Program on Education Policy and Governance Working Papers Series

Virtual Schooling and Student Learning: Evidence from the Florida Virtual School*

Matthew M. Chingos† and Guido Schwerdt+

PEPG 14-02

Harvard Kennedy School
79 JFK Street, Taubman 304
Cambridge, MA 02138
Tel: 617-495-7976 Fax: 617-496-4428
www.hks.harvard.edu/pepg/

* We thank the Florida Virtual School and the Florida Department of Education for providing the data used in this paper; Teresa King, Paul Peterson, and Martin West for helpful comments; and Ellie Klein and Katharine Lindquist for research assistance.

† Brown Center on Education Policy, Brookings Institution. mchingos@brookings.edu.
+ University of Konstanz, CESifo, and IZA. guido.schwerdt@uni-konstanz.de.

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Abstract

Online education options have proliferated in recent years, with significant growth occurring at state-sponsored virtual schools. However, there is no prior credible evidence on the quality of virtual courses compared to in-person courses in U.S. secondary education. We compare the performance of students who took core courses in algebra and English at their traditional public high school to the performance of students who took the same courses through the Florida Virtual School, the largest state virtual school in the U.S. We find that FLVS students are positively selected in terms of prior achievement and demographics, but perform about the same or somewhat better on state tests once their pre-high-school characteristics are taken into account. We find little evidence of treatment effect heterogeneity across a variety of student subgroups, and no consistent evidence of negative impacts for any subgroups. Differences in spending between the sectors suggest the possibility of a productivity advantage for FLVS.

Keywords: online learning, Florida Virtual School, virtual education, public schools

JEL classification: J24; J64; J31; I20

September 2014

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1. Introduction

Virtual schooling is rapidly gaining a foothold in K-12 education in the United States. In 2012-13, 30 states had multi-district, fully online schools with enrollment of about 310,000 students, and 26 states had state virtual schools with over 740,000 course enrollments (Watson et al. 2013). These numbers are a drop in the bucket of a public education system with 14.7 million high school students (and 49.7 million students in total).[1] But they are quickly increasing, with course enrollments more than doubling in just four years from a base of 320,000 in 2008-09 (Watson et al. 2009). In 2014 alone, 12 states enacted 17 laws related to the use of technology in education (Bleiberg and West 2014).

The impact of technology on educational outcomes has received significant attention by researchers, especially over the last decade, but this literature has largely focused on the effect of computer use at home and at school. Several studies have found a correlation between computer use at home and educational outcomes (see, e.g., Attewell and Battle 1999; Fairlie 2005; Schmitt and Wadsworth 2006; Beltran, Das and Fairlie 2010; Fiorini 2010) but it is not clear if this relationship is causal. Fuchs and Woessmann (2004) find that the initial positive association between computer use at home and student achievement turns negative after controlling extensively for student, school, and family background characteristics. For the use of computers at school, they find no effect on student performance.

Research using plausibly exogenous variation introduced by government programs in order to identify the effect of computer use at schools produces similar findings. Goolsbee and Guryan (2006) use variation from the E-Rate program in the U.S., which provided up to $2.25 billion per year for better computers and Internet connections at schools and libraries. Although the program significantly increased IT investments at schools, the authors do not find positive effects on student performance. Evaluations of government programs in other countries mostly find null impacts as well.[2]

This research says little, however, about the potential impact of virtual schooling on student outcomes. Providing computers, software, and internet access to schools is a very different intervention

[1] Information available at: http://nces.ed.gov/programs/coe/indicator_cga.asp

[2] Angrist and Lavy (2002) exploit a program by the Israeli government that provided more than 50,000 computers to schools. They do not find any positive effects of computer use at school on student achievement. Machin, McNally and Silva (2007) exploit a strategy change by the UK government that led some British primary schools to increase their ICT investments. They find that more ICT funding had a positive effect on student achievement for English and Science, but not for Mathematics. Two recent studies by Leuven and Lindahl (2007) and Malamud and Pop-Eleches (2011) use a regression discontinuity approach for identification. Leuven and Lindahl use a program targeted at Dutch primary schools with more than 70 percent disadvantaged students and do not find any positive effects of extra funding for computers and software. Malamud and Pop-Eleches analyze a voucher program for students from low-income families in Romania and find that computers at home do not improve student achievement.

from using technology to change the way that students learn. It is not surprising that providing computers has no independent effect on student learning on its own. But it still leaves open the possibility that specific technology-based interventions could have an impact. For example, Rouse and Krueger (2004) show that the use of the software "Fast ForWord" can help low performing students to better solve computer-based tests, although it has no effect on other standardized language tests. Ritter et al. (2007) studied Carnegie Learning's Cognitive Tutor Algebra I curriculum and found large but statistically insignificant impacts on performance on an end-of-course assessment. There is also some promising international evidence.[3]

Evaluations of education software are related to but still do not bear directly on what the recent increase in the availability of fully online courses (and schools) portends for student outcomes. A software product aimed at enhancing math or reading instruction in the context of a brick-and-mortar school is likely very different from an entire math or reading course offered over the internet. The promise of virtual education is that it can be personalized to the needs of individual students and deliver a high-quality product to students at any time in any location. But this promise has so far been untested. There is no existing high-quality research on the impact of fully online high school courses on student achievement in the U.S. This likely is due in large part to the fact that measuring the impact of virtual education is rife with methodological challenges (Chingos 2013).

There are at least two potential goals of virtual education. First, virtual education can increase access to education by enabling students to take courses that are not offered in their local school or that they cannot attend due to enrollment constraints or scheduling conflicts. Second, virtual education might improve the quality of education through personalization, competition resulting from increased choice among providers, and other channels. Even if virtual schools are no better than traditional schools, they may offer opportunities to increase productivity in education by operating at a lower cost.

Virtual schools meet the first goal, almost by definition, in that they provide a variety of courses that students can take from anywhere and at any time. However, how well they meet the second goal is much less clear. In this paper, we provide the first estimates of the effect of taking virtual courses by comparing the achievement of students in two traditional high school courses (algebra and English) to the achievement of students enrolled in the same traditional schools but who took one or both of these courses online through the Florida Virtual School (FLVS). FLVS is the largest state virtual school in the

[3] Banerjee et al. (2007) conducts a field experiment with about 6,000 Indian students and finds that low performing students perform better on mathematics tests when they regularly use specific training software. Linden (2008) conducts an experiment in India where students receive computer-based training on top of and instead of traditional class lectures. While students who use the computer instead of normal lessons perform worse than others, students who use the computer on top of normal lessons perform better than the control group.

country, with successful course enrollments that represented more than half of the total enrollment in state virtual schools nationwide in 2012-13 (Watson et al. 2013).

We use two complementary estimation strategies. First, we compare the 10th-grade test scores of students with similar 8th-grade test scores and demographics, some of whom took the algebra and English courses online with FLVS and others who took the same courses in person at their local public school. Second, we identify students that took one course online and the other course in person, and see if the test scores for the same student are higher or lower in the subject for which they took the course online.

Both approaches indicate that FLVS students perform about the same as or better than non-FLVS students on state tests in reading and math. We find no consistent evidence of subgroup effects, and no evidence that FLVS students are more likely to be absent from their regular school.

2. Florida Virtual School

Florida Virtual School, founded in 1997, is the nation's first statewide virtual public high school.[4] FLVS got off to a slow start, with only 11,500 course enrollments in 2003, its sixth year of existence (Peterson 2010). But the number of completed courses quickly rose to 154,000 in 2008-09 and 462,000 in 2012-13. The vast majority (97 percent) of FLVS students are part-time students who take the rest of their courses in another school. Three-quarters of completed courses are taken by students enrolled in public and charter schools, one-fifth are taken by homeschooled students, and the remaining five percent are taken by private school students (Florida Virtual School 2014).

FLVS enrollment will most likely continue to increase given the pro-virtual-education policy environment in Florida. State law prohibits public school districts from limiting access to FLVS courses or charging students to take them.[5] In 2011, state policymakers went even further by requiring students in the high school graduating classes of 2015 and later to take at least one online course in order to graduate.[6] However, FLVS is not the only provider of online courses. Many districts have set up their own online programs so that they can keep the funding that would otherwise go to FLVS.[7]

As with a traditional school, courses vary with different topic areas at FLVS. For example, the Outdoor Education class (which is eligible for physical education credit) begins with virtual lessons on safe sporting practices, proper techniques, and gear. Students then choose an outdoor activity, make a plan with their instructor, and keep track of their progress in their course journal. In FLVS's high school

[4] Information available at: http://www.flvs.net/areas/aboutus/Pages/default.aspx

[5] Information available at: http://www.flvs.net/areas/aboutus/Documents/Letter%20to%20Superintendents%206-27-13.pdf

[6] Information available at: http://www.flvs.net/areas/faqs/Pages/digital-learning-act.aspx#1

[7] Information available at: http://www.fldoe.org/schools/virtual-schools/

English course, students study the speeches of American Presidents and the work of Shakespeare while also learning how to conduct research, present findings, and cite sources. In Anatomy and Physiology, students complete lab assignments through a virtual microscope and perform a virtual surgery.[8]

All FLVS students have their own online dashboards that list their courses, along with information on each course homepage including teacher contact information, grades, and messages.[9] There is also a FLVS digital app that can be used as a study tool. FLVS students must have their own computers (or use computers at their traditional school) as they are not provided by FLVS.[10] Although course webpages may vary slightly in terms of their graphics and navigation, they all provide step by step videos and visual demonstrations, activities with corrective feedback, games, and practice tests that match the Florida End of Course (EOC) format.[11] Most courses also offer opportunities to work in teams with other classmates either through online messaging systems or video conferencing. The majority of course materials are provided online, but if a student needs a particular text, FLVS will send it to the students, and the parent/guardian is responsible for returning it to the school once the course is over.[12]

A staple of FLVS, and a promise they make frequently on their website, is the support of instructors. Instructors are available from 8am-8pm seven days a week by phone, email, text or instant message.[13] FLVS states that every course is taught by highly qualified, state certified instructors who are experts in their subject areas.[14] As of August 2013, the program had 1,140 full-time teachers and 45 part-time teachers.[15]

Most regular online courses (English, Science, etc.) are provided in two half credit segments. Courses such as Outdoor Education and Drivers Education are standalone half credit courses.[16] Regardless of the type, each FLVS course also allows students to establish their own pace with their teacher. FLVS states that "any pace" means your pace "as long as [students] are achieving, learning, and showing forward momentum weekly."[17] This is done via a pace chart that describes a course completion in 32-36 weeks as traditional, 32-36 weeks with honors credit as honors traditional, 16-18 weeks as accelerated, 16-18 weeks with honors credits as honors accelerated, and extended pace which has no set

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[8] Information available at: http://www.flvs.net/Students/Pages/CourseTours.aspx

[9] Information available at: http://flvs.net/myFLVS/student-handbook/Pages/QuickStart.aspx

[10] Information available at: http://flvs.net/areas/faqs/Pages/CourseFAQs.aspx

[11] Information available at: http://flvs.net/myFLVS/student-handbook/Pages/QuickStart.aspx

[12] Information available at: http://flvs.net/areas/faqs/Pages/CourseFAQs.aspx

[13] Information available at: http://flvs.net/areas/faqs/Pages/CourseFAQs.aspx

[14] Information available at: http://flvs.net/areas/faqs/Pages/CourseFAQs.aspx

[15] Information available at: http://kpk12.com/cms/wp-content/uploads/EEG_KP2013-lr.pdf

[16] Information available at: http://www.flvs.net/Students/Pages/find-course.aspx#highschool

[17] Information available at: http://flvs.net/Students/Pages/how-it-works.aspx

time frame and for which students must petition and gain documented approval from their parents.[18] Students may begin courses at any point during the year by selecting a preferred start month when registering, although placement is not guaranteed.[19]

For this study, FLVS shared all course records from the 2005-06 through 2010-11 school years.[20] Figure 1 shows that, over this time period, enrollment surged in FLVS, with course enrollments quadrupling from just under 70,000 to more than 300,000. The number of unique students taking FLVS courses increased fivefold, from about 30,000 to more than 150,000.[21] This enrollment growth translates into an increase in the share of high school students taking at least one FLVS course from four percent in 2005-06 to 16 percent in 2010-11 (Figure 2).

Summary statistics on all FLVS course records in our data are reported in Table 1, with a breakdown by subject area shown in Figure 3. FLVS students are a heterogeneous group in terms of their background characteristics (we take up below the question of how FLVS students compare to non-FLVS students enrolled in Florida public schools). The large majority (81 percent) of FLVS students are enrolled in public schools (including charters), with the remainder divided between home schools (12 percent) and private schools (7 percent).

FLVS courses cover a wide variety of subjects, with the large majority (76 percent) in core academic subjects (math, foreign language, English, social studies, and science). A significant minority of FLVS course attempts are not successful: 13 percent of courses end in withdrawals and another five percent are completed but failed, leaving a successful completion rate of 81 percent. FLVS students are largely enrolled in the high school grades (only 13 percent are middle school students). Given this fact, we restrict the remainder of our analysis to the high school grades.

3. Data and sample selection

For our analysis we obtained data from Florida Virtual School on all students registered for an online course since the 2005-06 school year. The FLVS data contain detailed information on the courses taken through FLVS that we merge with student-level data from the Florida Department of Education's

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[18] Information available at: http://flvs.net/myFLVS/student-handbook/Pages/QuickStart.aspx

[19] Information available at: http://flvs.net/areas/faqs/Pages/CourseFAQs.aspx

[20] At the beginning of each FLVS course, students have a 28-day trial period during which they can meet their teacher and try out the course before committing to take it for credit. We drop from our analysis the course records for which the student decided not to continue past the trial period (about 23 percent of the original sample).

[21] These numbers may not match publicly reported data because our data are for all course enrollments, whereas publicly reported data often focus on successful course completions. In Table 1 we show that 81 percent of courses in our data are completed successfully (excluding the courses that are dropped during the trial period, as explained above).

PK-20 Education Data Warehouse (EDW).[22] The EDW data contain information on all Florida students attending public schools in grades 3 to 10 from the 2000–01 through 2008–09 school years. Our data extract includes the school each student attends and its location; student characteristics such as ethnicity, gender, special education classification, and free lunch status; and annual measures of absences and state math and reading test scores. We normalize these test scores by subject, year, and grade to have a mean of zero and a standard deviation of one.

We construct three different estimation samples, all of which focus on high school students in grades 9 and 10 and exclude students who were missing information on relevant background characteristics.[23] First, to estimate the relationship between attending any course at FLVS in grades 9 and 10 and student outcomes, we construct a sample of students with complete information enrolled in grade 9 or 10 between 2006 and 2009. Second, to investigate whether attending a specific course at FLVS has an effect on student achievement, we construct two samples of students taking a specific course in grade 9 or 10 either at their local high school or at FLVS. In particular, we focus on the courses Algebra I (DOE number: 1200310) and English I (DOE number: 1001310). Arguably, attending Algebra I should have a larger impact on students' achievement on the math test while attending English I can be expected to have a larger impact on students' achievement on the reading test.

We define treatment as having taken a course (in a given subject) for the first time through FLVS at any point before taking the 10th-grade Florida Comprehensive Assessment Test (FCAT). We also examine the robustness of our results when limiting the FLVS treatment group to students who only took the course through FLVS, and also to students who took the course through FLVS after taking the course for the first time at their local public school.

We focus on the impact of taking FLVS courses on test scores in grade 10 rather than on the test immediately following the course because FLVS courses do not follow the same schedule as traditional courses. Our FLVS course data include the date of registration for the course, the date of activation, and the date of completion. FLVS course durations (i.e. the number of weeks between the activation and completion dates) vary widely, as shown in Figure A-1. Moreover, many students take these courses over the summer or complete them after the 9th-grade FCAT tests, which take place in March (see Figure A-2). Consequently, it would greatly reduce the sample to compare students who took the FLVS vs. non-FLVS

[22] The two data sets were merged by the Florida Department of Education based on full names and birth dates. The merged data set that we obtained from the Florida Department of Education contains anonymous student identifiers, but does not include students' names or dates of birth.

[23] All results presented in this paper are based on balanced samples including only students with complete background information to ease the comparison of estimation results across specifications. Results with varying numbers of observations depending on the specification are very similar and available upon request.

version of the same courses during ninth grade. Instead, we focus on 10^{th}-grade test scores as a somewhat longer term measure of achievement in the subjects covered by these courses.[24]

4. Estimation strategy

We are interested in the impact of FLVS participation on student outcomes. To empirically examine selection into FLVS courses, we start by estimating the following selection equation:

$$FLVS_{i,g} = \alpha_0 + Y_{i,g-1}\alpha_1 + X_{i,g}\alpha_2 + \varepsilon_{i,g}, \tag{1}$$

where $FLVS_{i,g}$ indicates whether student i observed in grade g participated in any FLVS course, $Y_{i,g-1}$ is a vector of student outcomes (math score, reading score, and days of absence) in grade $g-1$, $X_{i,g}$ is a control vector including student characteristics in grade g (gender, age, race, limited English proficiency, free or reduced-price lunch eligibility, special education status) as well as a complete set of school, grade, and year fixed effects. The error term in Equation (1), ε_{ig}, includes unobserved individual traits and other factors that influence the participation decision.

To provide a descriptive analysis of the association between FLVS participation and contemporaneous student outcomes, we model student outcomes in grade g, $Y_{i,g}$, as a linear function of FLVS participation and other covariates:

$$Y_{i,g} = \beta_0 + \beta_1\, FLVS_{i,g} + Y_{i,g-1}\beta_2 + X_{i,g}\beta_3 + \varphi_{i,g}, \tag{2}$$

where Equation (2) can also be estimated without lagged outcome measure but with individual student fixed effects.

To improve on the descriptive analysis of FLVS participation presented above, we focus on two core courses that high school students can opt to complete through FLVS: Algebra I (DOE number: 1200310) and English I (DOE number: 1001310). We define treatment as $FLVS(c)_i$ indicating that student i was registered at FLVS for course c in either grade 9 or 10 and estimate the following model:

$$Y_{i,10} = \gamma_0 + \gamma_1\, FLVS(c)_i + Y_{i,8}\gamma_2 + X_{i,10}\gamma_3 + \omega_i, \tag{3}$$

where $Y_{i,10}$ ($Y_{i,8}$) measures student achievement in grade 10 (8). The error term in Equation (3), ω_i, is assumed to be uncorrelated with FLVS participation conditional on the other covariates (including lagged achievement) in the model. If this assumption holds, the parameter of interest γ_1 identifies the causal effect of taking course c at FLVS on student achievement in grade 10. However, contemporaneous shocks (e.g. bad experience at local high school, health problems, divorce of parents, etc.) may affect achievement as well as the FLVS participation decision and thus lead to biased estimates of the true parameter γ_1.

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[24] We focus on the first time a student takes the 10^{th}-grade FCAT test.

To investigate whether such contemporaneous factors confound our estimate of γ_1, we additionally exploit variation in achievement within students across subjects by estimating the following model:

$$\Delta Y_{i,10} = \delta_0 + \delta_1 \Delta FLVS(c)_i + \Delta Y_{i,8}\delta_2 + \eta_i, \quad (4)$$

where $\Delta Y_{i,10}$ ($\Delta Y_{i,8}$) measures the difference between student *i*'s relative achievement on the math and reading test in grade 10 (8) and $\Delta FLVS_i$ is the difference between the dummy variable identifying students taking Algebra I through FLVS and the dummy variable identifying students taking English I through FLVS. The parameter δ_1 can be estimated using data on students who only take one of the two courses through FLVS. Arguably, contemporaneous shocks are less of a concern in this regression specification. To interpret our estimate of δ_1 causally we only have to assume that no confounding factors exist that affect achievement as well as the FLVS participation decision for only one course but not for the other. Additionally, we have to assume that there are no spillover effects of taking Algebra I (English I) through FLVS on reading (math) scores. However, note that such spillover effects would not affect the estimate of γ_1 in Equation (3).

A potential concern in both specifications is that selection into FLVS courses may depend on the quality of the teacher at the traditional school. A student may be more likely to take a course through FLVS if the teacher of that course at their local school is known to be lower quality, and more likely to take in-person courses with higher quality teachers. This would bias both across-student comparisons of FLVS and non-FLVS versions of the same course as well as the within-student, across-subject comparisons. In both cases, the bias would be in favor of the traditional version of the course, where students are more likely to be observed with higher quality teachers in their traditional school. Consequently, our estimates are likely lower bounds of the true FLVS effect.

5. Results

FLVS Participation

We first report the results of our descriptive analysis of which student-level characteristics are associated with participation in any FLVS course in grades 9-10. We have no way to examine the impact of FLVS participation given that we do not have access to outcomes measures in these grades that align with the wide variety of FLVS course offerings. Instead, we focus on whether certain types of students are more or less likely to take a FLVS course than other students. We address this question using two approaches that are essentially two sides of the same coin. First, we examine the average characteristics of FLVS and non-FLVS students. Second, we examine which characteristics predict FLVS participation, both on their own and in combination with other characteristics.

Table 2 reports summary statistics for the 31,841 FLVS student-year observations in our data and the 1,096,458 non-FLVS observations. Compared to non-FLVS students, FLVS students are 14 percentage points less likely to be eligible for a free or reduced-price lunch, five points less likely to be in special education programs, and 12 points more likely to be white. On the 8th-grade state tests in math and reading, FLVS students scored 0.35 standard deviations higher, on average, than non-FLVS students. In sum, FLVS students are a more advantaged group. The final column of Table 2 reports average differences in characteristics within the same grade, year, and school. These differences are somewhat smaller, suggesting that more advantaged students are more likely to take an FLVS course and schools with more advantaged students have higher school-wide participation rates.

We further probe the relationship between student characteristics and FLVS participation within the same schools, grades, and years by examining the ability of these characteristics to predict the likelihood of participation.[25] The first column of Table 3 indicates that a one-standard-deviation increase in prior-year math scores is associated with an increase of one percentage point in the FLVS participation rate among students in the same school, grade, and year. The relationship for reading scores is similar (shown in the second column). These differences are substantial, as they represent a change of more than 25 percent given the mean participation rate of four percent.

The third column of Table 3 examines whether students who are less engaged in school, as measured by their number of absences in the prior year, are more likely to take a FLVS course. The data suggests the opposite, with more absent students less likely to take a FLVS course, an estimated relationship that is statistically significant but very weak. An increase in absenteeism of 10 days (i.e. about one standard deviation) is only associated with a decreased FLVS participation rate of 0.04 percentage points. The final column of Table 3 reports the results from a multivariate model that includes test scores in both subjects, days absent, and a number of student demographic characteristics. This analysis largely confirms the single-variable comparisons in Table 2, with higher participation rates among higher-scoring students, non-minority students, and students who are not eligible for free or reduced-price lunch. The coefficient on days absent in the prior year changes sign, but remains weak.

Tables 2 and 3 compare the fixed and pre-high-school characteristics of students who do and do not take at least one FLVS course. We next examine whether FLVS students experience better outcomes in terms of test scores and school attendance during the year in which they take an FLVS course, relative to non-FLVS students. The top two panels of Table 4 show that FLVS students score much higher on state math and reading tests than non-FLVS students. This is exactly what we would expect given that FLVS students had higher average levels of achievement to begin with and were also concentrated among

[25] We obtain similar results when we estimate a probit model instead of a linear probability model.

demographic groups that tend to be higher scoring. Including demographic controls shrinks this relationship substantially, and adding controls for prior-year test scores reduces it even further, to 0.06 and 0.08 standard deviations in math and reading, respectively (adding school fixed effects has little impact on the results).

These results indicate that FLVS students score modestly higher than we would expect based on their demographic characteristics and prior achievement than non-FLVS students. But it does not mean that FLVS participation causes them to score higher, as these students could have higher levels of unmeasured characteristics positively associated with student achievement growth, such as perseverance and motivation. We further probe this relationship by estimating a model with student fixed effects, which compares the test scores of students during years when they take an FLVS course to the scores of the same students during years when they do not participate. The estimates, reported in column 5, indicate no within-student relationship between FVLS course-taking and test scores.

The bottom panel of Table 4 examines whether there is any relationship between FLVS participation and absenteeism. This analysis tests the concern that virtual students might be less engaged with their physical school, and less likely to show up as a result. All models show a negative but weak relationship between taking a FLVS course and the number of days absent, with all point estimates indicating a difference of less than one day absent. This implies that students are slightly less likely to be absent from school during the year they took an FLVS course compared to the year that they didn't. This estimated relationship takes the opposite direction from the concern that virtual students are less engaged, but is small in magnitude.

These results indicate at most small overall differences in the outcomes available in our dataset between FLVS and non-FLVS students. However, it is unclear how to interpret differences in math and reading performance given that many FLVS courses are in other subjects. It could be the case that FLVS courses have significant impacts on learning in the relevant subject, but our crude combination of all subjects is biased toward null findings due to using an inappropriate outcome variable (e.g., math scores to measure the effect of a physical education course). We next focus our analysis on two core courses, Algebra I and English I, which are taken by most Florida high school students and are available through FLVS.

Effect of Algebra I and English I FLVS Courses

Algebra I and English I are both courses that are taken by most Florida high school students and are usually taken in the first year of high school (grade 9). In the 2008-09 school year, 41 (52) percent of all 9^{th}-grade students took Algebra I (English I), while only 7 (4) percent of all 10^{th}-grade students took Algebra I (English I). Taking these courses through FLVS is associated with the same background characteristics as overall FLVS participation, with FLVS students having higher prior achievement and coming from more advantaged families. Table 5 shows these summary statistics; almost all of the differences are statistically significant given the large sample size of the non-FLVS group.

As described above, we use two strategies to mitigate bias from student selection into FLVS courses in algebra and English when measuring impacts on 10^{th}-grade test scores. First, we estimate value-added-type models that control for 8^{th}-grade scores, since 8^{th}-grade scores are correlated with FLVS participation and are strong predictors of 10^{th}-grade scores. Second, we estimate within-student models that compare the achievement of the same student in the two different subjects, one of which the student took in-person and the other of which she took online through FLVS.

The results for all students are reported in Table 6. Within schools (columns 2 and 5), students who took English I or Algebra I through FLVS score higher on the reading or the math test than non-FLVS students. Controlling for 8^{th}-grade scores produces smaller but still statistically significant estimates of the FLVS impact in both subjects, with point estimates of 0.07 in reading and 0.04 in math. The within-student, across-subject estimator produces a coefficient of 0.03, which is statistically insignificant from zero.

In our preferred specification, we define the FLVS treatment status based on where a student took a course for the first time. Some students are enrolled in a course at FLVS as well as at their local public school in the same school year. The third row of Table A-1 shows that treating these students as controls does not change our main results. Our preferred treatment group excludes students who retake a course through FLVS after having taken the course previously at their local public school. The second row of Table A-1 shows that including these students in the treatment group leads to small negative estimates in the value-added-type models that control for 8th-grade scores. The estimate of the within-student model, however, remains small in magnitude and insignificant.

Students who re-take a course through FLVS that they already took at their local school likely failed the course when they first took it. Consequently, we strongly suspect that these students are negatively selected on unobserved characteristics that we cannot control for in our analysis. Table A-2 provides empirical support for this hypothesis, showing positive estimates for the FLVS-only group and larger, negative estimates for the re-take group.

Effect Heterogeneity

The results indicating a null or positive overall effect could mask heterogeneity in effects across different groups of students. For example, students who are lower achieving or from historically underserved groups might fare less well in an online environment than better-off students. Table 7 reports results for our three preferred models: reading and math scores with controls for prior-year scores, and the within-student estimator. We find little consistent evidence of positive or negative impacts for the 13 subsamples in Table 7 defined in terms of student characteristics. Estimates are never statistically significant for all three specifications. However, the within-student estimator is quite imprecise, likely due to small samples in many of the subgroups. There are a number of subgroups for which both of the across-student estimates are positive and statistically significant. Additionally, we find very little evidence of negative FLVS effects—there are no subgroups for which all three point estimates are negative, and none of the negative point estimates are statistically significant.

Table 7 also presents separate results for each of three years of our data.[26] We might expect the quality of FLVS courses to improve as they are fine-tuned by the creators and students gain in experience with the technology. We find at best suggestive evidence of more positive point estimates in the later years, but it is not robust across all three specifications and does not appear to be part of a monotonic trend. However, it is important to note that the number of years is limited and the last year of our EDW extract (2009) is more than five years old.

6. Conclusion

There are at least two potential goals of virtual education, as we discussed above: increasing access to education and improving quality. The first goal is more easily attainable than the second, as a student who takes a virtual course not otherwise available to him clearly has gained access to the course as a result of the virtual option. We can measure one part of the increased choice created by FLVS by examining enrollment in Advanced Placement (AP) courses, the availability of which may be most constrained, especially in smaller high schools. In 2008-09 (the most recent year of our linked data), at least 1,384 AP courses (916 unique students) were taken by students enrolled in high schools where those courses were not offered. For the 877 courses for which we have test results, 55 percent reflect a passing score (three or better) on the AP exam.[27]

It is pretty clear that virtual education increases access to courses (by definition), but critics have raised concerns about quality. Specifically, they worry that students will learn less in virtual courses than they would in the classroom. Our results suggest that these concerns are not supported by the evidence, both overall and for various subgroups of students. We also do not find any evidence that FLVS students are more likely to be absent from their regular school. The true FLVS effects may be more positive than

[26] We do not report results for 2006 given the small FLVS sample from that year.

[27] An additional 1,895 AP courses (1,260 students) were taken by students who were enrolled in schools where those courses were offered (with a pass rate of 52 percent based on 1,133 courses).

those reported here if students tend to take FLVS courses to avoid lower quality teachers at their traditional school.

These findings are subject to a few important limitations. First, although our study encompasses thousands of students at the largest state virtual school in the country, the last year of our linked data is 2008-09. It is possible that the quality of FLVS courses relative to the courses in traditional public schools has changed since then. Second, we are only able to compare student performance in two courses (Algebra I and English I), which make up just 8.7 percent of all FLVS course enrollments. Third, it is possible that our results are biased by unmeasured characteristics of students who choose to take these courses through FLVS versus at their local public school or by differences in teacher quality that lead students to take some courses through FLVS but not others. Finally, we are unable to measure any competitive effects that the availability of FLVS courses has on the quality of courses at traditional public schools.

Despite these limitations, this analysis yields important new findings on virtual education, a topic that has generated much hype but little serious evidence. The results are mixed regarding the promise of technology to increase the quality of education through personalization (as of 2009), but they do strongly suggest that fears of reductions in the quality of education are misplaced. We do not find any evidence of negative effects of virtual education on student learning, and a finding of equivalent quality, on average, between FLVS and non-FLVS courses may suggest a higher level of productivity in the FLVS courses.

Figure 4 shows per-pupil funding at FLVS and non-FLVS schools. Over the four years covered by our analysis, per-pupil funding was 10 percent lower for FLVS, suggesting that FLVS was producing similar outcomes at a lower cost. However, this comparison does not account for the fixed costs of educating FLVS part-time students at their local brick-and-mortar schools. For example, many students likely take FLVS courses while sitting at a computer in a classroom in a traditional school. Additionally, the comparison does not take into account services offered by traditional schools, such as extracurricular activities and cafeteria services, which are not offered by FLVS.

Figure 4 shows that the cost difference between FLVS and other public schools increased to an average of over 20 percent for the four years following 2008-09. If the relative quality of FLVS courses stayed the same or increased, then the likelihood of a productivity advantage would be even larger. This important set of questions around education quality and cost are ripe for future research in Florida and beyond.

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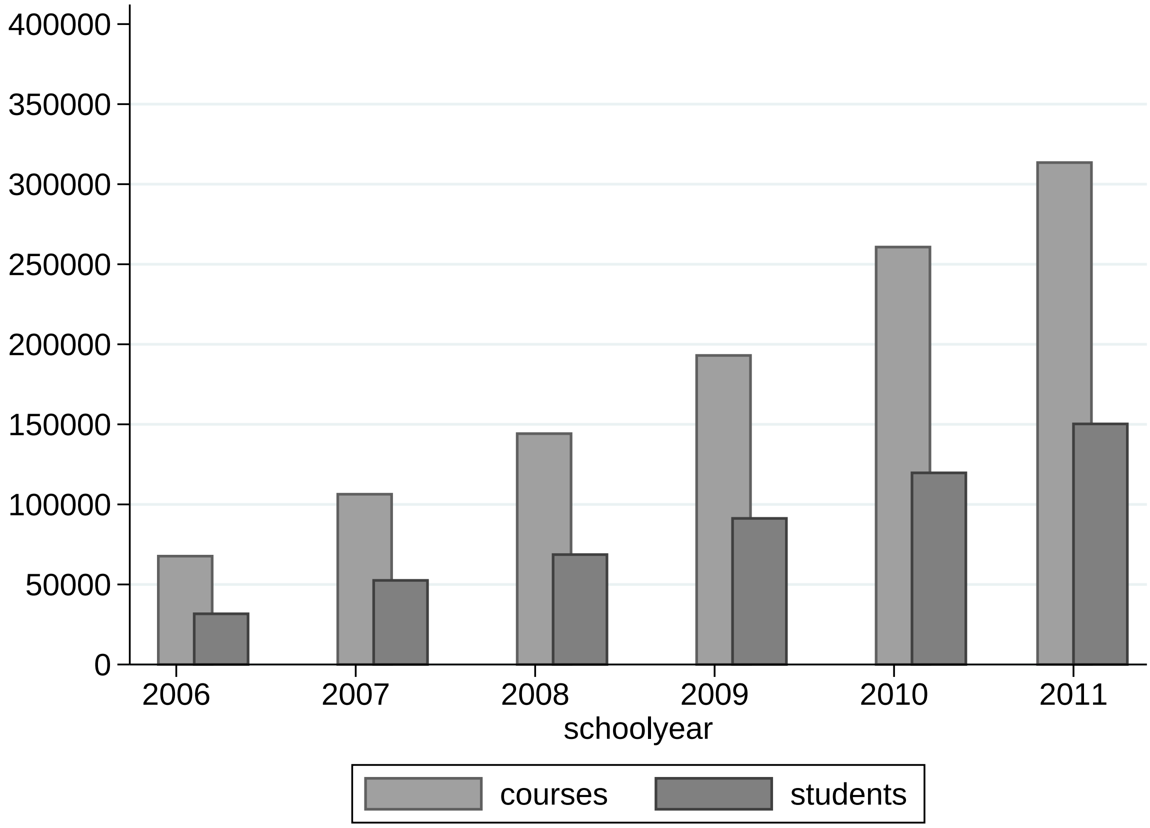
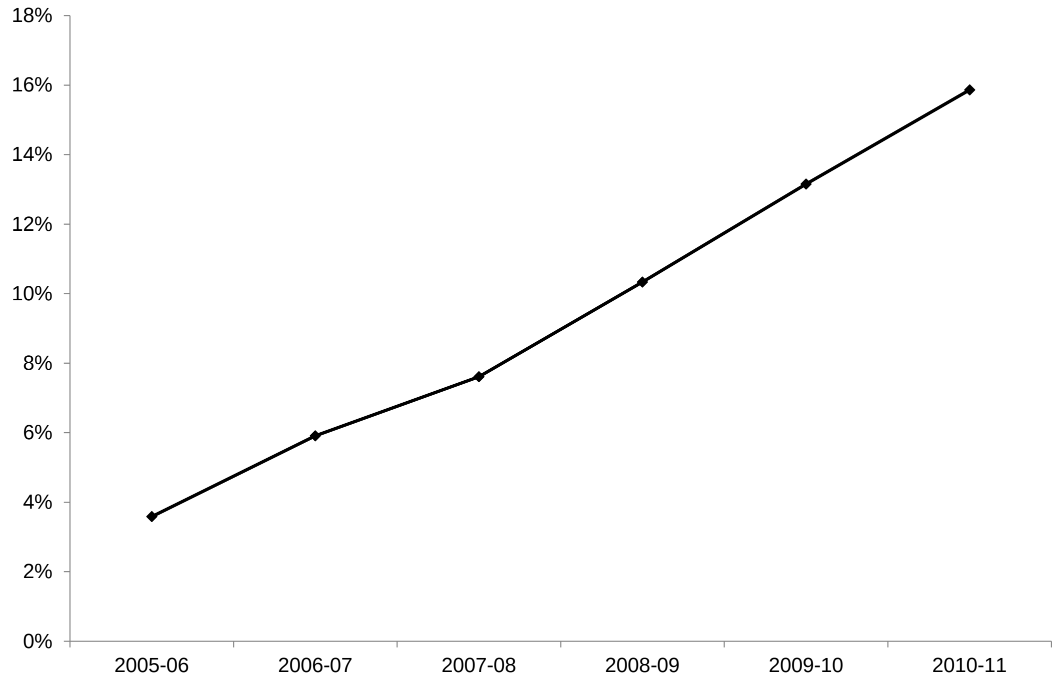
Figure 1: Enrollment in FLVS courses by School Year (spring)



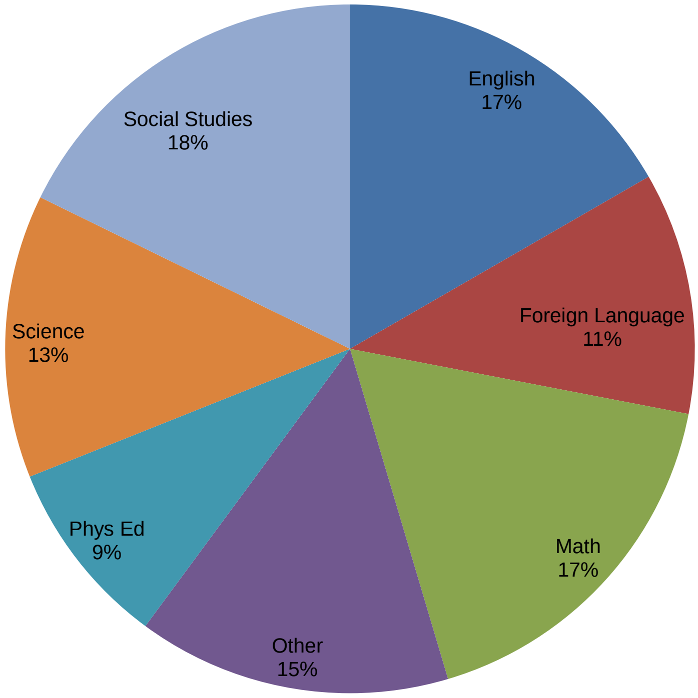
Note: Based on all students attending at least one FLVS course between 2006 and 2011 in grades 6 to 12.

Figure 2: Percent of high school students taking at least one FLVS course



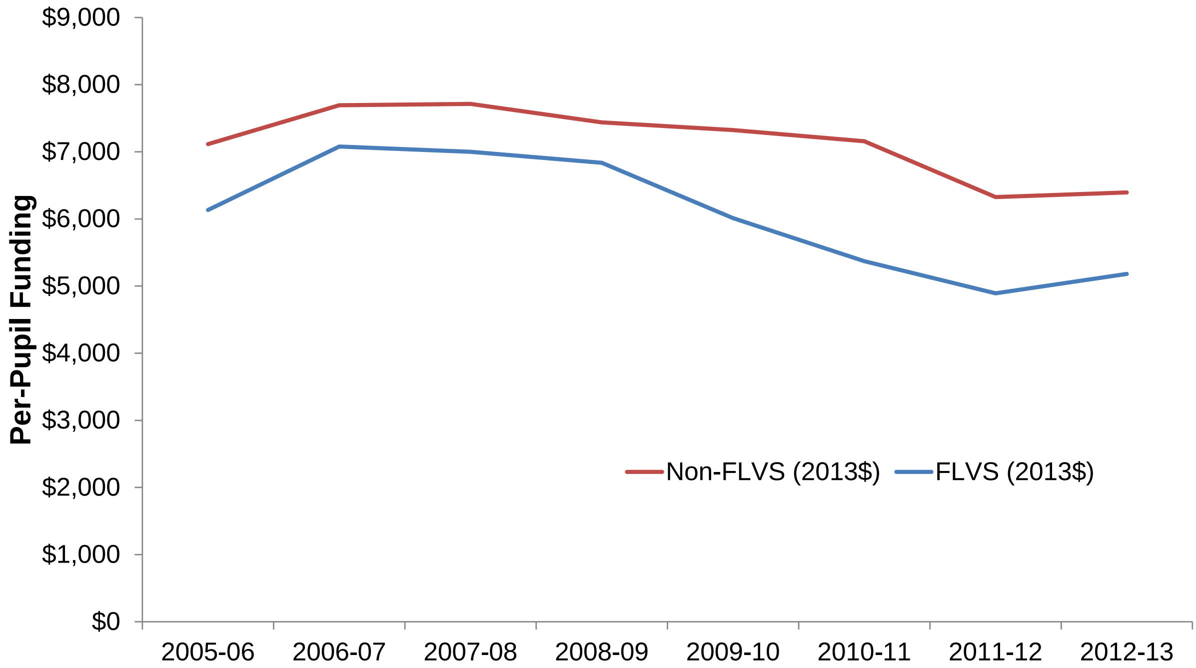
Note: Authors' calculations based on FLVS course records and public enrollment data from 2005-06 to 2010-11 for grades 9-12.

Figure 3: Breakdown of FLVS course enrollment by subject area



Note: Based on FLVS course records from 2008-09 to 2010-11 for grades 9-12.

Figure 4: Per-pupil funding: FLVS vs. traditional schools



Source: Authors' calculations from budget documents available at http://www.fldoe.org/fefp/offrfefp.asp.

Table 1: Summary Statistics for all FLVS Students

Total number			
Students	514,119	Courses	1,085,462
Gender and Age			
Female	0.58	Average age at activation	15.75
Lunch and LEP Status			
Free or reduced-price lunch	0.26	LEP student	0.04
Ethnicity			
White	0.58	Black	0.15
Asian	0.03	Hispanic	0.19
Native American	0.00	Multi-Ethnic	0.05
Year of Enrollment			
2006	0.06	2007	0.10
2008	0.13	2009	0.18
2010	0.23	2011	0.29
Grade Level			
6	0.02	7	0.04
8	0.07	9	0.15
10	0.22	11	0.28
12	0.22		
School Type			
Public	0.79	Home	0.12
Private	0.07	Charter	0.02
Final Enrollment Status			
Complete	0.81	Complete Failing	0.05
Withdrawn Failing	0.13		
Final Grade Received			
A	0.42	B	0.26
C	0.12	D	0.03
F	0.05		

Note: Unweighted statistics based on all students attending at least one FLVS course between 2006 and 2011 in grades 6 to 12.

Table 2: Summary Statistics by FLVS Participation in any course

	FLVS Participation		Difference	
	no	yes	unconditional	conditional on grade, year, and school
Female	0.50	0.60	0.10 ***	0.10 ***
Age	15.28	15.51	0.23 ***	-0.04
LEP	0.17	0.10	-0.07 ***	-0.04
Free/reduced lunch	0.38	0.24	-0.14 ***	-0.09
Special Ed	0.11	0.06	-0.05 ***	0.10 ***
White	0.50	0.62	0.12 ***	0.06 ***
Black	0.22	0.13	-0.09 ***	-0.05
Hispanic	0.23	0.16	-0.07 ***	-0.04
Asian	0.02	0.05	0.02 ***	0.02 ***
Other race	0.03	0.04	0.02 ***	0.01 ***
Days absent	8.98	8.07	-0.91 ***	-0.56
FCAT Math ($8^{th} grade$)	0.15	0.49	0.35 ***	0.24 ***
FCAT Reading ($8^{th} grade$)	0.15	0.50	0.35 ***	0.24 ***
City	0.27	0.24	-0.03 ***	
Urban fringe	0.55	0.53	-0.02 **	
Town or rural	0.18	0.23	0.04 ***	
Charter school	0.03	0.02	-0.00 ***	
Students	1,096,458	31,841		

* p<0.10, ** p<0.05, *** p<0.01

Note: Unweighted statistics based on FLVS students matched to EDW data between 2006 and 2009 in grades 9 and 10.

Table 3: Predictors of FLVS Participation (in any course)

Outcome	FLVS Participation (Mean: 0.04)			
	(1)	(2)	(3)	(4)
Math score t-1	0.0101***			0.0061***
	[0.0002]			[0.0003]
Reading score t-1		0.0103***		0.0050***
		[0.0002]		[0.0003]
Days absent t-1 ($*\frac{1}{10}$)			–0.0004**	0.0015***
			[0.0002]	[0.0002]
Boy				–0.0109***
				[0.0003]
Age				0.0017***
				[0.0002]
Asian				0.0156***
				[0.0013]
Black				–0.0038***
				[0.0005]
Hispanic				–0.0062***
				[0.0005]
Other race				0.0103***
				[0.0012]
Free- or reduced lunch				–0.0065***
				[0.0003]
Special Ed				0.0028***
				[0.0005]
Year FE	√	√	√	√
Grade FE	√	√	√	√
School FE	√	√	√	√
N	1,128,300	1,128,300	1,128,300	1,128,300
R^2	0.032	0.032	0.029	0.035

* p<0.10, ** p<0.05, *** p<0.01

Note: Dependent variable is a dummy indicating FLVS participation in a given school year. Balanced sample includes students with complete information in grades 9 to 10 between 2006 and 2009. Robust standard errors in brackets.

Table 4: FLVS Participation (in any course) and Student Outcomes

Outcome			Math Score		
	(1)	(2)	(3)	(4)	(5)
FLVS	0.369***	0.235***	0.063***	0.064***	0.003
	[0.005]	[0.004]	[0.003]	[0.003]	[0.005]
Math score t-1			0.770***	0.755***	
			[0.001]	[0.001]	
Year FE	√	√	√	√	√
Grade FE	√	√	√	√	√
Student controls		√	√	√	
School FE				√	
Student FE					√
N	1,128,300	1,128,300	1,128,300	1,128,300	1,128,300
R^2	0.009	0.272	0.694	0.699	0.953
Outcome			Reading Score		
	(1)	(2)	(3)	(4)	(5)
FLVS	0.394***	0.245***	0.082***	0.079***	0.004
	[0.005]	[0.005]	[0.003]	[0.003]	[0.006]
Reading score t-1			0.727***	0.710***	
			[0.001]	[0.001]	
Year FE	√	√	√	√	√
Grade FE	√	√	√	√	√
Student controls		√	√	√	
School FE				√	
Student FE					√
N	1,128,300	1,128,300	1,128,300	1,128,300	1,128,300
R^2	0.009	0.250	0.636	0.642	0.944
Outcome			Days absent		
	(1)	(2)	(3)	(4)	(5)
FLVS	–0.892***	–0.446***	–0.442***	–0.387***	–0.378***
	[0.053]	[0.052]	[0.043]	[0.042]	[0.080]
Days absent t-1			0.636***	0.605***	
			[0.002]	[0.002]	
Year FE	√	√	√	√	√
Grade FE	√	√	√	√	√
Student controls		√	√	√	
School FE				√	
Student FE					√
N	1,128,300	1,128,300	1,128,300	1,128,300	1,128,300
R^2	0.002	0.053	0.328	0.365	0.899

* p<0.10, ** p<0.05, *** p<0.01

Note: Dependent variables are FCAT scores normalized to have mean zero and standard deviation one by year, grade, and subject in the two top panels and the number of days a student is absent from school during a school year in the bottom panel. Student controls include gender, age, race, limited English proficiency, free or reduced-price lunch, special education status. Balanced sample includes students with complete information in grades 9 and 10 between 2006 and 2009. Robust standard errors in brackets.

Table 5: Summary Statistics by FLVS Participation, Algebra I and English I

Course	Algebra I		English I	
FLVS	yes	no	yes	no
	(1)	(2)	(3)	(4)
Student background				
Female	0.52	0.49	0.49	0.45
Age	15.88	15.92	15.96	16.03
LEP	0.09	0.21	0.07	0.17
Free/reduced lunch	0.28	0.42	0.30	0.44
Special Ed	0.09	0.11	0.09	0.16
White	0.61	0.46	0.63	0.48
Black	0.17	0.24	0.17	0.26
Hispanic	0.15	0.26	0.14	0.23
Asian	0.02	0.01	0.01	0.01
Other race	0.05	0.03	0.04	0.03
FCAT Reading				
Grade 10	0.21	-0.12	0.16	-0.24
Grade 8	0.24	-0.03	0.28	-0.16
FCAT Math				
Grade 10	0.11	-0.13	0.18	-0.17
Grade 8	0.14	-0.08	0.27	-0.16
Days absent				
Grade 10	10.81	10.59	12.72	11.31
Grade 8	9.58	9.03	11.18	9.32
Students	1,218	143,222	962	182,258

Note: Columns 1 and 2 report average characteristics for students taking Algebra I (DOE number: 1200310), while columns 3 and 4 report average characteristics for students taking English I (DOE number: 1001310). Balanced sample includes students with complete information in grades 9 to 10 between 2006 and 2009.

Table 6: Estimation Results: English I and Algebra I

Outcome:	Reading score grade 10			Math score grade 10			Math-Read
Course :	English I			Algebra I			Alg I-Eng I
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FLVS	0.311***	0.297***	0.068***	0.156***	0.147***	0.038**	
	[0.024]	[0.023]	[0.019]	[0.020]	[0.019]	[0.015]	
Dif in FLVS status							0.028
							[0.025]
Reading score grade 8			0.491***			0.095***	
			[0.002]			[0.002]	
Math score grade 8			0.213***			0.583***	
			[0.002]			[0.003]	
Dif in test scores							0.395***
							[0.003]
Student controls	√	√	√	√	√	√	
Year FE	√	√	√	√	√	√	
School FE		√	√		√	√	
Observations	183,220	183,220	183,220	144,440	144,440	144,440	96,346
R^2	0.204	0.260	0.528	0.219	0.288	0.548	0.134

* p<0.10, ** p<0.05, *** p<0.01

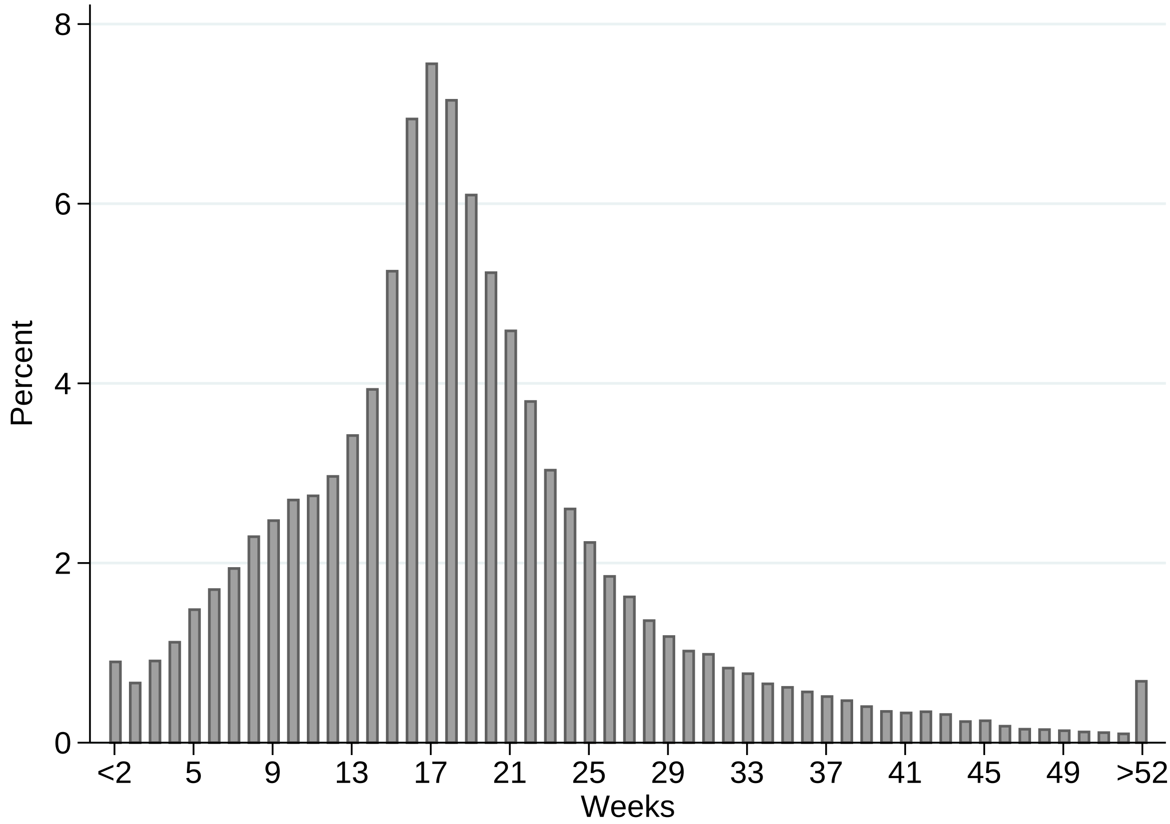
Note: Dependent variables are FCAT reading scores in grade 10 in columns 1 to 3 and FCAT math scores in grade 10 in columns 4 to 6. All scores are normalized to have mean zero and standard deviation one by year, grade. In column 7 the dependent variable is the difference between normalized 10th grade math and reading scores. Student controls include gender, age, race, limited English proficiency, free or reduced-price lunch, special education status. Balanced samples include students with complete information in grades 9 to 10 between 2006 and 2009. In columns 1 to 3 samples are further restricted to students taking English I, while samples in columns 4 to 6 include students taking Algebra I. In column 7 the sample includes students taking English I and Algebra I in grades 9 to 10 between 2006 and 2009. Robust standard errors in brackets.

Table 7: Subgroup Results: English I and Algebra I

Outcome: Course :	Reading score grade 10 English I (1)	Math score grade 10 Algebra I (2)	Diff test score grade 10 Diff Algebra I-English I (3)
Baseline	0.067***	0.046***	0.031
	[0.018]	[0.015]	[0.025]
Boys	0.060**	0.043**	–0.020
	[0.025]	[0.020]	[0.034]
White	0.049**	0.039**	0.014
	[0.022]	[0.015]	[0.028]
Asian	–0.112	–0.003	0.199
	[0.147]	[0.092]	[0.194]
Black	0.102**	0.047	0.097
	[0.048]	[0.046]	[0.069]
Hispanic	0.034	0.049	–0.020
	[0.049]	[0.042]	[0.063]
Other race	0.194*	0.051	0.095
	[0.102]	[0.060]	[0.123]
Math 8 above median	0.040**	0.021*	0.004
	[0.018]	[0.012]	[0.026]
Math 8 below median	0.062*	0.035	0.043
	[0.038]	[0.033]	[0.043]
Reading 8 above median	0.054***	0.024**	0.018
	[0.017]	[0.012]	[0.024]
Reading 8 below median	0.007	0.043	0.056
	[0.044]	[0.040]	[0.050]
Free- or reduced lunch	0.072**	0.043	–0.009
	[0.035]	[0.032]	[0.045]
Special ed	–0.061	0.053	0.014
	[0.082]	[0.083]	[0.101]
LEP	–0.002	0.015	–0.046
	[0.069]	[0.060]	[0.095]
Year 2009	0.090***	0.044**	0.033
	[0.026]	[0.019]	[0.030]
Year 2008	0.020	0.046	–0.057
	[0.036]	[0.036]	[0.057]
Year 2007	0.042	0.052	0.096
	[0.049]	[0.052]	[0.080]

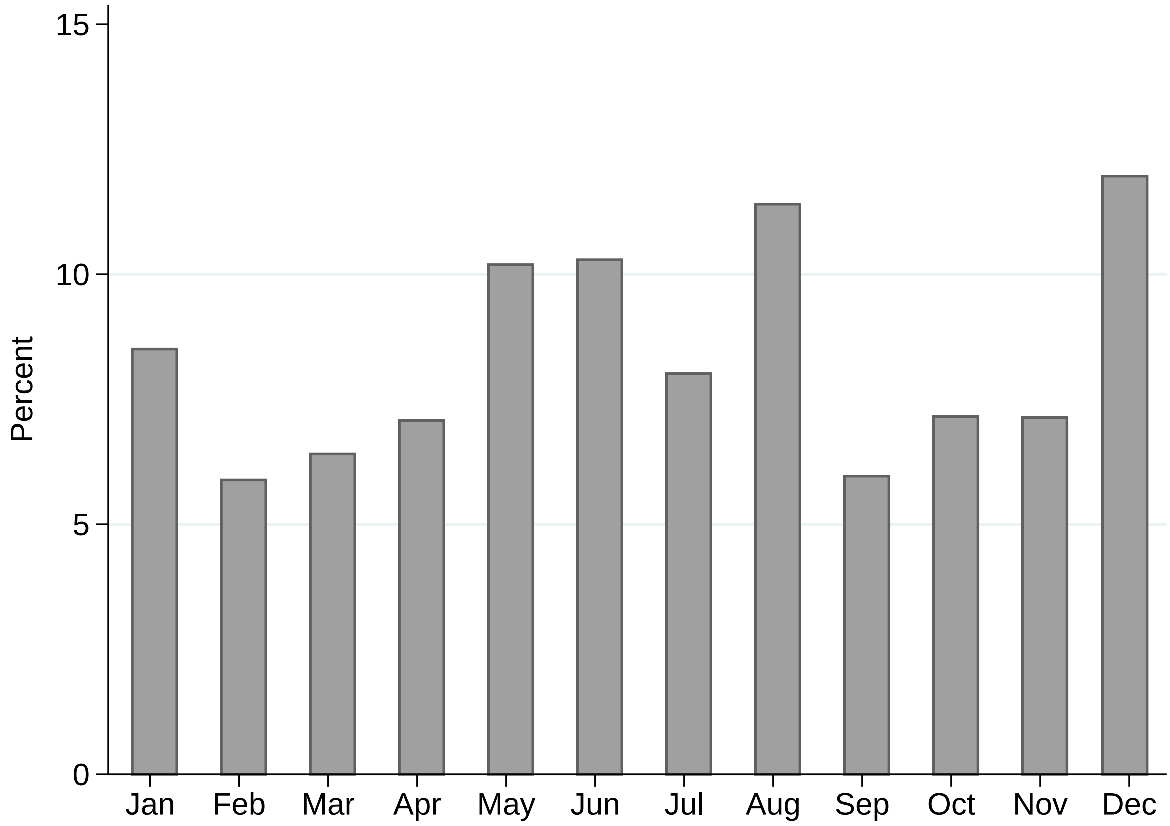
Note: Table reports estimates of the FLVS school effect for subgroups of students indicated in each row. Each estimate stems from a different regression. Regression specifications in column 1 correspond to the specification in column 3 of Table A-2, specifications in column 2 correspond to the specification in column 6 of Table A-2, and specifications in column 3 correspond to the specification in column 7 of Table A-2. Dependent variables are FCAT reading scores in grade 10 in column 1 and FCAT math scores in grade 10 in column 2. All scores are normalized to have mean zero and standard deviation one by year, grade. In column 3 the dependent variable is the difference between normalized 10th grade math and reading scores. Balanced sample includes students with complete information in grades 9 to 10 between 2006 and 2009. In column 1 samples are further restricted to students taking English I, while samples in column 2 include students taking Algebra I. In column 3 samples include students taking English I and Algebra I in grades 9 to 10 between 2006 and 2009. Robust standard errors in brackets.

Figure A-1: FLVS Course Duration in Weeks



Note: Based on all FLVS course records of students enrolled in grade 9, who completed a course between 2006 and 2009. Course duration is defined as the number of weeks between when a student was activated into a course and when he/she received their final grade.

Figure A-2: FLVS Course Completion by Month



Note: Based on all FLVS course records of students enrolled in grade 9, who completed a course between 2006 and 2009.

Table A-1: Robustness Check: Alternative Definitions of Treatment

Outcome:	Reading score grade 10	Math score grade 10	Diff test score grade 10
Course :	English I	Algebra I	Diff Algebra I-English I
	(1)	(2)	(3)
Baseline	0.068***	0.038**	0.028
	[0.019]	[0.015]	[0.025]
Ever FLVS	–0.029**	–0.043***	–0.008
	[0.012]	[0.014]	[0.015]
Only FLVS	0.084***	0.047***	0.042
	[0.020]	[0.016]	[0.027]

Note: Table reports estimates of the FLVS school effect for different definitions of the treatment status indicated in each row. The baseline specifications defines FLVS participation based on the first time a student takes a course. The specification in the second row considers also students as FLVS students who retake a course through FLVS after first taking the course at their local public school. In the third row students who take a course through FLVS as well as at their local public school at the same time (during the same school year) are not considered as FLVS students. Each estimate stems from a different regression. Regression specifications in column 1 correspond to the specification in column 3 of Table A-2, specifications in column 2 correspond to the specification in column 6 of Table A-2, and specifications in column 3 correspond to the specification in column 7 of Table A-2. Dependent variables are FCAT reading scores in grade 10 in column 1 and FCAT math scores in grade 10 in column 2. All scores are normalized to have mean zero and standard deviation one by year, grade. In column 3 the dependent variable is the difference between normalized 10th grade math and reading scores. Balanced sample includes students with complete information in grades 9 to 10 between 2006 and 2009. In column 1 samples are further restricted to students taking English I, while samples in column 2 include students taking Algebra I. In column 3 samples include students taking English I and Algebra I in grades 9 to 10 between 2006 and 2009. Robust standard errors in brackets.

Table A-2: Estimation Results: English I and Algebra I

Outcome:	Reading score grade 10			Math score grade 10			Math-Read
Course :	English I			Algebra I			Alg I-Eng I
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FLVS	0.310***	0.295***	0.067***	0.155***	0.145***	0.037**	
	[0.024]	[0.023]	[0.019]	[0.020]	[0.019]	[0.015]	
FLVS (retake)	–0.167***	–0.173***	–0.098***	–0.106***	–0.130***	–0.077***	
	[0.020]	[0.020]	[0.016]	[0.019]	[0.018]	[0.014]	
Dif in FLVS							0.025
							[0.025]
Dif in FLVS (retake)							–0.021
							[0.017]
Reading score grade 8			0.491***			0.095***	
			[0.002]			[0.002]	
Math score grade 8			0.213***			0.583***	
			[0.002]			[0.003]	
Dif in test scores							0.395***
							[0.003]
Student controls	√	√	√	√	√	√	
Year FE	√	√	√	√	√	√	
School FE		√	√		√	√	
Observations	183,220	183,220	183,220	144,440	144,440	144,440	96,346
R^2	0.204	0.260	0.528	0.220	0.288	0.548	0.134

* p<0.10, ** p<0.05, *** p<0.01

Note: Dependent variables are FCAT reading scores in grade 10 in columns 1 to 3 and FCAT math scores in grade 10 in columns 4 to 6. All scores are normalized to have mean zero and standard deviation one by year, grade. In column 7 the dependent variable is the difference between normalized 10th grade math and reading scores. Student controls include gender, age, race, limited English proficiency, free or reduced-price lunch, special education status. Balanced samples include students with complete information in grades 9 to 10 between 2006 and 2009. In columns 1 to 3 samples are further restricted to students taking English I, while samples in columns 4 to 6 include students taking Algebra I. In column 7 the sample includes students taking English I and Algebra I in grades 9 to 10 between 2006 and 2009. Robust standard errors in brackets.