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

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The COVID-19 pandemic has put virtual schooling at the forefront of policy concerns, as millions of children worldwide shift to virtual schooling with hopes of "slowing the spread". Given the emergency shift to online education coupled with the large increase in demand for virtual education over the last decade it is imperative to explore the impacts of virtual education on student outcomes. This paper estimates the causal effect of full-time virtual school attendance on student outcomes with important implications for school choice, online education, and education policy. 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 behavioral outcomes. The existing evidence on the impact of online education on students' outcomes 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 full-time 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 and future economic opportunities, as well as a sub-optimal use of taxpayer money.

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

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Abstract

The COVID-19 pandemic has put virtual schooling at the forefront of policy concerns, as millions of children worldwide shift to virtual schooling with hopes of "slowing the spread". Given the emergency shift to online education coupled with the large increase in demand for virtual education over the last decade it is imperative to explore the impacts of virtual education on student outcomes. This paper estimates the causal effect of full-time virtual school attendance on student outcomes with important implications for school choice, online education, and education policy. 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 behavioral outcomes. The existing evidence on the impact of online education on students' outcomes 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 full-time 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 and future economic opportunities, as well as a sub-optimal use of taxpayer money. (*JEL* I21, I24, I28)

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1 Introduction

The COVID-19 pandemic has forced many institutions to treat in-person services and online delivery of services as substitutes. Despite being treated as substitutes, the question as to whether online delivery of services is comparable to in-person delivery still stands and becomes extremely salient during this health crisis that mandates social distancing. In the field of education, online delivery of instruction has grown exponentially in the last decade and full-time virtual school is the fastest-growing type of school choice in the United States (Watson et al., 2010; Miron and Gulosino, 2016) but we don't have much evidence on their impact on student academic outcomes. Closely examining full-time virtual schools—where all classes are online, although different from emergency shift to online learning, gives insights into the impact of this educational setting on student performance. The COVID-19 pandemic, which has forced millions of students into virtual school setting, coupled with increase demand for full-time virtual schools, begs the question how does attending a full-time virtual school impact student performance in comparison to brick-and-mortar schools?

This paper measures the impact of attending a full-time virtual school on students' cognitive and behavioral outcomes-including test scores, graduation, and attendance. 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 true effect of full-time virtual school and the students who self-select into virtual schools would perform the same as they would at a brick-and-mortar school. 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 individual-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 by implementing interrupted panel method (Imberman, 2011). Second, I use a semi-parametric cell analysis to compare the outcomes for students who were in the same 4^{th} grade school, cohort, 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).

There are many reports which provide cross-sectional comparisons virtual and traditional schools with mixed findings(e.g. Rittner (2012); Center for Research on Education Outcomes (2012)). However, these studies cannot account for selection into virtual schooling (e.g. U.S. Department of Education (2009); Barth et al. (2012); Hubbard and Mitchell (2011); Miron et al. (2012); Sass (2016)). Full-time virtual charter school is the newest school choice on the market in comparison to homeschool, brick-and-mortar charters, and private school vouchers. There is large amount of causal evidence that demonstrates the positive impact of No Excuses brick-and-mortar charters schools on inner-city and historically marginalized students (Angrist et al., 2013, 2016b,a; Dobbie and Fryer, 2013); and the viability and positive impacts of expanding No Excuse brick-and-mortar charters schools (e.g. Abdulkadiroğlu et al. (2016); Cohodes et al. (2020)). In contrast, brick-and-mortar charters schools not characterized by No Excuse have more mixed impact on student's academic outcomes (e.g. Zimmer et al. (2012)). There is also evidence that brick-and-mortar charter schools' have positive effects on earnings in adulthood (Sass et al., 2016). For private school vouchers, there is evidence of modest positive spillover impacts for students who remain in public schools in Florida (Figlio and Hart, 2014) and negative impact on math test scores for students in Louisiana (Abdulkadiroğlu et al., 2018). Part-time virtual k-12 classes literature finds that students who attend part-time perform better or about the same as those in traditional schools when it comes to student academic outcomes (Chingos and Schwerdt, 2014), mostly due to positive selection of students. Whereas Hart et al. (2019) find that later academic outcomes are negative for students taking a virtual class for first time but positive impact for students taking a course as credit recovery. The Center for Research on Education Outcomes (2015) is the most comprehensive report on full-time virtual schools, studying 158 full-time virtual charter schools in 17 states and the District Columbia. Using peer matching method, they find that students attending full-time virtual schools do worse than students attending brick-and-mortar schools in math and English.

This paper contributes to the literature by establishing a causal link between student performance and full-time virtual school attendance. Previous papers, such as Chingos and Schwerdt (2014) and Hart et al. (2019) only analyze a single institution, the Florida Virtual School, which is a part-time virtual school where students also take classes in brick-and-mortar schools not a full-time virtual school. 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 and semi-parametric methods. Thus, this study advances the discussion regarding the impacts of full-time 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 a loss of approximately 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. I show descriptive evidence that students who return to brick-and-mortar schools after attending a full-time virtual school almost fully recover from their drop in test scores. For behavioral outcomes, I find that ever attending a full-time 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 2 provides background information about the full-time virtual schools in Georgia. Section 3 describes the data. Section 4 and 5 explain the theoretical foundation and econometric methods that I use. Section 6 presents the results. Section 7 discusses the policy implications of these findings and concludes.

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 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.

[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 6-12^{th} 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.

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. 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 2, 66 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 4 percent of first time virtual students are in kindergarten or first grade (i.e. they have never previously attended school). As seen in Table 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 2 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 attend virtual school for one year. Table 5c attempts to better understand the distribution of students who are attending a virtual school for one 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, 5 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 I am unsure if they will continue to attend a virtual school in the future).

3 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

[4]Note that the data is right censored and I only have data till 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.

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 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. 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.

4 Conceptual Framework

4.1 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 decreased performance, I 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

[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

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

schools, that are utilized to 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 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

[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

[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 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.

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:

$$Y_{ij} = y_j(X_i, S_{it}, \epsilon_i), \tag{1}$$

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 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

$$U_{iv} = u(Y_{iv}, X_i, S_{vt}, Int_{ivt}, TC_{ivt}, \omega_{iv}), \tag{2}$$

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

$$U_{ib} = u(Y_{ib}, X_i, S_{bt}, P_{bt}, D_{ibt}, TC_{ibt}, \omega_{ib}), \tag{3}$$

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:

$$
\begin{aligned}
U_{iv} - U_{ib} &= u(Y_{iv}(X_i, S_{it}\epsilon_i), X_i, S_{vt}, Int_{ivt}, TC_{ivt}, \omega_{iv}) - u(Y_{ib}(X_i, S_{it}\epsilon_i), X_i, S_{bt}, P_{bt}, D_{ibt}, TC_{ibt}, \omega_{ib}) \\
&= u_j(X_i, S_{vt}, S_{bt}, Int_{ivt}, P_{bt}, D_{ibt}, TC_{ivt}, TC_{ibt}, \Omega_i),
\end{aligned} \tag{4}
$$

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 environment or lower school quality in the student's local school, the more likely the student would choose to attend full-time virtual school. Independent of school quality, peers at local schools could impact 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 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

[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.

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.

4.2 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]

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, 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,

[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.

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.

5 Estimation Framework

5.1 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 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:

$$VirtualSch_{igt} = \alpha_0 + \alpha_1 \mathbf{X}_i + \alpha_2 \mathbf{A}_{it-1} + \epsilon_{igt}, \tag{5}$$

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.

5.2 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 :

$$A_{it} = \alpha_0 + \alpha_1 X_i + \alpha_2 VirtualSch_{igt} + \alpha_3 A_{it-1} + \epsilon_{igt}, \tag{6}$$

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, Semykina, and Harris, Sass et al.). $VirtualSch$ is an indicator variable if the student attended a virtual school or not.[12] Lastly, ϵ_{igt} is the 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 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) and affect the preferences of school attributes which determine the choice of school type (equations 2 and 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

[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

performance at a virtual school is compared to their own performance at a brick-and-mortar school.

I estimate:

$$A_{it} = \alpha_0 + \alpha_1 VirtualSch_{igt} + \delta_i + \epsilon_{igt}, \tag{7}$$

$$A_{it} = \alpha_0 + \alpha_1 VirtualSch_{igt} + \alpha_2 A_{it-1} + \delta_i + \epsilon_{igt}, \tag{8}$$

where δ_i is the individual or student fixed effect. As Imberman (2011) explains, it is important to do individual fixed effects with and without lags 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 classical 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, papers (e.g. Angrist et al. (2016a, 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:

$$A_{it} = \alpha_0 + \sum_m \alpha_2 VirtualSch_{itv} + \alpha_3 A_{it-1} + \sigma_{cell} + \epsilon_{it}, \tag{9}$$

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.

6 Results

6.1 Predicting attendance into Virtual school

Table 8a presents the estimates for selection into virtual schools outlined in equation 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 0.114 percentage points in the likelihood of attending a virtual school that year. In other words, a student with a better score last year is less likely to go to a virtual school this year. Column 3 has last year's student's percent of attendance and shows that the higher the student's attendance last year the less likely they will attend virtual school the following year. The last column includesprior year ELA score, mathematics score, and attendance, as well as student demographics. Again, here we see in general a negative selection into virtual schools, based on prior performance.

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, Table 8b 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, there is a negative selection into virtual schools but a slightly smaller association. For example, one standard deviation increase in prior year mathematics test score is associated with a decrease of 0.04 percentage points in the likelihood of attending a virtual school that year, whereas the previous table estimates 0.114 percentage points.

6.2 Ordinary Least Squares

Estimates from ordinary least squares are presented in Table 9a. Table 9a shows that attending a virtual school is associated with lower test scores across all four subjects, while controlling for same-subject lagged test scores and demographics. More specifically, 9a says attending a virtual school is associated with a statistically significant reduction of 0.011 standard deviation 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 subjects 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 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, 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 10 restricts the population to only charter school students in order to see if this is a virtual school or a charter school effect. These results are similar 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.

6.3 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 that they are not switching because of the outcome. As stated earlier, I present estimates for individual fixed effects both with and without last year lagged score, these two numbers serve as a bound of the impact of virtual school on student test scores. Table 11 shows that when controlling for these 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 3 through 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 virtual school and enter a virtual school in grades 3 through 8. Figure 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 4 tells the same story even though the population excludes those who only attended a virtual school for one year. Figure 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. Similarly, Figure 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 12 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 estimating 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.

Table 13 through 15 presents heterogeneous effects across demographics and grade level. Table 13 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, although it does seem that males do slightly worse on ELA test than females. 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 stndard deviation worse while in a full-time virtual school. Table 14 and 15 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 14 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 are slightly better than elementary students but the negative impact remains. Table 15 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.

6.4 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 16, 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.

6.5 Probit Model -Graduation and Attendance

Table 17 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 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-percentage point decline in ever graduating high school. Table 18 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.

7 Summary and Conclusion

One of the most debated education issues today is school choice, and the fastest growing option is full-time virtual school. The debate centers around parents' educational choice for their children and if these alternatives are better for students than the existing public-school system. The COVID-19 crisis has made this debate even more salient given the rush to online instruction in hopes of slowing the spread of infection. Key to framing this debate and creating sound educational policy is understanding if full-time virtual school attendance will have an overall positive impact on students, due to their individualized structure, or a negative impact, due to the lack of in-person instruction. Using individual fixed-effects and semi-parametric cell analysis, this paper ascertains that the lack of in-person instruction and classroom socialization negatively impacts students' outcomes.

In this paper, I find that attending a full-time virtual school in Georgia 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. These results are robust to implementing interrupted panel method that mitigates the Ashenfelter dip students experience prior to enrolling in a virtual school and semi-parametric cell analysis used in the charter school literature. I also perform sub-sample analysis and find that those who attend a full-time virtual school for one year perform worse than what we expect them to do in comparison to how they perform in non-virtual schools; however, when these students return to a brick-and-mortar school their outcomes improve to the level of pre-virtual school attendance. These negative impacts also hold in the sub sample analysis, across gender,FRL status, and race. I also find that elementary students preform slightly worse than middle school students. Furthermore, for high school students, attending a full-time virtual school is also associated with a reduction in graduation rate of about 2 to 10 percentage-points. These impacts are large; both socially 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' outcomes.

The current health pandemic, COVID19, has impacted the world in various areas, including the education sector. Unlike full-time virtual schools, parents did not have a choice to go to a virtual setting and teachers were not prepared to instruct students online. Given current circumstances, parents and education leaders want to know how does transitioning to virtual schooling impacts students academic and behavioral outcomes. I present evidence that full-time virtual schools leads to negative impact on elementary and middle school students. These results suggest that students impacted by COVID-19 and forced to switch to virtual learning will lose educational attainment given the erupt transition to virtual schooling. It can also be inferred from the sub-sample analysis of non-white students that virtual schooling is going to likely increase inequality especially given the disproportional impact COVID19 has had on non-white population's health and that Blacks and Latinx parents are more likely to be essential workers. The negative impact of COVID19 on Black and Latinx populations in addition to the negative impacts of full-time virtual school points to the need of more funding and resources for these populations in and out of the education setting. One positive descriptive evidence I present is that students who re-enter brick-and-mortar school almost fully recover, therefore getting student's safely back to brick-and-mortar should be prioritized in education policy.

Given these results and the money invested in these schools, it seems that full-time virtual school as a school choice is not the best alternative for the average parent and their children. Given the little research done on full-time virtual schools, this is evidence that full-time 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 as impact COVID-19 erupt transition to virtual learning. Likewise, more research needs to be done on long-run outcomes such as college enrollment, persistence, and labor force participation.

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

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Figure 1: Grade Level of Initial Enrollment in Georgia Full-Time Virtual Schools, 2010-2016

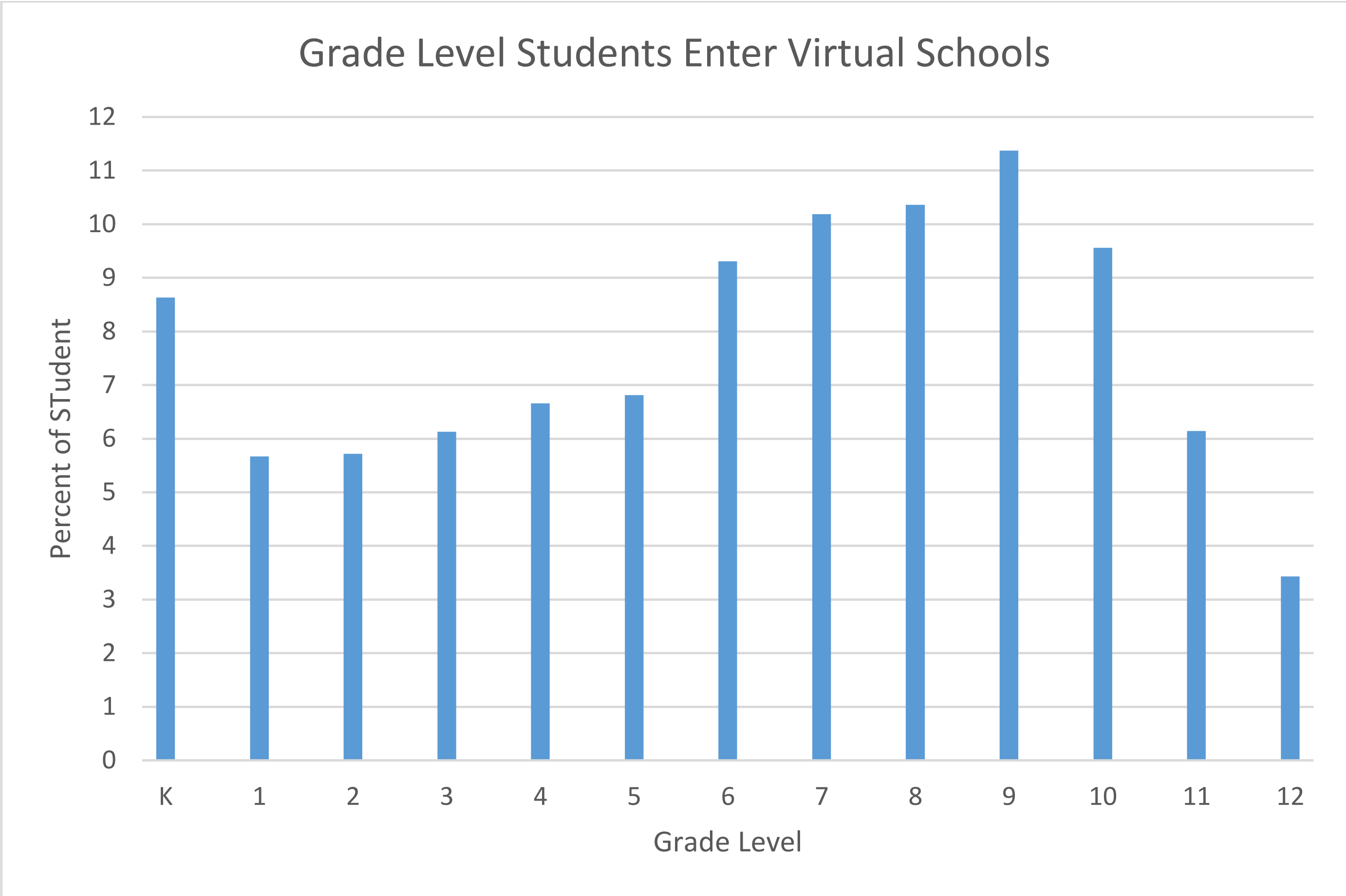


Figure 2: Grade Level at Which First-Time Georgia Virtual School Students Exit A Full-Time Virtual School, 2010-2016

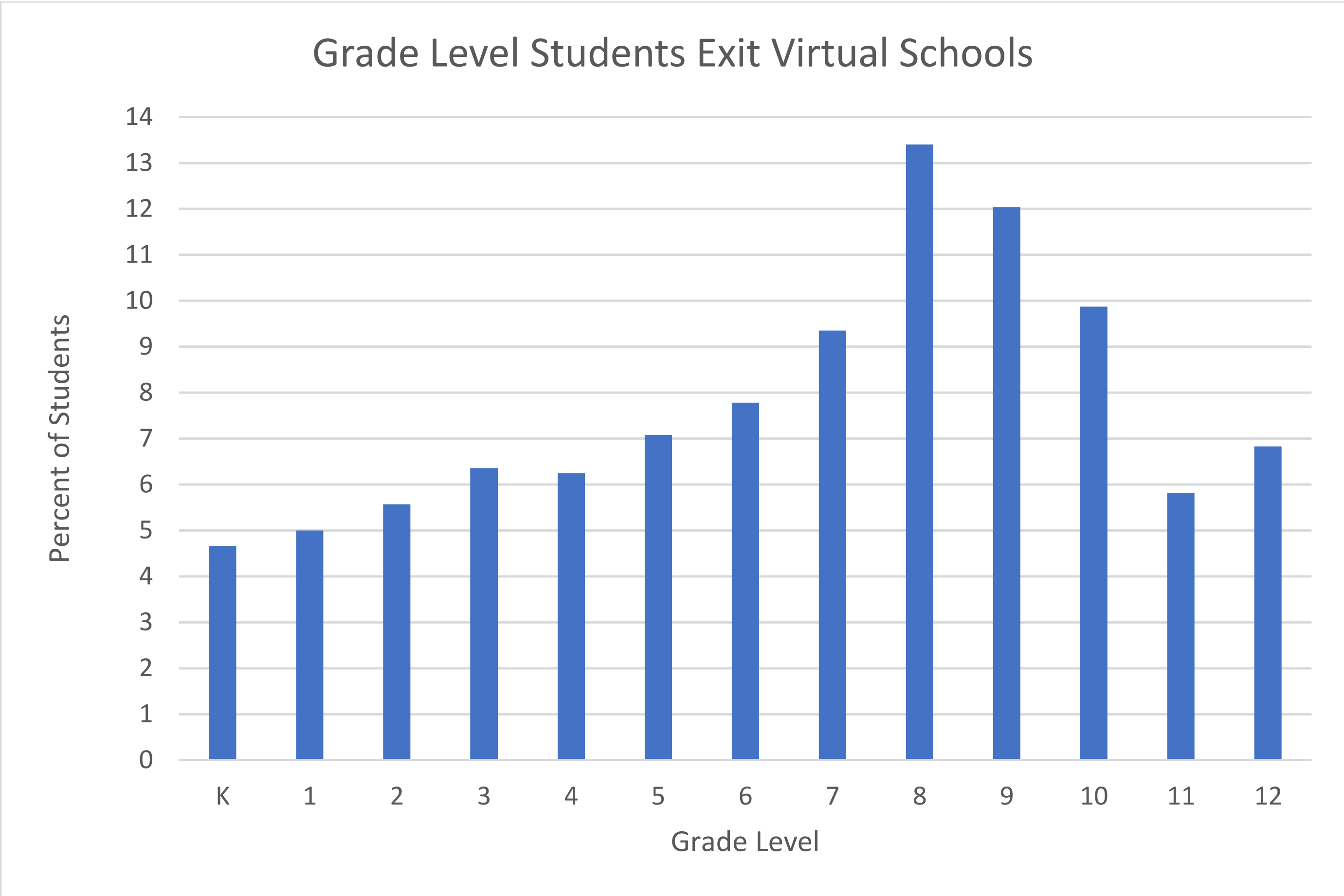
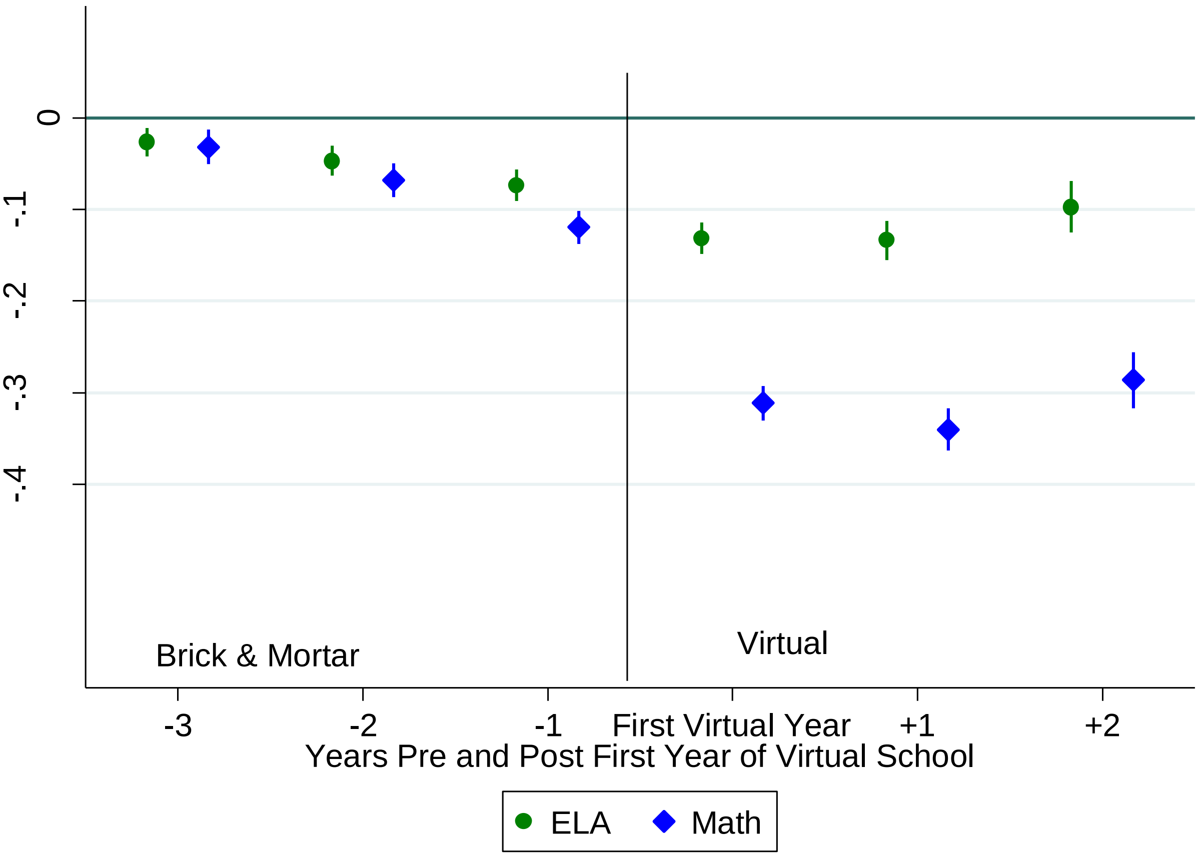
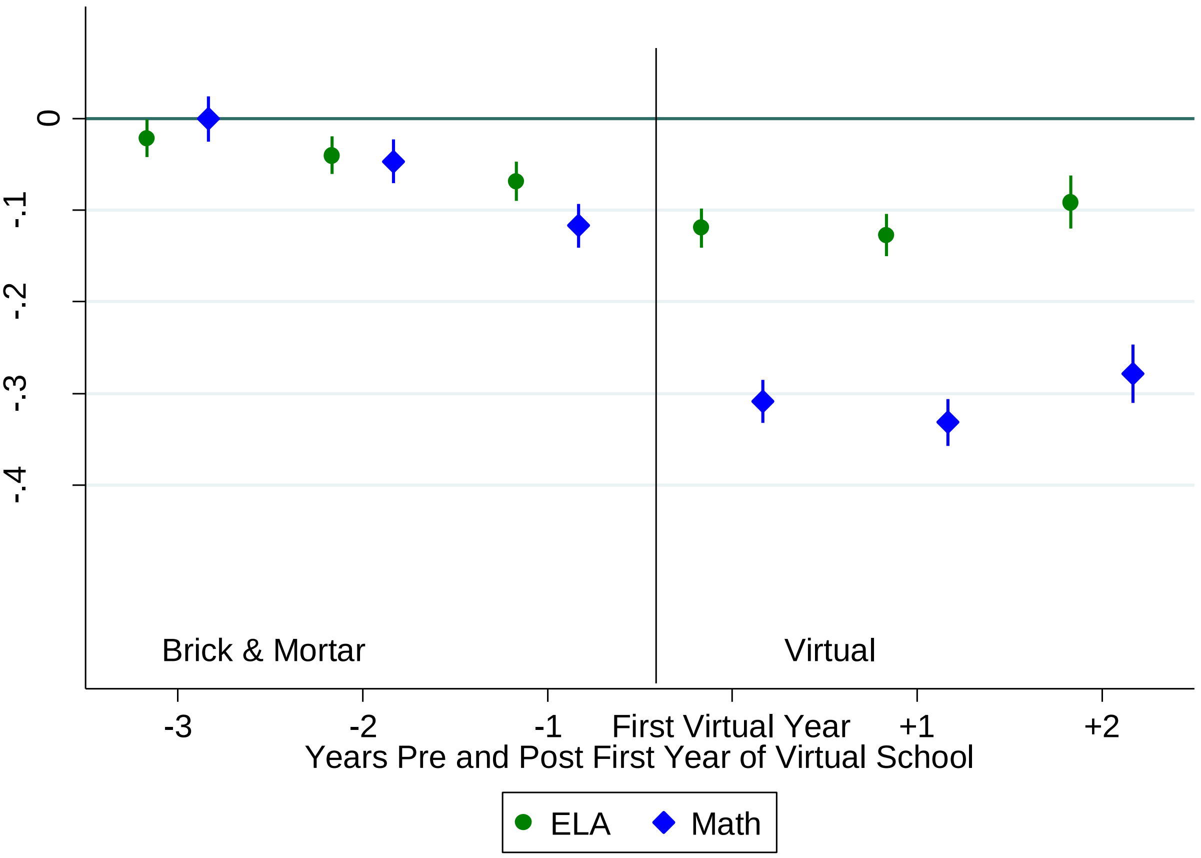


Figure 3: Student Test Scores by School Type for Students who Transition between Brick and Mortar and Virtual School, attend a Virtual School and do not Exit, and Enter a Virtual School in grades 3-8 for School Years 2007-2016.



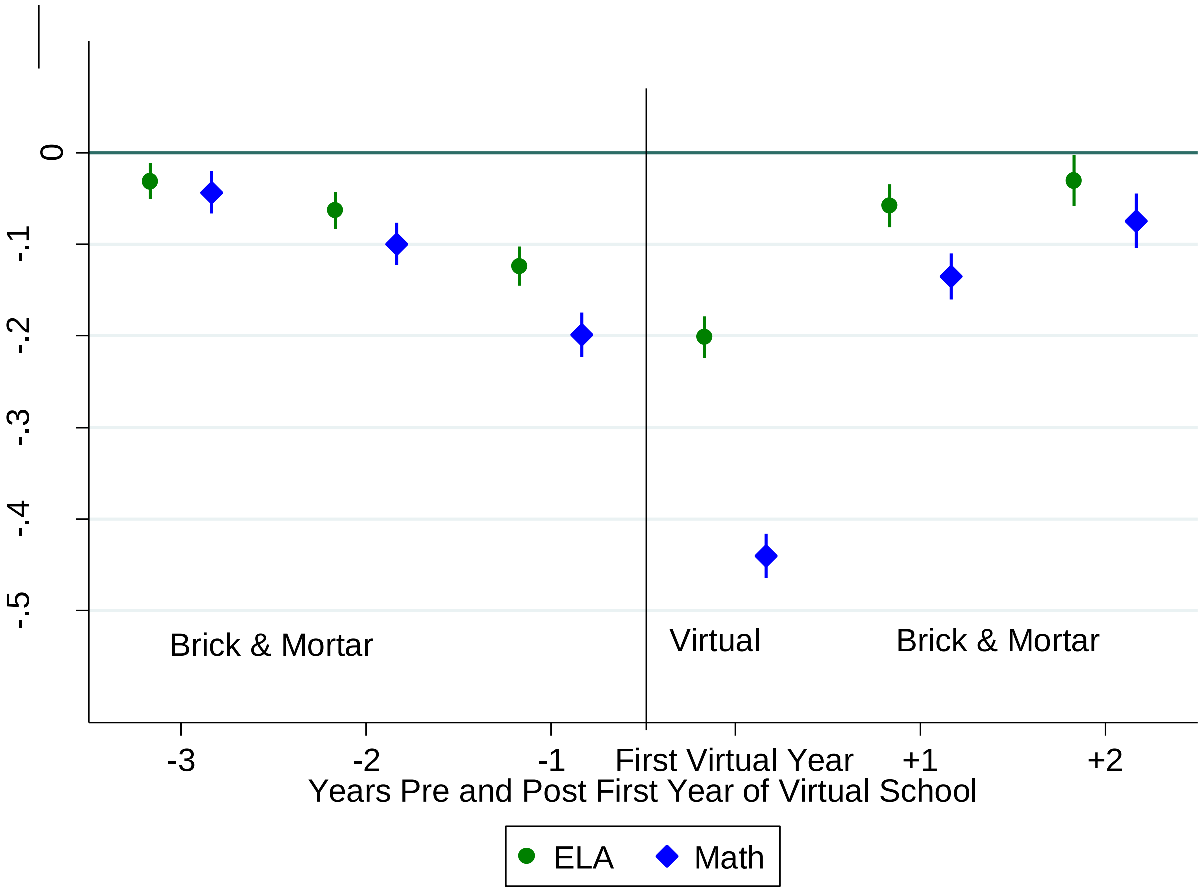
Notes: Coefficients of indicator variables are plotted on the graph, where the variable equals one if they were x years before or after entering a virtual school. Vertical band represent +/- 1.96 confidence intervals. The sample is limited to students who enter a virtual school in grades 3 through 8.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

Figure 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.



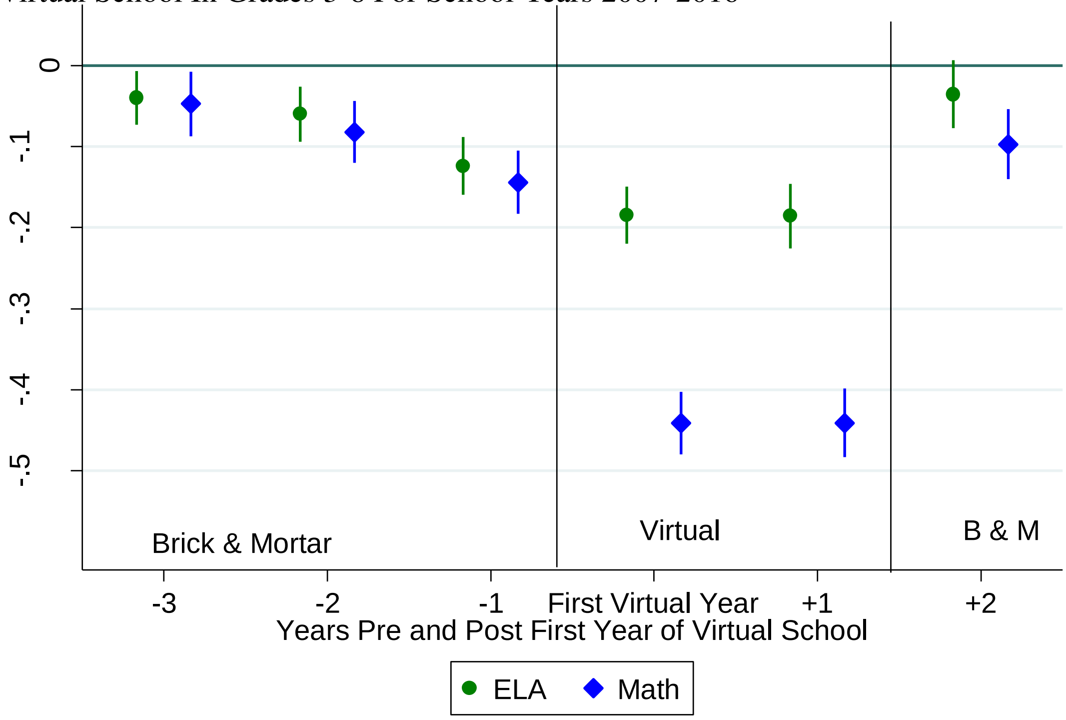
Notes: Coefficients of indicator variables are plotted on the graph, where the variable equals one if they were x years before or after entering a virtual school. Vertical band represent +/- 1.96 confidence intervals. The sample is limited to students who enter a virtual school in grades 3 through 8.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

Figure 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 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

8 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 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 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

Table 3: Previous District for First-Time Virtual School Students from 2010-2016

Sending District	Freq.	Percent
Gwinnett County	1,207	7.71
DeKalb County	1,090	6.96
Cobb County	923	5.9
Fulton County	725	4.63
Clayton County	625	3.99
Henry County	487	3.11
Cherokee County	439	2.8
Richmond County	379	2.42
Chatham County	357	2.28
Coweta County	350	2.24
Paulding County	346	2.21
Atlanta Public Schools	328	2.09
Douglas County	306	1.95
Newton County	285	1.82
Columbia County	261	1.67
Houston County	253	1.62
Bibb County	221	1.41
Forsyth County	215	1.37
Rockdale County	213	1.36
Muscogee County	194	1.24
Bartow County	163	1.04
Fayette County	162	1.03
Walton County	146	0.93
Carroll County	142	0.91

Notes: Percent indicates the percent of fist time students that attended that district in the previous year

Table 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

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
One Year in Virtual School: Enter and Exit a Virtual School	27,333	84.4%
One Year in the Ga. Public School Sys. Panel and School Year is not 2016	3,344	10.3%
One Year in Virtual School: During the Last Available Year of the Panel-2016	1,722	5.3%
Total	3,538,400	100%

Table 6: Means of Characteristics of Students School Year: 2016

	All Student Observations	Non-Virtual Student Observations	Virtual Student Observations	
	Mean	Mean	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 Mean Score	507.5	507.5	501.0	-6.54***
Math Mean Score	514.5	514.7	496.1	-18.59***
Science Mean Score	506.2	506.3	496.2	-10.17***
Social Std. Mean Score	507.1	507.3	489.2	18.09***
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 School Student Oberservations	Charter Virtual School Student Observations	
	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	0.004	-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 Mean Score	510.8	501.0	-9.83***
Math Mean Score	513.7	496.1	-17.55***
Science Mean Score	505.2	496.2	- 9.06***
Social Std. Mean Score	506.4	489.2	- 17.16***
Observations	95002	21058	116060

Table 7: Means of Characteristics of Students School Year 2016 by Full-Time Virtual School

	Non-Virtual Student Mean	Georgia Cyber Mean	Georgia Conn. Mean	Grad. Achievement 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 .. Lu h	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 Mean Score	507.52	498.23	512.90	.
Math Mean Score	514.70	495.48	498.88	.
Science Mean Score	506.33	494.43	503.39	.
Social Std. Mean S e	507.28	487.81	495.21	.
Observations	1801274	14530	4142	2386

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

	(1)	(2)	(3)	(4)
Lagged ELA Score	-0.0000386 (0.0000302)			0.00253*** (0.0000503)
Lagged Math Score		-0.00114*** (0.0000286)		-0.00264*** (0.0000471)
Lagged Percent Present			-0.000129*** (0.00000110)	-0.0000544*** (0.00000165)
Female				-0.000502*** (0.0000580)
Black				-0.00484*** (0.0000677)
Asian				-0.00229*** (0.000166)
Hispanic				-0.00722*** (0.0000944)
Ever SPED				0.0000775 (0.0000821)
Ever LEP				-0.00568*** (0.000928)
Ever Migrant				-0.00229*** (0.000398)
Ever Homeless				-0.00407*** (0.000112)
Ever Free or Red. Lunch				0.00646*** (0.0000735)
Year FE	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓
Observations	6383112	6369127	13956527	6349054

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)
ELA Lagged	-0.00007**			0.0009***
	(0.00002)			(0.00004)
Math Lagged		-0.0004***		-0.0008***
		(0.00002)		(0.00003)
Lagged Percent Present			-0.0001***	-0.00008***
			(0.0000008)	(0.000001)
Female				0.000005
				(0.00004)
Black				-0.00225***
				(0.00005)
Asian				-0.00169***
				(0.000116)
Hispanic				-0.00321***
				(0.0000659)
Ever SPED				0.000293***
				(0.0000574)
Ever LEP				-0.00227***
				(0.000647)
Ever Migrant				-0.00131***
				(0.000277)
Ever Homeless				-0.00175***
				(0.0000782)
Ever Free or Red. Lunch				0.00274***
				(0.0000513)
Year FE	✓	✓	✓	✓
Grade FE	✓	✓	✓	✓
Observations	6359033	6345149	13893707	6325188

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*** (0.003)	-0.169*** (0.003)	-0.107*** (0.003)	-0.190*** (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 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 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 12: 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 13: 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 14: 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 15: 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 16: 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 17: 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 18: 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.