72	-0.13	0.15
Math norm	-0.22	-0.70	-0.17	0.032
Soc Std. norm	-0.17	-0.74	-0.13	0.27
Science norm	-0.24	-0.77	-0.18	0.085
Observations	179469	29595	124133	25741

Figure 2.1: Elementary Schools Serving Grades 4 and 5 Attendance, 2013-2018

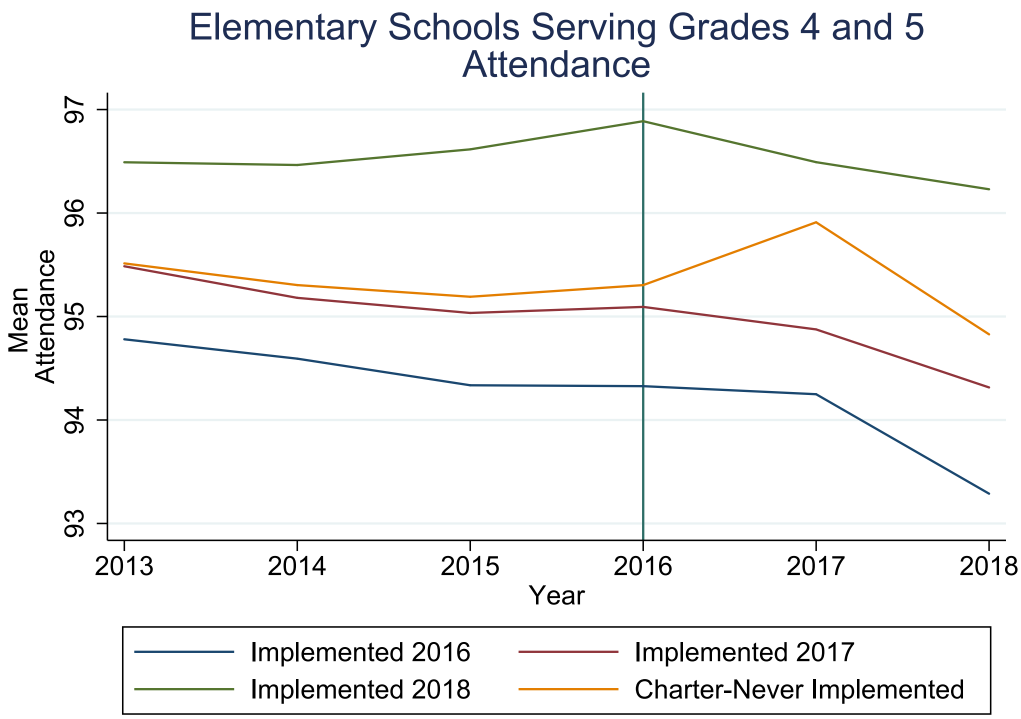


Figure 2.2: Elementary Schools Serving Grades 4 and 5 Disciplinary Incidents, 2013-2018

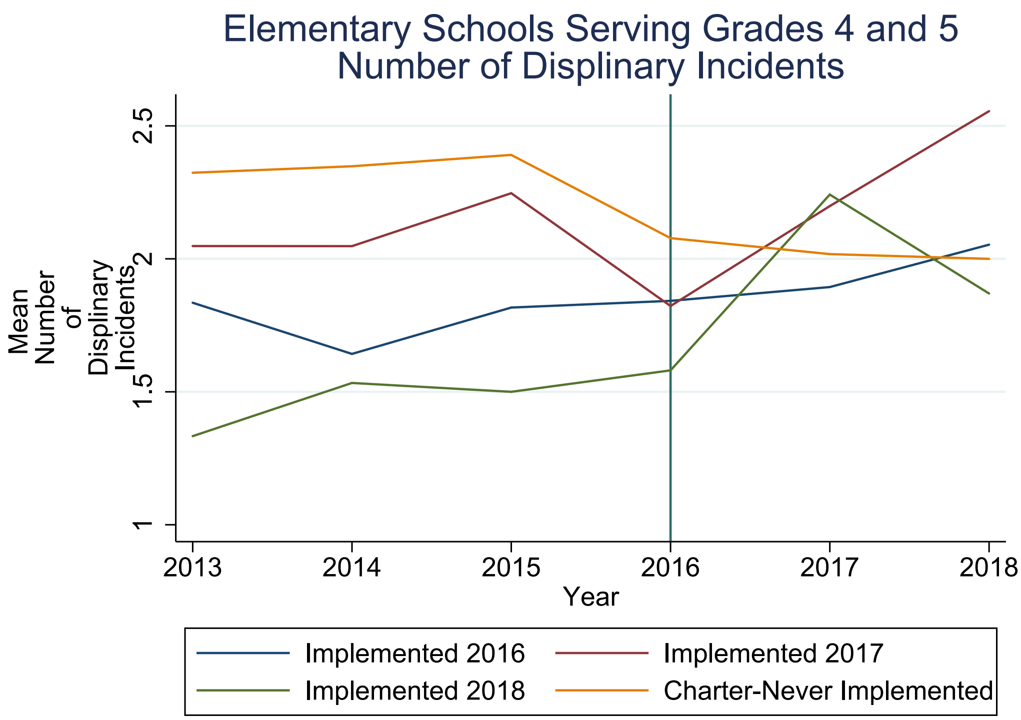


Figure 2.3: Elementary Schools Serving Grades 4 and 5 ELA Norm Score, 2013-2018

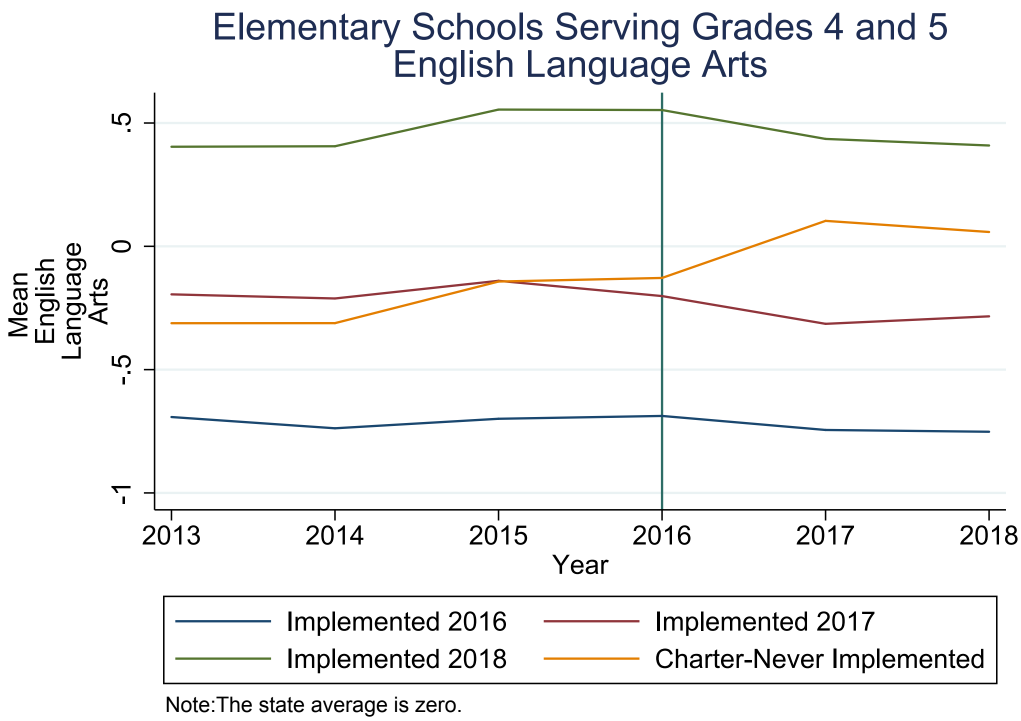


Figure 2.4: Elementary Schools Serving Grades 4 and 5 Mathematics Norm Score, 2013-2018

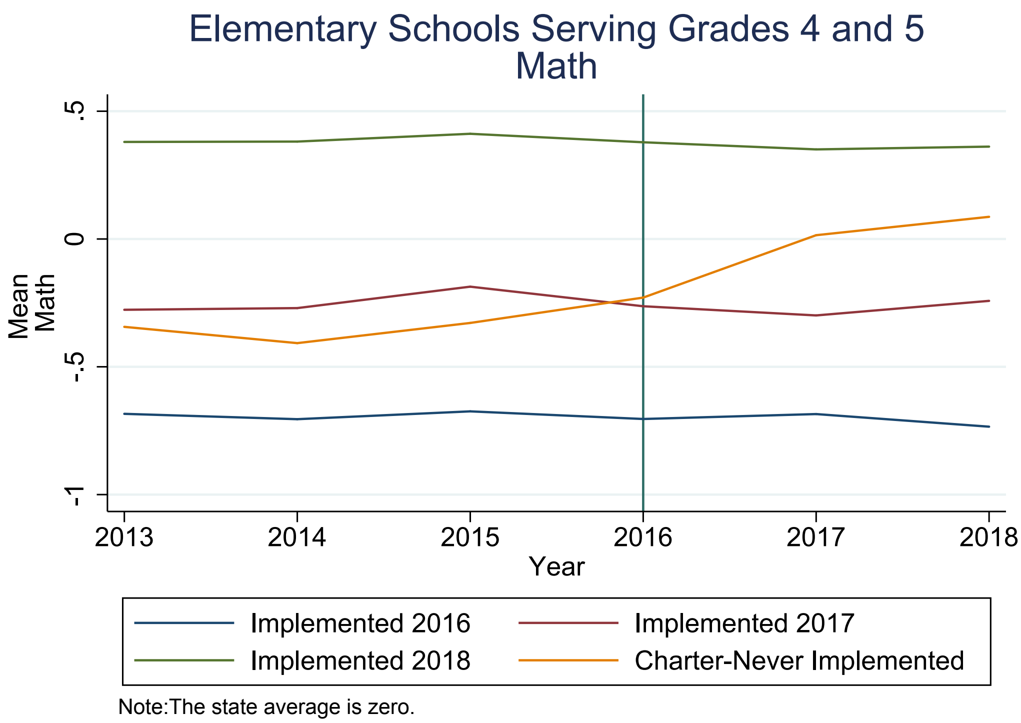


Figure 2.5: Elementary Schools Serving Grades 4 and 5 Science Norm Score, 2013-2018

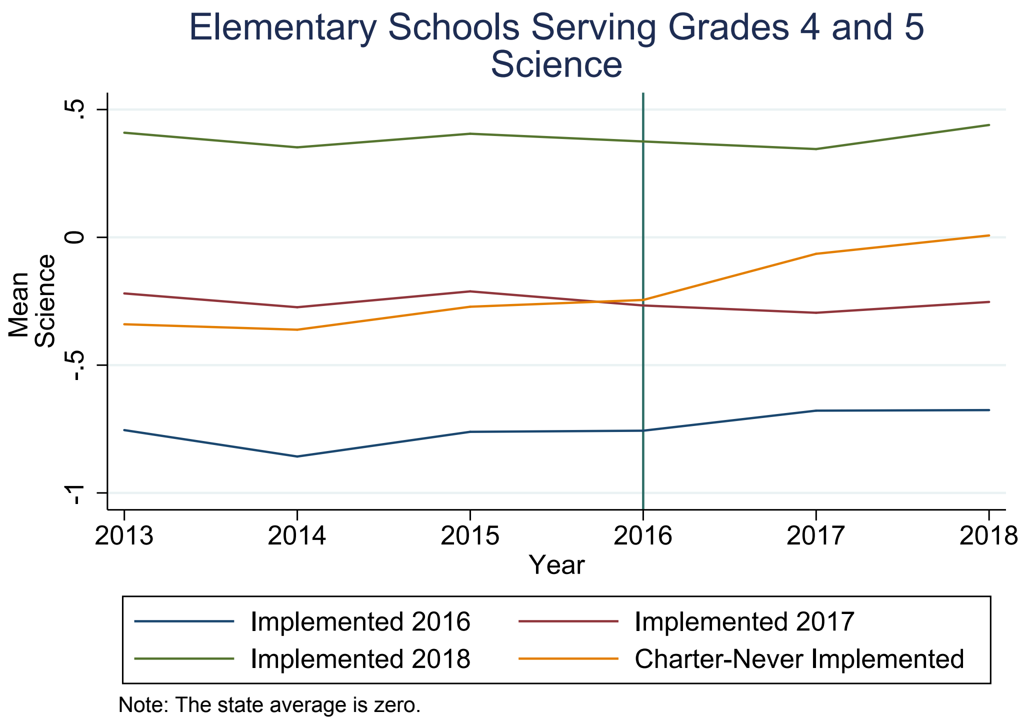


Figure 2.6: Elementary Schools Serving Grades 4 and 5 Social Studies Norm Score, 2013-2018

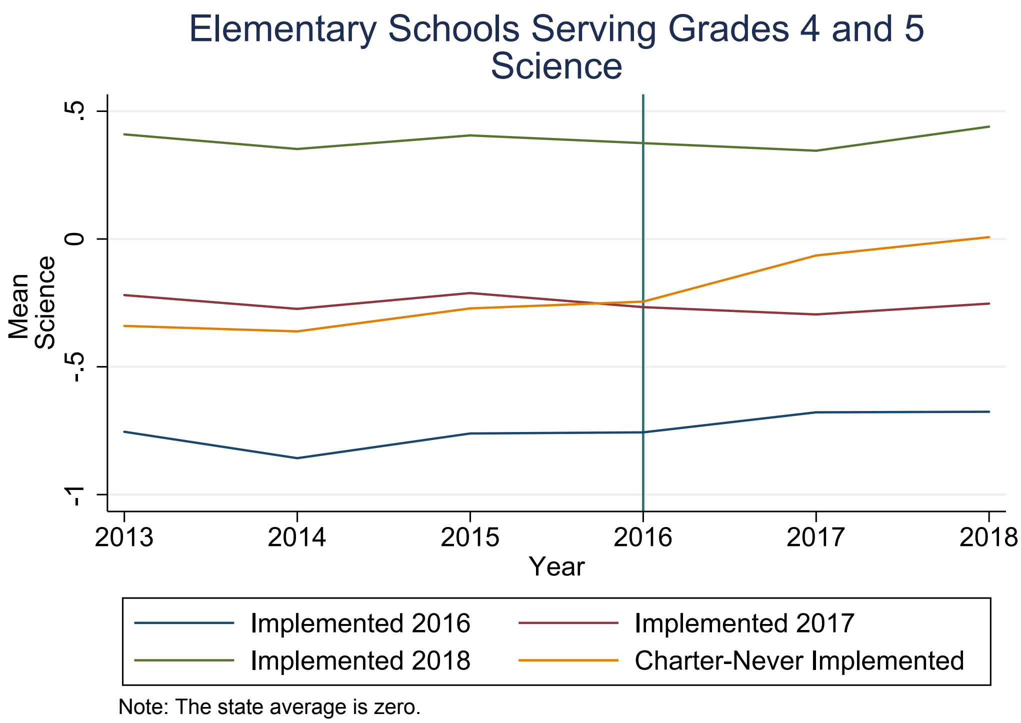


Figure 2.7: Middle Schools Serving Grades 6-8 Attendance, 2013-2018

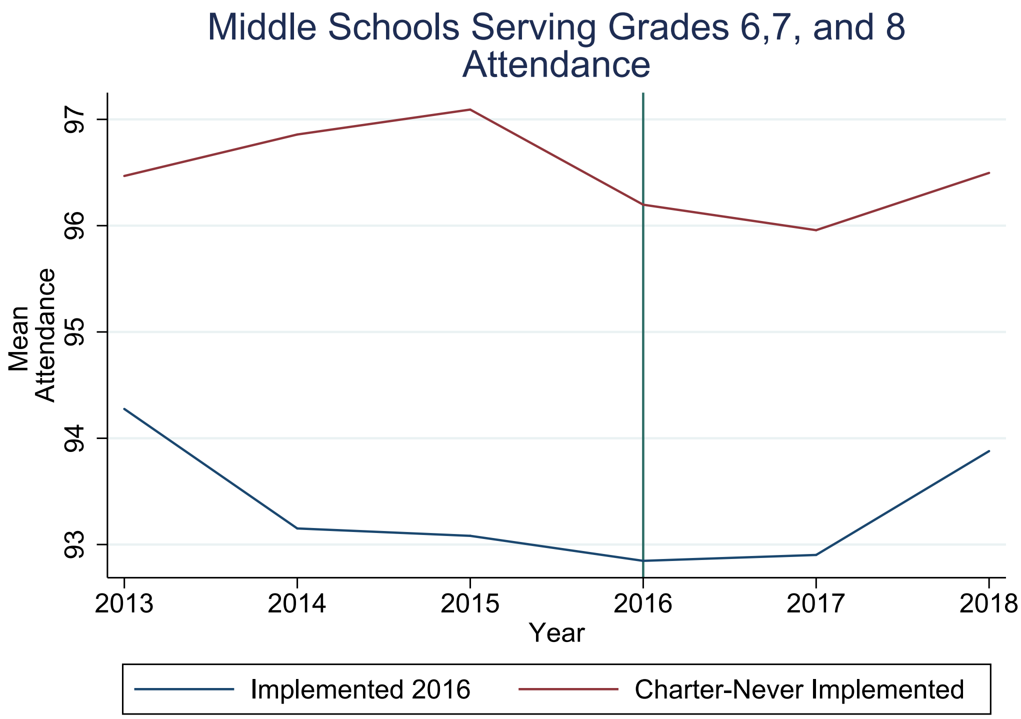


Figure 2.8: Middle Schools Serving Grades 6-8 Disciplinary Incidents, 2013-2018

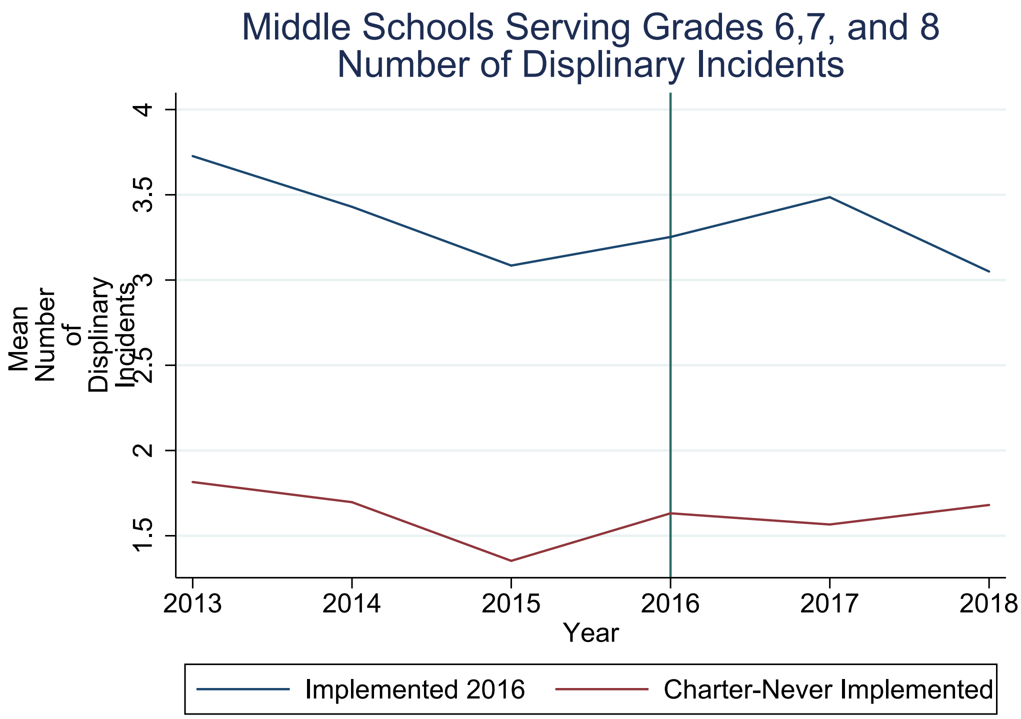


Figure 2.9: Middle Schools Serving Grades 6-8 ELA Norm Score, 2013-2018

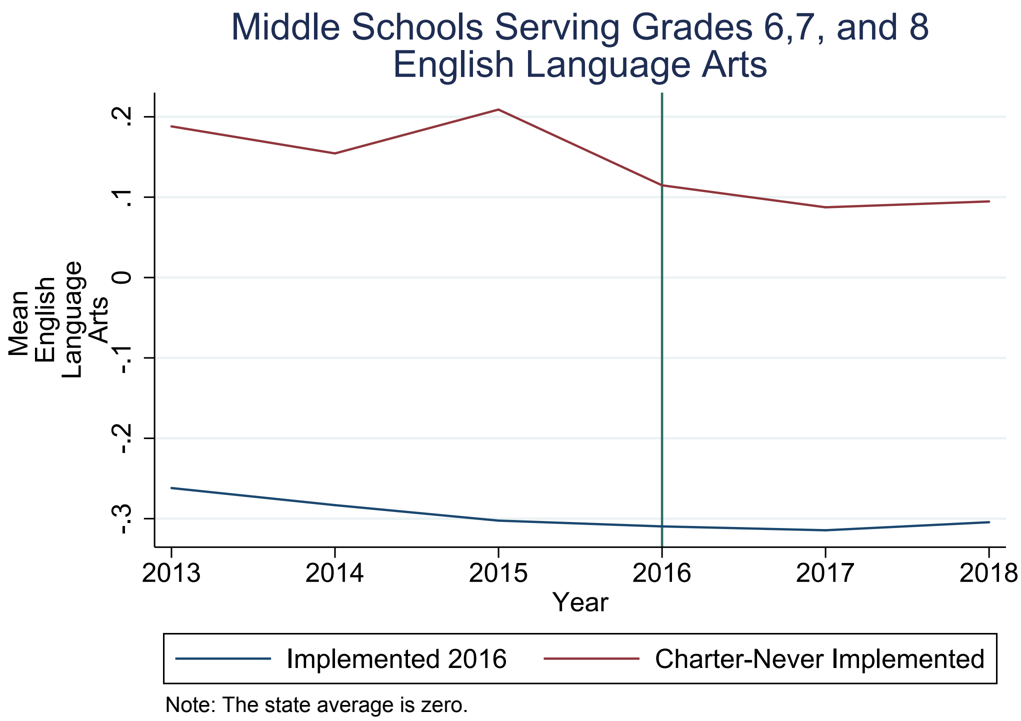


Figure 2.10: Middle Schools Serving Grades 6-8 Mathematics Norm Score, 2013-2018

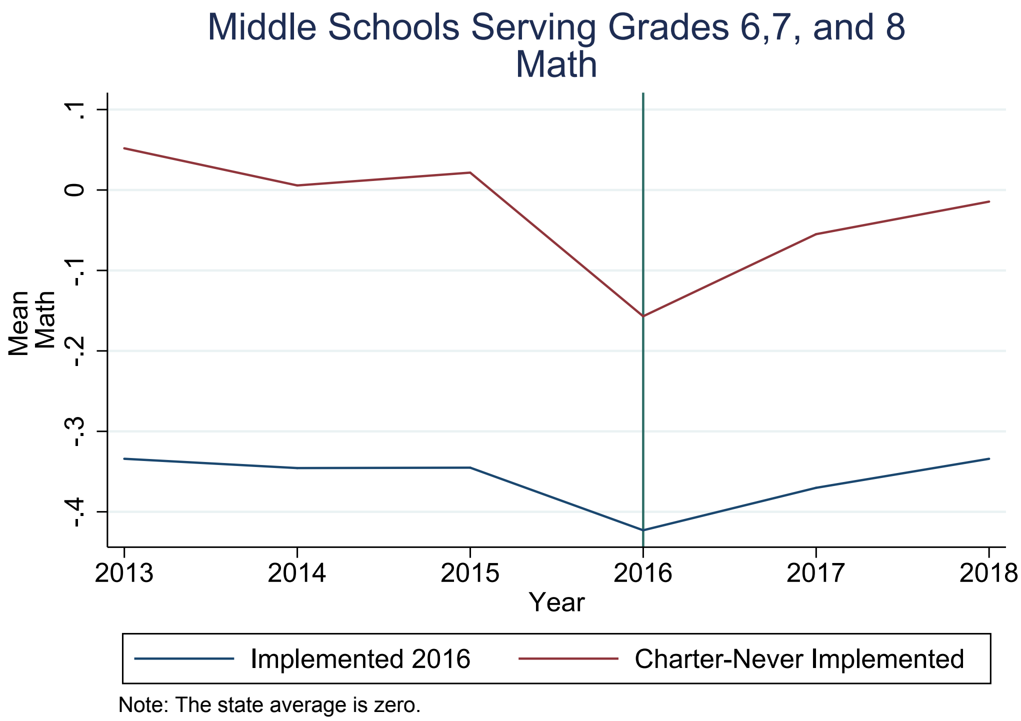


Figure 2.11: High Schools Serving Grades 9-12 Attendance, 2013-2018

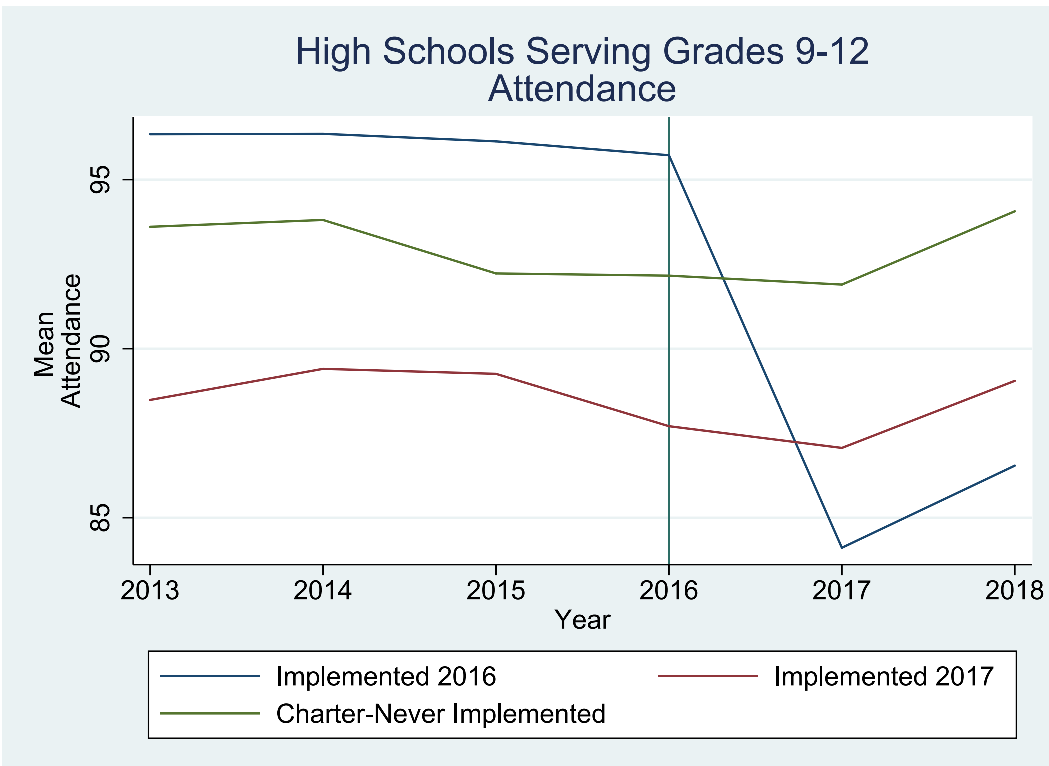


Figure 2.12: High Schools Serving Grades 9-12 Number of Disciplinary Incidents, 2013-2018

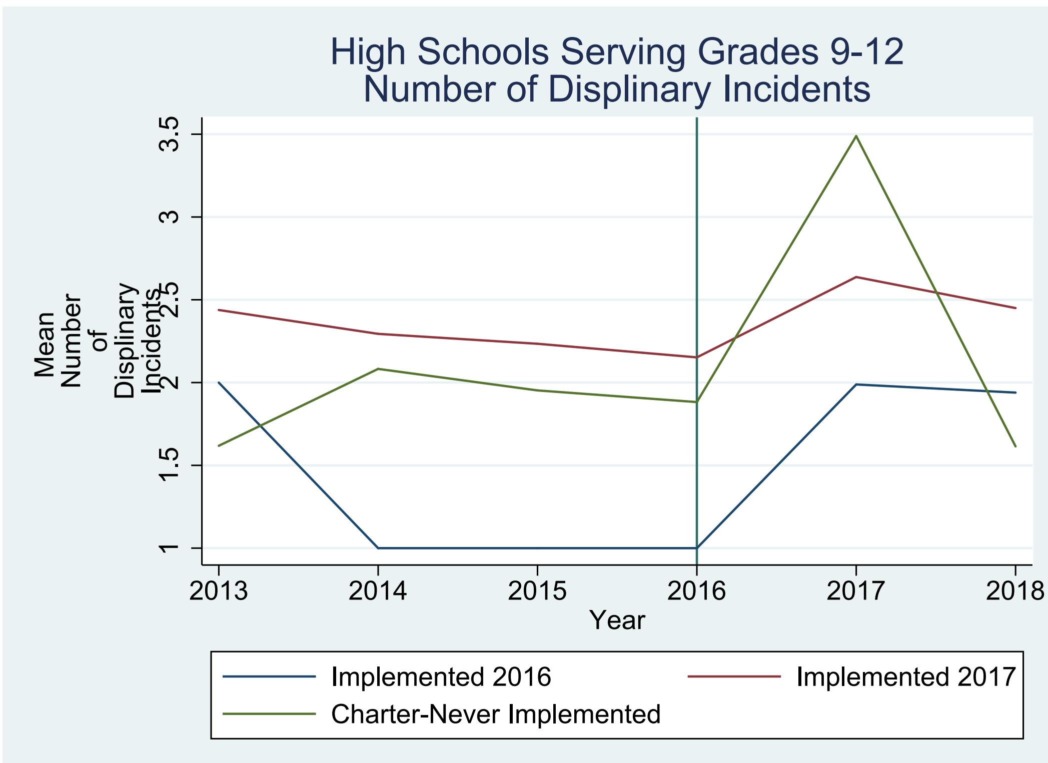


Figure 2.13: High Schools Serving Grades 9-12 2013-2018

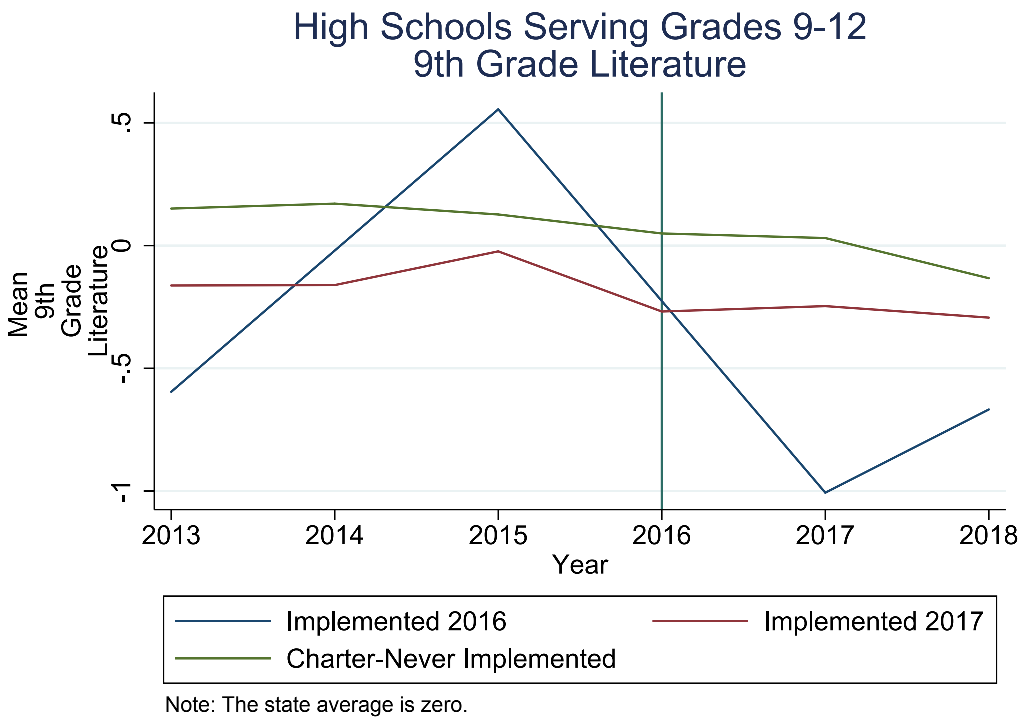


Figure 2.14: High Schools Serving Grades 9-12 2013-2018

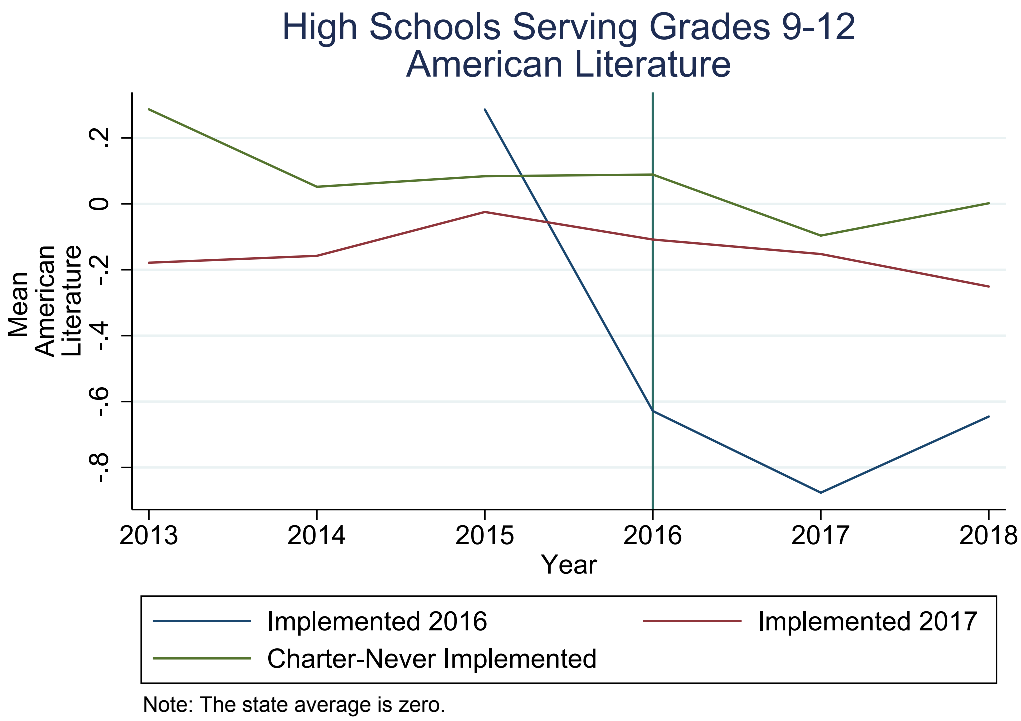


Figure 2.15: High Schools Serving Grades 9-12 2013-2018

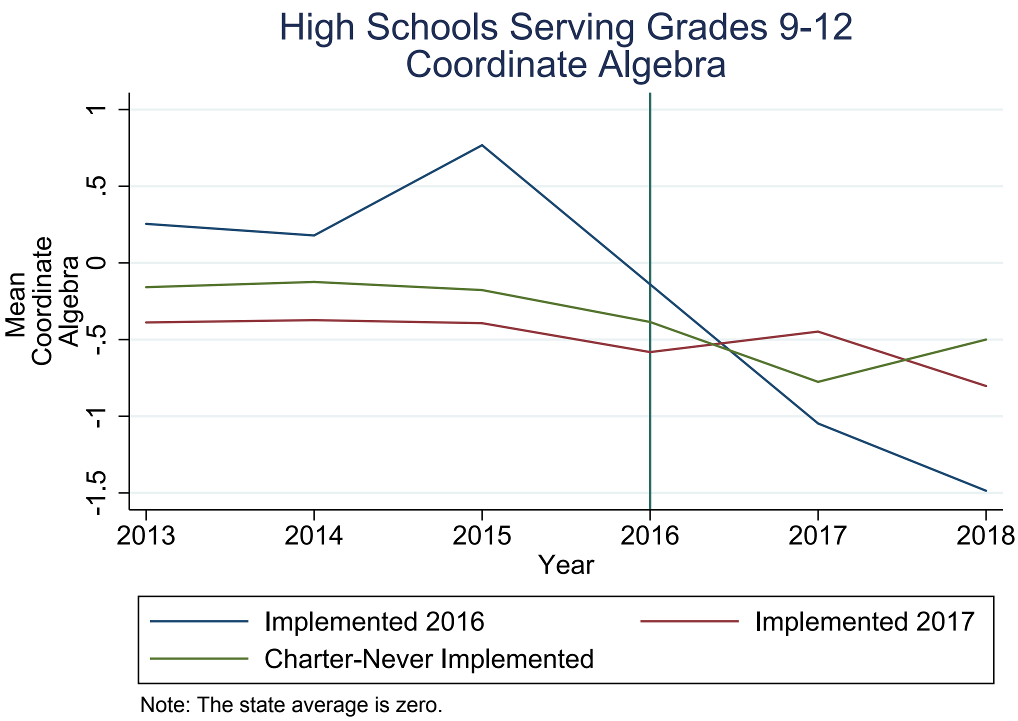


Figure 2.16: High Schools Serving Grades 9-12 2013-2018

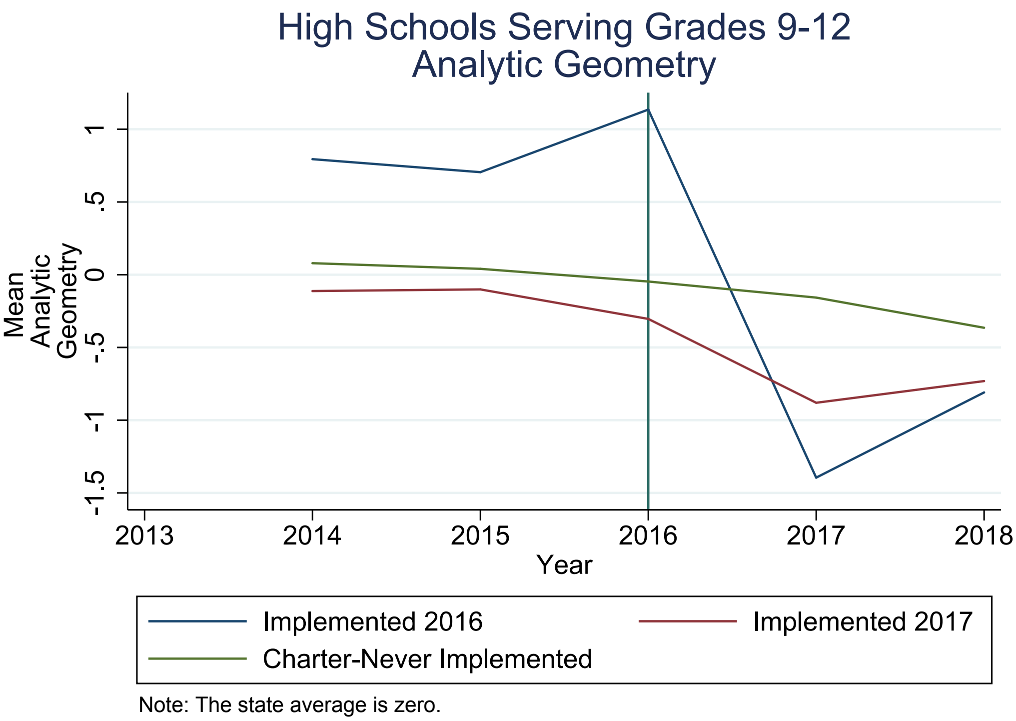


Figure 2.17: High Schools Serving Grades 9-12 2013-2018

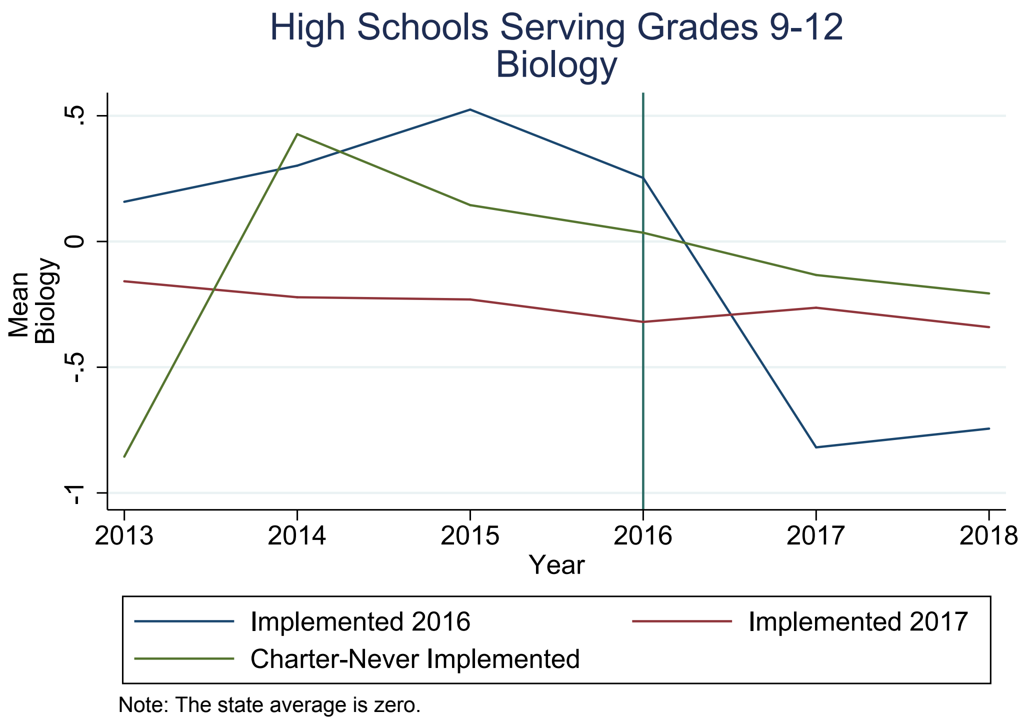


Figure 2.18: High Schools Serving Grades 9-12 2013-2018

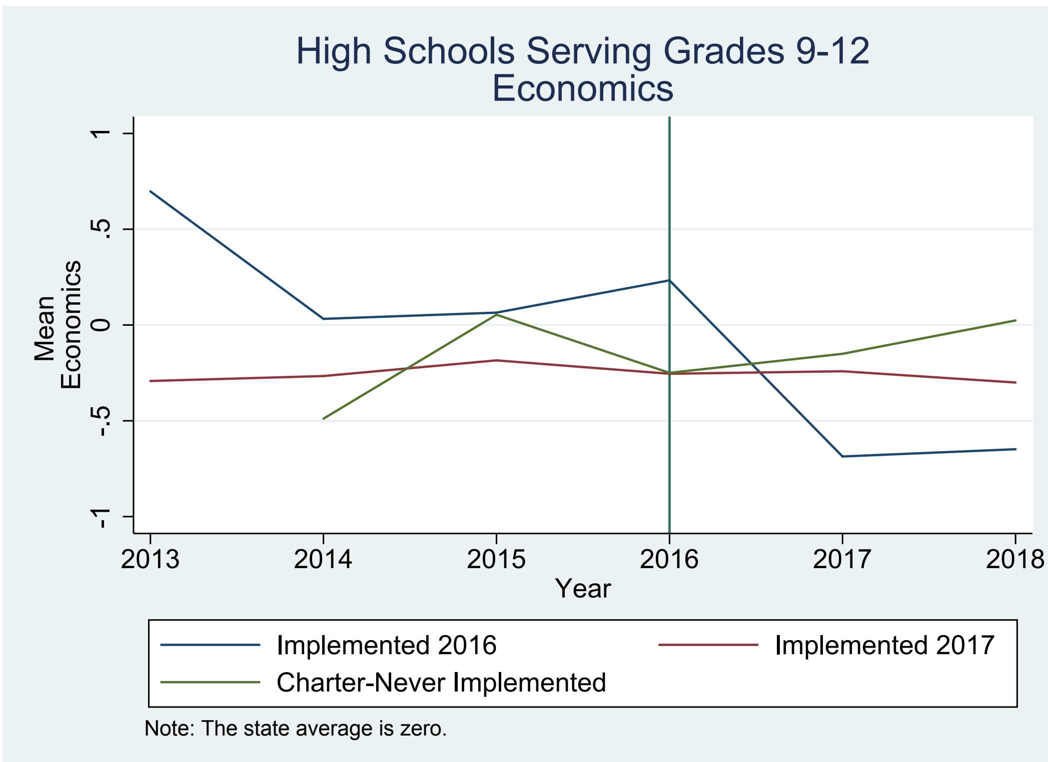


Figure 2.19: High Schools Serving Grades 9-12 2013-2018

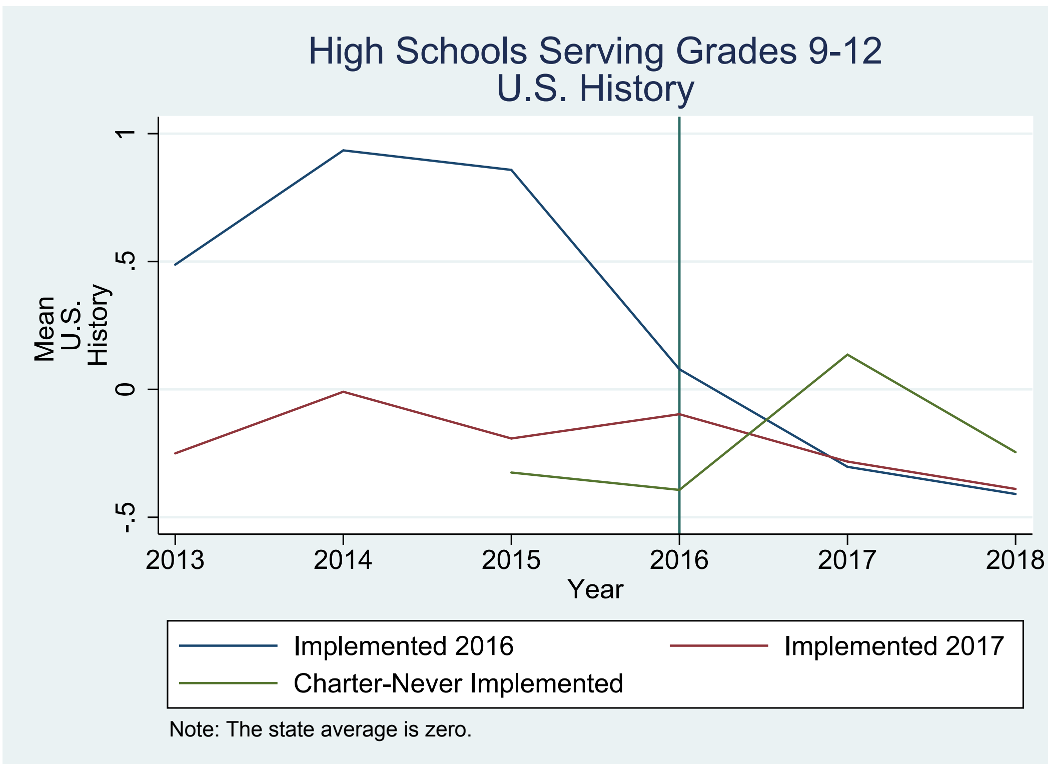


Table 2.2: Means of Characteristics of Elementary School Students by First Year of Implementation Status for School Years 2013-2018

	Implemented 2016 Mean	Not Implemented 2016 Mean	Difference
Demographics			
Female	0.48	0.48	0.01
Asian	0.00	0.02	0.02***
Black	0.96	0.67	-0.28***
Hispanic	0.03	0.07	0.04***
White	0.002	0.21	0.20***
LEP	0.02	0.04	0.02***
Special Edu.	0.09	0.09	0.01**
Free or Reduced Lunch	0.88	0.65	-0.24***
Outcomes			
Percent Attendance	94.3	95.2	0.88***
Number Incident	1.87	2.24	0.36***
Ela norm	-0.72	-0.13	0.59***
Math norm	-0.70	-0.17	0.53***
Soc Std. norm	-0.74	-0.13	0.61***
Science norm	-0.77	-0.18	0.58***
Observations	29595	124133	153728

Table 2.3: Means of Characteristics of Middle School Students School Years 2013-2018

	All Mean	Implemented 2016 Mean	Not Implemented 2016 Mean
Demographics			
Female	0.49	0.49	0.52
Asian	0.0092	0.0095	0.0077
Black	0.78	0.78	0.80
Hispanic	0.058	0.066	0.021
White	0.12	0.12	0.13
LEP	0.011	0.013	0.0030
Special Edu.	0.13	0.14	0.11
Free or Reduced Lunch	0.74	0.75	0.69
Outcomes			
Percent Attendance	93.9	93.4	96.5
Number Incident	3.21	3.35	1.64
Ela norm	-0.22	-0.30	0.14
Math norm	-0.30	-0.36	-0.031
Soc Std. norm	-0.29	-0.36	0.094
Science norm	-0.34	-0.41	0.040
Observations	47223	39195	8028

Table 2.4: Means of Characteristics of High School Students School Years 2013-2018

	All Mean	Implemented 2016 Mean	Not Implemented 2016 Mean	Charter Mean
Female	0.51	0.53	0.51	0.55
Asian	0.007	0.002	0.007	0.004
Black	0.84	0.96	0.82	0.93
Hispanic	0.049	0.033	0.052	0.016
White	0.090	0.002	0.100	0.041
Percent Attendance	87.6	88.0	87.2	92.8
Number Incident	2.44	1.95	2.47	2.34
LEP	0.007	0.000	0.008	0.000
Special Edu.	0.12	0.11	0.12	0.086
Free or Reduced Lunch	0.75	0.90	0.74	0.74
Ela 8th grade norm	-0.19	-0.33	-0.20	0.095
Math 8th grade norm	-0.30	-0.37	-0.32	0.033
Soc Std. 8th grade norm	-0.30	-0.36	-0.32	0.071
Science 8th grade norm	-0.32	-0.34	-0.35	0.026
Coordinate Algebra	-0.45	0.37	-0.50	-0.18
Analytic Geometry	-0.25	0.82	-0.31	0.012
9th Grade Literature	-0.30	-0.69	-0.32	0.037
American Literature	-0.26	-0.63	-0.26	0.004
Biology	-0.36	-0.54	-0.38	0.005
U.S. History	-0.34	-0.54	-0.34	-0.13
Economics	-0.26	-0.049	-0.29	-0.27
Observations	78920	5163	68791	4966

Table 2.5: Means Characteristics of High School School Students by First Year of Implementation Status for School Years 2013-2018

	Implemented 2016 Mean	Not Implemented 2016 Mean	Difference
Demographics			
Female	0.53	0.51	-0.02*
Asian	0.002	0.007	0.00***
Black	0.96	0.82	-0.14***
Hispanic	0.033	0.052	0.02***
White	0.002	0.100	0.10***
LEP	0.00	0.01	0.01***
Special Edu.	0.11	0.12	0.02***
Free or Reduced Lunch	0.90	0.74	-0.16***
Ela 8th grade norm	-0.33	-0.20	
Math 8th grade norm	-0.37	-0.32	
Soc Std. 8th grade norm	-0.36	-0.32	
Science 8th grade norm	-0.34	-0.35	
Outcomes			
Percent Attendance	88.0	87.2	-0.84***
Number Incident	1.95	2.47	0.52***
Coordinate Algebra	0.37	-0.50	-0.87***
Analytic Geometry	0.82	-0.31	-1.13***
9th Grade Literature	-0.69	-0.32	0.38***
American Literature	-0.63	-0.26	0.37***
Biology	-0.54	-0.38	0.16***
U.S. History	-0.54	-0.34	0.20***
Economics	0.049	-0.29	-0.24***
Observations	5163	68791	73954

Table 2.6: Student Non-Cognitive Outcomes for all Students, Years 2013-2018

	(1) Percent Attendance (se)	(2) Number Incident (se)
Social Emotional Learning	-0.060	0.026
	(0.176)	(0.062)
Observations	278768	278780

Table 2.7: Student Non-Cognitive Outcomes for all Non-Charter Students, Years 2013-2018

	(1) Percent Attendance (se)	(2) Number Incident (se)
Social Emotional Learning	-0.088	0.034
	(0.249)	(0.077)
Observations	241528	241537

Table 2.8: Student Discipline Outcomes Broken Out by Interpersonal Incidents for All Students, Years 2013-2018

	(1) Cheating (se)	(2) Fighting (se)	(3) Disruption (se)	(4) Skipping (se)	(5) Bullying (se)
Social Emotional Learning	0.000	0.033	0.004	-0.034	0.002
	(0.000)	(0.057)	(0.028)	(0.068)	(0.002)
Observations	278780	42459	278780	42459	278780

Table 2.9: Student Non-Cognitive Outcomes for Elementary Students, Years 2013-2018

	(1) Percent Attendance (se)	(2) Number Incident (se)
Social Emotional Learning	-0.025	0.026
	(0.133)	(0.020)
Observations	159904	11334

Table 2.10: Student Non-Cognitive Outcomes for all Elementary Non-Charter Students, Years 2013-2018

	(1) Percent Attendance (se)	(2) Number Incident (se)
Social Emotional Learning	-0.012	0.012
	(0.143)	(0.024)
Observations	136826	10325

Table 2.11: Student Discipline Outcomes Broken Out by Interpersonal Incidents for Elementary Students, Years 2013-2018

	(1) Cheating (se)	(2) Fighting (se)	(3) Disruption (se)	(4) Skipping (se)	(5) Bullying (se)
Social Emotional Learning	0.000	0.014	-0.007	0.033	-0.001
	(0.000)	(0.121)	(0.009)	(0.017)	(0.001)
Observations	159908	11334	159908	11334	159908

Table 2.12: Student Non-Cognitive Outcomes for All Middle School Students, Years 2013-2018

	(1) Percent Attendance (se)	(2) Number Incident (se)
Social Emotional Learning	0.322	-0.191
	(0.361)	(0.226)
Observations	51283	15454

Table 2.13: Student Non-Cognitive Outcomes for All Non-Charter Middle School Students, Years 2013-2018

	(1) Percent Attendance (se)	(2) Number Incident (se)
Social Emotional Learning	-0.418	-0.316
	(0.453)	(0.361)
Observations	50115	15316

Table 2.14: Student Discipline Outcomes Broken Out by Interpersonal Incidents for Middle School Students, Years 2013-2018

	(1) Cheating (se)	(2) Violence (se)	(3) Disruption (se)	(4) Skipping (se)	(5) Bullying (se)
Social Emotional Learning	0.001	-0.078	-0.166	0.000	0.004
	(0.001)	(0.068)	(0.085)	(0.102)	(0.010)
Observations	41888	11704	41888	11704	41888

Table 2.15: Student Non-Cognitive Outcomes for All High School School Students, Years 2013-2018

	(1) Percent Attendance (se)	(2) Number Incident (se)
Social Emotional Learning	0.029	-0.072
	(0.909)	(0.156)
Observations	54391	13247

Table 2.16: Student Non-Cognitive Outcomes for All Non-Charter High School Students, Years 2013-2018

	(1) Percent Attendance (se)	(2) Number Incident (se)
Social Emotional Learning	1.799*	0.222*
	(0.699)	(0.092)
Observations	51858	12472

Table 2.17: Student Discipline Outcomes Broken Out by Interpersonal Incidents for High School Students, Years 2013-2018

	(1) Cheating (se)	(2) Violence (se)	(3) Disruption (se)	(4) Skipping (se)	(5) Bullying (se)
Social Emotional Learning	0.002	0.028	0.032	-0.720***	0.009
	(0.002)	(0.075)	(0.080)	(0.167)	(0.008)
Observations	57422	13829	57422	13829	57422

Table 2.18: Elementary and Middle School Student's Test Score Outcomes, Years 2013-2018, Grades 4-8

	(1) ELA (se)	(2) Math (se)	(3) Science (se)	(4) Social Std. (se)
Social Emotional Learning	0.011	-0.040	-0.002	0.028
	(0.012)	(0.020)	(0.029)	(0.029)
Observations	92291	90961	68017	67938

Table 2.19: Elementary School Student's Test Score Outcomes, Years 2013-2018, Grades 4-5

	(1) ELA (se)	(2) Math (se)	(3) Science (se)	(4) Social Std. (se)
Social Emotional Learning	0.039*	-0.033	0.039	0.033
	(0.019)	(0.036)	(0.039)	(0.047)
Observations	41828	41765	31413	31301

Table 2.20: Middle School Student's Test Score Outcomes, Years 2013-2018, Grades 6-8

	(1) ELA (se)	(2) Math (se)	(3) Science (se)	(4) Social Std. (se)
Social Emotional Learning	0.037	-0.057	0.007	0.076
	(0.027)	(0.035)	(0.081)	(0.101)
Observations	34067	33897	22836	22741

Table 2.21: High School's Math Test Score Outcomes, Years 2013-2018

	(1) Coordinate Algebra (se)	(2) Analytic Geometry (se)
Social Emotional Learning	-0.061	-0.053
	(0.223)	(0.204)
Observations	71	57

Table 2.22: High School's ELA Test Score Outcomes, Years 2013-2018

	(1) 9th Grade Literature (se)	(2) American Literature (se)
Social Emotional Learning	0.070	0.327
	(0.088)	(0.262)
Observations	126	124

Table 2.23: High School's Science Test Score Outcomes, Years 2013-2018

	(1) Biology (se)
Social Emotional Learning	0.057 (0.090)
Observations	135

Table 2.24: High School's Social Studies Test Score Outcomes, Years 2013-2018

	(1) U.S. History (se)	(2) Economics (se)
Social Emotional Learning	0.099 (0.134)	0.063 (0.106)
Observations	122	109

Table 2.25: High School Student's Graduation Outcomes, Years 2013-2018

Graduated	(1) LPM	(2) Probit
Social Emotional Learning	-0.036 (0.018)	-0.007 (0.015)
Observations	10859	10855

3 Predicting Who Will be a Highly Effective Teacher

3.1 Introduction

Research in economics consistently finds that teachers' contribution to student achievement is the most crucial component of a school's effect on student learning and there is considerable heterogeneity in teacher productivity within and across schools (Chetty et al. (2014); Angrist et al. (2016); Rockoff (2004); Rivkin et al. (2005); Kane et al. (2008)). Thus, finding ways to enhance the quality of classroom teachers is essential to improving the learning gains of students and reducing gaps in achievement across groups of students.

One way to enhance the average quality of teachers is to improve the quality of new hires. However, improving the quality of new teachers is no easy task. For a given talent pool, selecting the best candidates is difficult because there are not strong linkages between pre-service characteristics, such as the education of teachers and leaders which are observable at the time of hiring and their future productivity. Work in North Carolina finds some teacher credentials, e.g., experience and teacher licensure test score, are correlated with teacher effectiveness, particularly at the secondary level, (Clotfelter et al. (2006, 2010); Goldhaber and Anthony (2007); Henry et al. (2014). Although some previous research found a relationship, the bulk of the evidence across many studies and jurisdictions finds little or no connection between observable traits (other than early career experience) and teacher productivity (e.g., Harris and Sass (2011); Jackson et al. (2014)). One possible explanation for the inability of existing research to identify the determinants of teacher productivity is that researchers have not measured the characteristics that truly affect productivity. Recent work in labor economics suggests that non-cognitive traits, such as conscientiousness, play a nontrivial role in determining worker productivity (e.g., Heckman et al. (2006)).

This research project studies whether non-cognitive traits are related to teacher productivity and whether information on these characteristics can improve the selection of teachers relative to selection on pre-service credentials alone. In particular, I examine the predictive power of the non-cognitive traits measured in TeacherInsight™ (TI) testing tool in comparison to other measures of prospective teachers' abilities, like educational credentials, SAT scores, and certifications. The TeacherInsight™ surveys have been administered to prospective teachers in a medium-size district in Florida for many years and are designed to identify whether an applicant has the traits that make for an effective classroom teacher. This project will evaluate how a teacher's scores on the TeacherInsight™ test relates to their value-added, i.e., how much they contribute to their student's test score gains that school year and with teachers' observational score.

This work is important for multiple reasons. First, previous studies have argued for more research on the effect of teacher's non-cognitive skills on student achievement, as it can help teacher preparations programs better prepare their teachers for their future job (Henry et al., 2014). This research also helps principals make better staffing decisions by having a better grasp of which characteristics are most predictive of effective teachers. Third, to the extent that the characteristics that impact teacher effectiveness are malleable, the results of this study can be used to develop training, curriculum, and professional development programs for prospective and current teachers. This project's results contribute to the literature on how we select and improve high-performing teachers in an effort to promote student achievement.

The rest of the paper is structured as follows. Section 3.2 provides background information and describes the data. Section 3.3 presents prior literature. Section 3.4 explains the econometric methods used. Section 3.5 presents the results. Section 3.6 discusses the policy implications of these findings and concludes.

3.2 Background and Data

TeacherInsight™ "is an automated online interview used by many districts to help identify the best potential teachers" (TeacherInsight™ FAQ, 2016). The online interview is developed by Gallup and asks all applicants "the same questions, and they are evaluated exactly the same way. The questions have been thoroughly researched and tested to be sure they identify potentially superior teachers" (TeacherInsight™ FAQ, 2016). In 2011, a new version of the test was released to better identify potential candidates. TeacherInsight™ is composed of three types of questions: (1) multiple choice questions about the applicant (50 seconds per question) (2) forced-choice where the applicant has to pick the best of two responses (50 seconds per question) and (3) Likert questions, where the applicant reads a statement and chooses the degree to which they agree with the statement (20 seconds per question). The applicants can score between 0 to 100; districts can decide what score they use at a cutoff for hiring decisions. The TI questions applicants on twelve broad themes: mission, focus, empathy, rapport drive, individualization, listening, investment, input drive, activation, innovation, perception drive, and objectivity. Over 1,500 school districts use TI in the U.S. (National Council on Teacher Quality, 2007).

To study the relationship between scores on the TI test and the ability of the teacher to promote student achievement, I will analyze data from a midsize district in Florida during the school years 2011/12 through 2013/14. The district has over sixty thousand students (above the average district size in Florida), where over half the population is on free or reduced lunch, about twenty percent participate in special education, and over five percent are English Language Learners (ELL). Data on teacher characteristics and their value-added scores come from the Florida Department of Education's Education Data Warehouse (EDW). The EDW is a rich administrative longitudinal data set that tracks students from kindergarten through college and into the workforce. The district has over four thousand instructional staff per school year. Teacher data include teacher demographics, such as race, sex, age, certification type, certification subject, certification dates, years of experience, and courses they teach. These administrative data be linked to the teachers' TI test scores, observational scores, and value added scores calculated from their students' math and English tests scores, which have been provided by the district. As mentioned above, Gallup implemented a new version of TI, TeacherInsight$^{\text{TM}}$ 2.0, in

2011 and the district only provided TeacherInsight™ for school years 2011/12-2013/14. In addition, the district provided teacher observational scores for 2011/12-2012/13.

Table 3.1 presents the summary statistics of all teachers in the district throughout school years 2010-11 to 2012-13. The demographic variables, certification, and experience are used as controls in the econometric models[1] I have a total of 11,113 teachers-year observations. The teachers in the district are predominately white, 84 percent, and female, 79 percent. The teachers' average age is 44 years-old and 13.5 total average years of experience. The TeacherInsight™ ranges from 41 to 94 with an average of 67 in the sample. The observational score as measured by the Danielson rating, ranges from 0 to 4.35. The first of the three Value-added Measure (VAM), FSA VAM score, is a combined English Language Arts and Math 3-year aggregate scores, which includes teachers who are in their first or second year of teaching. The FSA Vam score is standardized. The Algebra 8 VAM score, and Algebra 9 VAM Score are one year raw scores from -7.74 to 11.9 depending the VAM score[2].

[1]SAT and ACT scores are not used due to the almost 90 percent of the teachers in the sample do not have these scores.

[2]Florida DOE notes that the FSA VAM scores are not comparable to the Algebra VAM Scores hence I run different regressions for each of these tests

3.3 Literature Review

Cognitive and Non-Cognitive Traits Impact on Labor Outcomes and Student Achievement

Heckman et al. (2006) find that both non-cognitive skills (measured by the Rotter Locus of Control Scale and Rosember Self- Esteem Scale) and cognitive skills (measured by AFQT) play an important role in determining education and labor outcomes as well as participation in risky behaviors. Unlike previous research, they create models that incorporate schooling and family influence on the measurement of the cognitive and non-cognitive latent skills. In this way, their paper addresses issues of measurement error, imperfect proxies, and reverse causality. Interestingly they also find that non-cognitive skills have a larger impact on wages for women than for men. Given that the majority of the teacher workforce are woman, these results suggest that non-cognitive skills could be especially important for determining the productivity of teachers.

Grönqvist and Vlachos (2016) use data on Swedish teachers to study how cognitive and social abilities affect student achievement. They estimate achievement models that employ student- and subject-fixed-effects to control for potential selection bias from teacher-student matching and self-selection of teachers to subjects areas. They find that being taught by a male teacher with higher cognitive ability, as measured by a national military test, increased the achievement gap between high and low-ability students. In contrast, they find that high social skills increased achievement for foreign-born students and low-achieving students, hence decreasing the achievement gap between high- and low-ability students. When analyzing both female and male teachers they find that only male GPA, which they argue is composed of both cognitive and non-cognitive skills, has a positive relationship with student achievement of the magnitude of .13 standard deviations. They conclude that different abilities can benefit different types of students with varying learning strengths and student-teacher matching could be a solution to maximize student achievement. Their main limitation of their study is that their cognitive and non-cognitive results are based on men who took the military qualification test, but male teachers constitute only a small fraction of K-12 teachers in the United States. Another drawback is the only measure they have for both female and male instructors is GPA, which a is not direct measure of non-cognitive skills and it is unclear how much of the GPA is attributed to cognitive skills versus non-cognitive skills.

Teacher Screening Test, Teacher Traits and Student Achievement

A series of studies have examined school districts' use of TI, its predecessor, the Teacher Perceiver Interview, and similar screening tests, such as the Haberman Star Teacher Evaluation Prescreener. Brown (2004) found that teachers hired using the Teacher Perceiver Interview had higher retention rates than other teachers, and educators who performed higher on the interview were more likely to be rated as effective teachers by administrators. Rockoff et al. (2011) combined administrative data, Haberman Star Teacher Evaluation Prescreener data, and survey data to evaluate the relationship between teacher characteristics and teacher effectiveness. In addition to the Haberman, their survey collected non-cognitive characteristics on 602 new elementary and middle school math teachers in New York City. They found a small positive association between teacher scores on the Haberman Prescreener and student achievement. The drawbacks of this study are that they evaluate only 600 math teachers, a small number of observations and only one subject.

Koerner (2007) examines the relationship between performance on the TI test and the growth in student test scores in a North Central Texas school district. The author finds that higher TI scores are positively correlated with student test score growth. Novotny (2009) studied the relationship between TI scores and the Professional Development and Appraised System (PDAS), a measure of teacher effectiveness. Studying 527 teachers in Texas, he finds little to no correlation between an individual's TI score and the eight PDAS domain scores. Stewart (2014) evaluated the relationship between the teacher's TI score and students' exam scores. Analyzing data from fourth- and fifth-grade teachers between 2008-2011, he finds that teachers' scores are not predictive of student achievement. Both of these studies are limited as they have a small and limited sample.

3.4 Methods

The state of Florida requires researchers to use the established value-added measures that the Florida Department of Education has calculated for Florida public school teachers who teach courses with end-of-course exam. The Florida Department of Education in partnership with American Institutes for Research (AIR) implemented covariate adjusted Value-Added Model to evaluate their teachers[3]. To calculate teacher value-added scores, Florida Department of Education (2015) implemented equation 3.1, which is run separately by grade, subject, and year:

$$y_{ti} = X_i\beta + y_{t-1,i}\gamma_1 + y_{t-2,i}\gamma_2 + Z_{1i}\theta_1 + Z_{2i}\theta_2 + \epsilon_{ti} \tag{3.1}$$

Where y_{ti} is test score for individual student i at the end of their t^{th} school year. X_i is a vector of student covariates such student and classroom demographics. The student's prior year achievement is $y_{t-1,i}$ and a twice lagged student achievement is $y_{t-2,i}$. θ_1 and θ_2 are vectors of teacher and school random effects respectively. Finally, $\epsilon_t i$ is normally distributed error term or residual. The Student Growth Implementation Committee incorporated a 50% School Component when calculating the Teacher Value Added score in attempt to level the playing field across schools (Florida Department of Education, 2015). Florida Department of Education (2015) explains if they do not adjust for school characteristics in the teacher value-added score then: "adding none of the school component (0%) to teachers' value-added scores essentially creates a model with different growth expectations for otherwise similar students who attend different schools". Hence they use equation 3.2 to calculate teacher value-added score (Florida Department of Education, 2015):

$$\text{Teacher Value-Added Score} = \text{Unique Teacher Component} + .50 * \text{Common School Component} \tag{3.2}$$

Second, information about the individual characteristics of teachers, including their scores on the TI tools is used in a multivariate regression model to predict the

[3]Taken from "Recommendations of the Florida Student Growth Implementation Committee" on Florida Department of Education website www.fldoe.org/core/fileparse.php/3/urlt/value-added-model-white-paper.doc

value-added scores and observational scores of individual teachers. This second stage yields estimates of the determinants of teacher effectiveness, which are at the heart of the research questions delineated above.

$$\delta_{kt} = \beta_1 T_{kt} + \beta_2 S_{mt} + \beta_3 TeacherInsight_{kt} + \eta_{ti} \tag{3.3}$$

For predicting classroom observation score:

$$ObsValue_{kt} = \beta_1 T_{kt} + \beta_2 S_{mt} + \beta_3 TeacherInsight_{kt} + \eta_{ti} \tag{3.4}$$

where δ_{kt} is teacher's value-added score and where the outcome variables are: δ_{kt}, teacher's value-added score, and $ObsValue_{kt}$, the teacher's observational score. T_{kt} is a vector of teacher characteristics, race, experience, and certification status. The dependent variable of interest, $TeacherInsight_{kt}$ is the teacher's TeacherInsight^{TM} score. The coefficient of interest for both 3.3 and 3.4 is β_3 which represents the relationship between the Teacher Insight score and the value-added or observational scores.

3.5 Results

Table 3.2 shows the relationship between the Florida Scholar Assessment Value Added Score and Teacher Insight Score. Overall the Teacher Insight score does not have much predictive power on which teachers will be effective in raising students test scores. As the cited literature finds, total years of experience is the only teacher characteristic that predicts teacher effectiveness. Table 3.3 and Table 3.4 presents the results of the relationship between the Teacher Insight Score and one year VAM score Algebra 8 and Algebra 9. Table 3.3 shows there is not a statistically significant relationship between the Algebra 8 EOC VAM Score and Teacher Insight score. Although positive, Table 3.4 shows no statistically significant relationship between the Algebra 9 EOC VAM Score and Teacher Insight score. The lack of statistical significance in both of these could be due in part to the small number of teachers in the sample which have both of these scores.

Table 3.5 presents the relationship of the observational score and the Teacher Insight score for all teachers with an observational score. Table 3.5 suggests that the Teacher Insight score, a proxy for teacher non-cognitive skills has more predictive power for teacher's productivity as measured by their observational score. Column 5 presents the results including all the controls, where a one point increase in Teacher Insight score is associated with a .04 increase in teacher observation score. Also in column 5, we see that an additional year of experience is associated with a .012 increase in teacher observation score. In that same column, having a professional certificate versus a temporary or part- time certification is associated with .122 increase in teacher observation score. Finally, column 6 adds in school fixed effects and we see that the results are consistent with previous column. Tables 3.6 - 3.8 show the same relationship of Table 3.5 but broken out by grade levels. In general we see the same relationship except the relationship between the observational score and Teacher Insight score is not statistically significant.

3.6 Conclusion

Teachers are one of the most important inputs in students' education production function and future earning. Hiring new effective teachers is one way to improve student outcomes. Previous literature has found mixed results about how predictive teacher characteristics are for student success. Many districts screen their teachers by administrating TeacherInsight™ test, in hopes of finding the most effective teacher. It is important to evaluate if this testing tool has predictive power for teacher's value added and their observational score. In this paper I study both the relationship of the Teacher Insight score with Value-Added Score and Teacher Insight score and Observational score. I find that the Teacher Insight score does not do a good job at predicting which teachers will be effective as measured by the teacher's value added score (FSA Vam, Algebra 8 EOC, and Algebra 9 EOC Score). In contrast, the Teacher Insight Score and the Observational score have a positive relationship. More specifically, a one point increase in Teacher Insight score is associated with a .04 increase in teacher observation score.

It is crucial for researchers to continue to find ways to assist districts in hiring more effective teachers. This study suggests that in this district the Teacher Insight score does not help to identify candidates who are likely to become effective teachers as measured by the teacher's ability to increase student test scores. I do find that the Teacher Insight score is associated with a more effective teacher as measured by observational score. As noted in the charter school literature (Sass et al., 2016), this could suggest that test scores are not capturing the complete picture of student success. When deciding if to implement an exam like Teacher Insight, districts and schools need to weigh the financial and time costs of these tests especially since I do not find any statistically significant relationship between the non-cognitive test and value-added scores, it could be that these resources are better spent on other areas. In the future, more research is needed to see if non-cognitive teacher characteristics are predictive of other long-term measures of student success such as high school graduation, college enrollment and persistence, as well as labor force participation.

3.7 Tables

Table 3.1: Teachers Summary Statistics from 2011/12-2013/14

	Mean	SD	Min	Max	N
Male	0.21	0.40	0	1	8006
Asian	0.0051	0.071	0	1	8006
Black	0.094	0.29	0	1	8006
Latinx	0.050	0.22	0	1	8006
Native Ame.	0.0022	0.047	0	1	8006
White	0.85	0.36	0	1	8006
Age	44.4	11.5	20	78	8005
Professional Certification	0.95	0.22	0	1	7172
Temporary Certification	0.049	0.22	0	1	7172
Part-Time Certification	0.00084	0.029	0	1	7172
SAT Verbal	487.0	95.7	230	775	588
SAT Math	481.1	105.8	200	790	1722
SAT Total	966.5	154.2	462	1435	1357
ACT Reading	23.6	5.21	13	36	84
ACT Math	20.9	4.07	11	29	92
ACT Comp	21.5	3.49	8	32	967
Year Exp. Florida Pub.	12.1	8.77	0	44	8222
Year Exp. Florida Priv.	4.27	4.16	1	25	466
Year Exp. Non-Florida Pub.	7.03	6.29	1	34	1458
Year Exp. Non-Florida Priv.	1	.	1	1	1
Total Years of Experience	13.6	9.80	0	44	8222
Teacher Insight Score	67.0	8.88	41	94	2943
Final Eval Obs. Score	2.77	0.64	0	4.35	7010
FSA 3 Year Agg ELA Math VAM Score	-0.067	0.27	-1.66	2.13	3594
FSA 3 Year VAM Rating Score	2.61	0.83	1	4	3594
Alg 9 1 Year EOC Vam Score	0.89	3.79	-5.54	11.9	66
Alg 9 1 Year EOC Rating Score	2.95	0.48	2	4	66
Alg 8 1 Year EOC Vam Score	1.24	3.71	-7.74	8.13	46
Alg 8 1 Year EOC Rating Score	2.96	0.36	2	4	46
Observations	8490				

Table 3.2: Relationship Between Teacher FSA 3-Year Vam score and Teacher Insight Score

	(1)	(2)	(3)	(4)	(5)
Teacher Insight Score	0.001	0.001	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total Years of Experience		0.004***			0.003**
		(0.001)			(0.001)
Professional Certification			0.017		-0.019
			(0.031)		(0.035)
Male				0.039	0.017
				(0.022)	(0.028)
Asian				0.002	-0.045
				(0.180)	(0.251)
Black				-0.008	-0.003
				(0.025)	(0.032)
Latinx				0.019	-0.001
				(0.027)	(0.033)
Native Ame.				-0.194	-0.274
				(0.128)	(0.144)
Constant	-0.118*	-0.177**	-0.127	-0.171**	-0.189*
	(0.059)	(0.062)	(0.078)	(0.058)	(0.080)
Observations	1270	1195	872	1199	758

Table 3.3: Relationship Between Teacher Algebra 8 EOC (1 Year Raw Score) Vam Score and Teacher Insight Score

	(1)	(2)	(3)	(4)
Teacher Insight Score	0.049	0.101	0.109	-0.071
	(0.122)	(0.128)	(0.157)	(0.150)
Total Years of Experience		0.373		
		(0.264)		
Professional Certification			5.507	
			(3.931)	
Male				-5.901
				(2.834)
Latinx				-2.269
				(2.911)
Constant	-1.539	-8.299	-11.332	9.493
	(8.289)	(9.566)	(11.849)	(10.532)
Observations	16	15	10	13

Table 3.4: Relationship Between Teacher Algebra 9 EOC (1 Year Raw Score) Vam Score and Teacher Insight Score

	(1)	(2)	(3)	(4)	(5)
Teacher Insight Score	0.050	0.052	0.101	0.006	0.034
	(0.058)	(0.059)	(0.073)	(0.065)	(0.108)
Total Years of Experience		-0.039			-0.059
		(0.108)			(0.139)
Professional Certification			-0.578		1.742
			(1.820)		(3.779)
Male				0.342	2.642
				(1.482)	(3.479)
Black				-2.584	-1.783
				(1.658)	(2.305)
Latinx				6.394	
				(3.503)	
Constant	-2.536	-2.443	-5.811	0.554	-3.606
	(3.851)	(3.918)	(4.972)	(4.096)	(5.805)
Observations	31	31	19	30	18

Table 3.5: Relationship Between Teacher Observational score and Teacher Insight Score Across All Grades

	(1)	(2)	(3)	(4)	(5)	(6)
Teacher Insight Score	0.002	0.004**	0.003	0.002	0.004**	0.004*
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Total Years of Experience		0.014***			0.012***	0.011***
		(0.002)			(0.002)	(0.002)
Professional Certification			0.222***		0.112*	0.133**
			(0.039)		(0.045)	(0.045)
Male				-0.112**	-0.063	-0.069
				(0.034)	(0.036)	(0.037)
Asian				-0.330	-0.157	-0.106
				(0.228)	(0.240)	(0.238)
Black				-0.108*	-0.064	-0.030
				(0.046)	(0.047)	(0.049)
Latinx				-0.041	-0.033	0.017
				(0.061)	(0.061)	(0.062)
Native Ame.				-0.729	-0.685	-0.555
				(0.644)	(0.632)	(0.626)
School FE						✓
Observations	2432	2278	2406	2311	2142	2142

Table 3.6: Relationship Between Elementary School Teacher Observational Score and Teacher Insight Score

	(1)	(2)	(3)	(4)	(5)	(6)
Teacher Insight Score	0.002	0.005*	0.003	0.002	0.004	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Total Years of Experience		0.015***			0.014***	0.013***
		(0.003)			(0.003)	(0.003)
Professional Certification			0.223**		0.169	0.166
			(0.085)		(0.095)	(0.095)
Male				-0.036	-0.031	-0.011
				(0.069)	(0.069)	(0.071)
Asian				-0.898	-0.640	-0.434
				(0.625)	(0.624)	(0.618)
Black				-0.108	-0.031	-0.022
				(0.071)	(0.075)	(0.082)
Latinx				0.013	0.087	0.125
				(0.088)	(0.090)	(0.091)
Native Ame.				-0.744	-0.674	-0.489
				(0.625)	(0.617)	(0.611)
Constant	2.561***	2.319***	2.331***	2.589***	2.199***	2.130***
	(0.139)	(0.146)	(0.163)	(0.144)	(0.175)	(0.212)
School FE						✓
Observations	1205	1137	1199	1140	1068	1068
r2_p						

Table 3.7: Relationship Between Middle School Teacher Observational Score and Teacher Insight Score

	(1)	(2)	(3)	(4)	(5)	(6)
Teacher Insight Score	0.004	0.005	0.004	0.004	0.005	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Total Years of Experience		0.010*			0.007	0.005
		(0.005)			(0.005)	(0.005)
Professional Certification			0.169*		0.064	0.121
			(0.075)		(0.087)	(0.089)
Male				-0.052	-0.015	-0.030
				(0.066)	(0.070)	(0.071)
Asian				-0.619	-0.614	-0.506
				(0.646)	(0.648)	(0.655)
Black				-0.239*	-0.183	-0.121
				(0.094)	(0.102)	(0.107)
Latinx				-0.041	-0.079	-0.063
				(0.122)	(0.123)	(0.126)
Constant	2.331***	2.251***	2.183***	2.389***	2.242***	2.082***
	(0.204)	(0.215)	(0.213)	(0.210)	(0.232)	(0.273)
School FE						✓
Observations	524	481	523	502	460	460

Table 3.8: Relationship Between High School Teacher Observational Score and Teacher Insight Score

	(1)	(2)	(3)	(4)	(5)	(6)
Teacher Insight Score	0.001	0.004	0.003	0.002	0.006	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Total Years of Experience		0.017***			0.013**	0.014**
		(0.004)			(0.004)	(0.005)
Professional Certification			0.246***		0.130	0.115
			(0.062)		(0.071)	(0.073)
Male				-0.168**	-0.127*	-0.142*
				(0.059)	(0.060)	(0.062)
Asian				-0.199	0.006	0.016
				(0.281)	(0.297)	(0.296)
Black				-0.033	-0.043	-0.019
				(0.084)	(0.084)	(0.087)
Latinx				-0.160	-0.194	-0.182
				(0.138)	(0.135)	(0.144)
Constant	2.570***	2.361***	2.285***	2.603***	2.213***	2.317***
	(0.205)	(0.206)	(0.216)	(0.212)	(0.225)	(0.519)
School FE						✓
Observations	644	605	625	616	565	565

References

Angrist, J. D. (2014). The perils of peer effects. *Labour Economics 30*, 98–108.

Angrist, J. D., S. Cohodes, S. Dynarski, P. A. Pathak, and C. R. Walters (2016). Stand and deliver: Effects of boston's charter high schools on college preparation, entry, and choice. *Journal of Labor Economics 34* (2), 275–318.

Angrist, J. D., P. A. Pathak, and C. R. Walters (2013). Explaining charter school effectiveness. *American Economic Journal: Applied Economics 5* (4), 1–27.

Barbour, M. K. and T. C. Reeves (2009). The reality of virtual schools: A review of the literature. computers and education. *Computers and Education 52* (2), 402–416.

Barth, P., J. Hull, and R. St. Andrie (2012). Searching for the reality of virtual schools. Technical report.

Bowles, S., H. Gintis, and M. Osborne (2001). The determinants of earnings: A behavioral approach. *Journal of Economic Literature 39* (4), 1137 – 1176.

Brown, K. (2004). *The impact of the Gallup teacher perceiver interview on hiring teachers as perceived by selected administrators in the Alamo Heights Independent School District, San Antonio, Texas*. Ph. D. thesis.

Carrell, S. and S. Carrell (2006). Do lower student to counselor ratios reduce school disciplinary problems? *Contributions to Economic Analysis & Policy 5* (1).

CASEL (2016). Collaborative for academic social & emotional learning. http://www.casel.org. Accessed:2016-09-30.

Center for Research on Education Outcomes, C. (2012). Charter school performance in pennsylvania. Technical report.

Center for Research on Education Outcomes, C. (2015). Online charter school study. Technical report.

Chetty, R., J. N. Friedman, and J. E. Rockoff (2014). Measuring the impacts of teachers ii: Teacher value-added and student outcomes in adulthood. *The American Economic Review 104*(9), 2633–2679.

Chingos, M. and G. Schwerdt (2014). Virtual schooling and student learning: Evidence from the florida virtual school. Working paper.

Clotfelter, C. T., H. F. Ladd, and J. L. Vigdor (2006). Teacher-Student Matching and the Assessment of Teacher Effectiveness. *Journal of Human Resources 41*(4).

Clotfelter, C. T., H. F. Ladd, and J. L. Vigdor (2010). Teacher Credentials and Student Achievement in High School: A Cross-Subject Analysis with Student Fixed Effects. *Journal of Human Resources 45*(3).

Cox, C. M. (1926). The early mental traits of three hundred geniuses. *Genetic studies of genius 2*, –.

Deming, D. (2014). Using school choice lotteries to test measures of school effectiveness. *American Economic Review 104*(5), 406–11.

Dobbie, W. and R. Fryer (2016). Charter schools and labor market outcomes. Working paper, National Bureau of Economic Research.

Dobbie, W. and R. G. Fryer (2013). Getting beneath the veil of effective schools: Evidence from New York City. *American Economic Journal: Applied Economics 5*(4), 28–60.

Duckworth, A. L., C. Peterson, M. D. Matthews, and D. R. Kelly (2007). Grit: Perseverance and passion for long-term goals. *Journal of Personality and Social Psychology 92*(6), 1087–101.

Durlak, J., R. Weissberg, A. Dymnicki, R. D.Taylor, and K. B. Schellinger (2011). The impact of enhancing students' social and emotional learning: A meta-analysis of school based universal interventions. *Child Development 82*(1), 405–432.

Ferreyra, M. M. and G. Kosenok (2015). Charter school entry and school choice: the case of washington, d.c. *Policy Research Working Paper Series 7383*, –.

Florida Department of Education, F. (2015). Florida vam methodology. Technical report.

Glomm, G., D. Harris, and T. Lo (2005). Charter school location. *Economics of Education Review 24*(4), 451–457.

Goldhaber, D. and E. Anthony (2007). Can teacher quality be effectively assessed? national board certification as a signal of effective teaching. *The Review of Economics and Statistics 89*(1), 134–150.

Goodman, J., J. Melkers, and A. Pallais (2018). Can online delivery increase access to education? *Journal of Labor Economics 0*(0), 000–000.

Greenberg, M. T., R. P. Weissberg, M. U. O'Brien, J. E. Zins, L. Fredericks, H. Resnik, and M. Elias (2003). Enhancing school-based prevention and youth development through coordinated social, emotional, and academic learning. *American Psychologist 58*(6-7), 466–474.

Grönqvist, E. and J. Vlachos (2016). One size fits all? the effects of teachers' cognitive and social abilities on student achievement. *Labour Economics 42*, 138 – 150.

Hanushek, E. (1979). Explaining charter school effectiveness. *The Journal of Human Resources 14*(3), 351–388.

Harris, D. N. and T. R. Sass (2011). Teacher training, teacher quality and student achievement. *Journal of Public Economics 95*(7-8), 798–812.

Heckman, J., R. Pinto, and P. Savelyev (2013). Understanding the mechanisms through which an influential early childhood program boosted adult outcomes. *American Economic Review 103*(6), 2052–2086.

Heckman, J. and Y. Rubinstein (2001). The importance of noncognitive skills: Lessons from the ged testing program. *American Economic Review 91*(2), 145–149.

Heckman, J., J. Stixrud, and S. Urzua (2006). The effects of cognitive and noncognitive ablties on labor market outcomes and social behavior. *Journal of Labor Economics 24*(3), 411–482.

Heinrich, C., J. Darling-Aduana, A. Good, and H. E. Cheng (2018). A look inside online educational settings in high school: Promise and pitfalls for improving educational opportunities and outcomes. Working paper, Vanderbilt University.

Henry, G. T., K. B. Bastian, C. K. Fortner, D. C. Kershaw, K. M. Purtell, and C. L. Thompson (2014). Teacher preparation policies and their effects on student achievement. *Education Finance and Policy 9*(3), 264–303.

Hubbard, B. and N. Mitchell (2011, October 4). roubling questions about online education. *Education News Colorado*.

Imberman, S. A. (2011). Achievement and behavior in charter schools: Drawing a more complete picture. *The Review of Economics and Statistics 93*(2), 416–435.

Jackson, C. K., J. E. Rockoff, and D. O. Staiger (2014). Teacher effects and teacher-related policies. *Annual Review of Economics 6*(1), 801–825.

Jacob, B. and S. Loeb (2015). Virtual courses: The introduction and expansion of virtual schooling in florida and its effects on student academic outcomes. Technical report.

James, W. (1907). The energies of men. *Science 25*, 321–332.

Kane, T. J., J. E. Rockoff, and D. O. Staiger (2008). What does certification tell us about teacher effectiveness? Evidence from New York City. *Economics of Education Review 27*(6), 615–631.

Koerner, R. (2007). *The relationship between the TeacherInsight^{TM} score and student performance as measured by the Texas growth index.* Ph. D. thesis.

Mehta, N. (2017). Competition in public school districts: Charter school entry, student sorting, and school input determination. *International economic review. 58*(4), 1089–1116.

Miron, G. and C. Gulosino (2016). Virtual schools report 2016: Directory and performance review. Technical report.

Miron, G., A. Urschel, and Dailey (2012). Profiles of for-profit and nonprofit education management organization. Technical report, University of Colorado, Boulder.

Neal, D. A. and W. R. Johnson (1996). The role of premarket factors in black-white wage differences. *Journal of Political Economy 104*(5), 869 – 895.

Novotny, M. (2009). *The relationship between TeacherInsight^{TM} scores and professional development and appraisal system domain scores.* Ph. D. thesis.

Reback, R. (2010). Schools' mental health services and young children's emotions, behavior, and learning. *Journal of Policy Analysis and Management 29*(4), 698–725.

Rittner, G. W. (2012). Internal evaluation of the arkansas virtual academy school. Technical report.

Rivkin, S. G., E. A. Hanushek, and J. F. Kain (2005, March). Teachers, Schools, and Academic Achievement. *Econometrica 73*(2), 417–458.

Rockoff, J. E. (2004, May). The impact of individual teachers on student achievement: Evidence from panel data. *American Economic Review 94*(2), 247–252.

Rockoff, J. E., B. A. Jacob, T. J. Kane, and D. O. Staiger (2011). Can you recognize an effective teacher when you recruit one? *Education Finance and Policy 6*(1), 43–74.

Rouse, C. (2004). Putting computerized instruction to the test: a randomized evaluation of a "scientifically based" reading program. *Economics of Education Review 23*(4), 323 – 338.

Sass, T. (2016). The performance of state charter schools in georgia, 2014-2015. state charter schools performance evaluation. Technical report.

Sass, T., A. Semykina, and D. Harris (2014). Value-added models and the measurement of teacher productivity. *Economics of Education Review* (38), 9–23.

Sass, T. R., R. W. Zimmer, B. P. Gill, and T. K. Booker (2016). Charter high schools' effects on long-term attainment and earnings. *Journal of Policy Analysis and Management 35*(3), 683–706.

Singleton, J. (2017). Incentives and the supply of effective charter schools. Working paper.

U.S. Department of Education, Office of Planning Evaluation Policy Development, D. (2009). Evaluation of evidence-based practices in online learning: A meta-analysis and review of online learning studies. Technical report.

Walters, C. R. (2017, October). The demand for effective charter schools. Working Paper 20640, National Bureau of Economic Research.

Wang, H., J. Chu, P. Loyalka, T. Xin, Y. Shi, Q. Qu, and C. Yang (2016). Can social–emotional learning reduce school dropout in developing countries? *Journal of Policy Analysis and Management 35*(4), 818–847.

Watson, J., B. Gemin, J. Ryan, and M. Wicks (2010). Keeping pace with k-12 online and blended learning: An annual review of state-level policy and practice. Technical report.

4 Vita

Carycruz Miriam Bueno was born in 1988 in Derry, New Hampshire, and was raised in Orlando, Florida and Santo Domingo, Dominican Republic. In the fall of 2006, she attended Mount Holyoke College, the first all woman-college in the United States. She completed a BA with a major in Economics and Minor in Mathematics in 2010.

After graduation, Carycruz joined Teach For America Hawaii where she taught 7^{th} grade special education mathematics and received her post-bac in education at the University Of Hawaii-Manoa.

In the fall of 2013, Carycruz began her doctoral studies in Economics at Georgia State University. Her research interest include Education Economics, Labor Economics, and Health Economics. After Georgia State University, Carycruz will be a post-doc at the Annenberg Insititute at Brown University.