NATIONAL
CENTER for ANALYSIS of LONGITUDINAL DATA in EDUCATION RESEARCH

TRACKING EVERY STUDENT'S LEARNING EVERY YEAR

A program of research by the American Institutes for Research with Duke University, Northwestern University, Stanford University, University of Missouri-Columbia, University of North Carolina at Chapel Hill, University of Texas at Dallas, and University of Washington

Learning-Mode Choice, Student Engagement, and Achievement Growth During the COVID-19 Pandemic

Jennifer Darling-Aduana
Henry T. Woodyard
Tim R. Sass
Sarah S. Barry

WORKING PAPER No. 260-0122 • January 2022

Learning-Mode Choice, Student Engagement, and Achievement Growth During the COVID-19 Pandemic

Jennifer Darling-Aduana
College of Education & Human Development
Georgia State University

Henry T. Woodyard
Andrew Young School of Policy Studies
Georgia State University

Tim R. Sass
Andrew Young School of Policy Studies
Georgia State University

Sarah S. Barry
Andrew Young School of Policy Studies
Georgia State University

Contents

Acknowledgments

This work is supported by the National Center for Analysis of Longitudinal Data in Education Research (CALDER), which is funded by a consortium of foundations. For more information about CALDER funders, see www.caldercenter.org/about-calder.

CALDER working papers have not undergone final formal review and should be cited as working papers. They are intended to encourage discussion and suggestions for revision before final publication. Any opinions, findings, and conclusions expressed in these papers are those of the authors and do not necessarily reflect the views of our funders or any school district partner. Any and all errors are solely the responsibility of the authors.

CALDER • American Institutes for Research
1400 Crystal Drive 10th Floor, Arlington, VA 22202
202-403-5796 • www.caldercenter.org

Learning-Mode Choice, Student Engagement, and Achievement Growth During the COVID-19 Pandemic

Jennifer Darling-Aduana, Henry T. Woodyard, Tim R. Sass, Sarah S. Barry

CALDER Working Paper No. 260-0122
January 2022

Abstract

The COVID-19 pandemic initially resulted in an unanticipated and near-universal shift from in-person to virtual instruction in spring 2020. During the 2020-21 school year, schools began to re-open and families were faced with decisions regarding the instructional mode for their children. We leverage administrative, survey, and virtual-learning data to examine the determinants of family learning-mode choice and the effects of virtual education on student engagement and academic achievement. Family preference for virtual (versus face-to-face) instruction was most highly associated with school-level infection rates and appeared relatively uniform within schools. We find that students who were assigned a higher proportion of instructional days in virtual mode experienced higher rates of attendance, but also negative student achievement growth compared to students who were assigned a higher proportion of instructional days in face-to-face mode. Students belonging to marginalized groups experienced more positive associations with attendance but were also more likely to experience lower student achievement growth when assigned a greater proportion of instructional days in virtual mode. Insights from this study can be used to better understand family preference as well as to target and refine virtual learning in a post-COVID-19 society.

1. Introduction

The COVID-19 pandemic presented a shock to the US educational system, resulting in a near universal shift to virtual learning in spring 2020 (Goldstein, Popescu, and Hannah-Jones 2020). Over half of all students continued to receive only virtual instruction into fall 2020 (Roche 2020). While many students began to transition back to in-person learning in school year (SY) 2020-21, roughly one in five schools remained fully remote for most of the school year (Kaufman and Diliberti 2021). There is mounting evidence that the pandemic and associated disruptions to families and schools have led to reductions in student achievement growth, particularly among students belonging to marginalized groups (Kuhfeld et al 2020; Curriculum Associates 2021a; Curriculum Associates 2021b; Curriculum Associates 2021c; Kogan and Lavertu 2021; Lewis et al 2021; Renaissance 2021a; Renaissance 2021b; Pier et al 2021). This has the potential to exacerbate educational opportunity gaps in both the short and long-term.

There are many possible explanations for the observed reduction in the rate of achievement growth, including economic disruptions due to parental job loss; student, family and teacher health problems caused by COVID-19; and mental trauma from isolation and stress. However, most important from an educational policy perspective are factors within the control of schools, the most notable of which are the decisions of whether and how to employ virtual instruction. We therefore focus our analysis on the impacts of instructional mode on student outcomes, including attendance, engagement, and achievement. The pandemic necessitated expanded familiarity, proficiency, and infrastructure for virtual learning in the United States, all which are likely to lead to expanded use of this learning mode in future years (Kaufman and Diliberti 2021; St. George et al 2021). The likely future expansion of virtual education makes understanding the inherent strengths and limitations of this instructional mode critical to supporting quality education in a post-pandemic educational system.

As a secondary interest, we also examined the rise of family choice and its influence within traditional, public schools during the COVID-19 pandemic (Flannery 2020; Patrick et al 2021; Strauss 2021). During fall 2020, many districts allowed families to choose between remaining virtual or attending face-to-face schooling. This expansion of choice during COVID-19 provides important insight into pandemic-specific circumstances that shaped students' educational experiences and their learning mode. Further, through an enhanced understanding of family preferences, educational institutions may be able to better identify and respond to families' evolving expectations and priorities in a post-pandemic society.

To address the related issues of instructional mode choice and the impacts of instructional mode on student outcomes, we seek to answer the following research questions: (1) What were families' preferences for virtual learning during the COVID-19 era when face-to-face options were offered? (2) How did student attendance, engagement, and learning vary by learning mode? And (3) to what extent were student characteristics associated with differential preferences, attendance, engagement, and learning? To do this we first develop an empirical model of family instructional choice, based on tradeoffs between student safety and achievement growth. We then estimate the model using detailed data from a large school district in a Southeastern state. To account for potential selection bias, we use the instructional-mode-choice model as the first stage of a two-stage-least squares estimator to produce unbiased estimates of the impact of instructional mode on student engagement, attendance, and achievement. We use these findings to identify for whom (and in what contexts) the form of virtual learning provided during the pandemic was beneficial for students. This included investigating the underlying instructional models (and programs) that appeared to support effective instruction in a virtual environment.

2. Equity in Virtual Learning Before, During, and After the COVID-19 Pandemic

Historically, family choice, digital access, and academic achievement have been closely intertwined with race and social class (Carter and Welner 2013; Heinrich et al 2020). For instance, students belonging to minoritized groups often have lower performance in school as evidenced by test scores and graduation rates that are less than those of their White counterparts due at least in part to structural inequities in society (Carter and Welner 2013; Gaias et al 2020; Jones, Fleming, and Williford 2020). Further, recent studies of virtual learning have shown differences by student and classroom characteristics, with educational inequities often appearing even more salient when examining the use of technology in education due to differential access to and experiences within the instructional environment (Besecker and Thomas 2020; Gonzales, Calarco, and Lynch 2020; Heinrich et al 2020; Kim and Padilla 2020).

Despite this, students belonging to marginalized groups were more likely to attend schools that remained fully virtual during the COVID-19 pandemic; these schools reported lower rates of curriculum coverage and instructional time nationally (Kaufman and Diliberti 2021). Further, early in the COVID-19 pandemic, the Los Angeles Unified School District found lower engagement among students identified as low-income, belonging to minoritized groups, English language learners (ELL) and students receiving special education services (SPED) (Besecker and Thomas 2020). Similarly, over half of all middle school students across six Tennessee districts reported challenges with motivation during fall 2020, with students identified as ELL and SPED reporting less frequent engagement in virtual learning (Patrick et al 2021). The same study found rates of chronic absenteeism rose substantially more for students identified as Black and Hispanic (by 80-165 percent) during the 2020-21 school year compared to students identified as White (which saw increases of 4-31 percent) (Patrick et al 2021). One reason for this finding might be that technology-facilitated learning often exacerbates existing disparities in academic engagement and achievement due to increased onus on students to self-regulate and direct their learning (Jacob et al 2016; Darling-Aduana, Good, and Heinrich 2019; Heinrich et al 2020). Based on this literature and the equity implications of differential access and experiences with virtual learning by subgroup, we purposefully examined outcome variation across income, racial-ethnic identity, gender, ELL, and SPED status.

At the same time, there may be benefits from virtual learning (through self-directed pacing, anytime-anywhere access, personalized just-in-time formative feedback etc.) that allow schools to better meet the educational needs of some students when compared to traditional models of face-to-face instruction (Jacob et al 2016; Darling-Aduana et al 2019; St. George et al 2021). Additionally, continuing virtual learning options for some students might result in spillover benefits for students who remain in face-to-face classrooms (i.e., Darling-Aduana 2019, 2021; Hart et al 2019). As virtual learning is likely to play an increased role in students' educational experiences in coming school years, continued study is merited to identify how to most effectively leverage virtual learning to achieve the goals of enhancing the educational experiences of all students, with an eye toward minimizing existing educational opportunity gaps.

2.1 Family Choice and Virtual Learning

In recent decades, alternatives to traditional brick-and-mortar public schools (e.g., physical charter schools, private school vouchers, and virtual schooling) have grown in popularity (Torre 2013). However, while a part of the larger school choice movement, virtual schools differ from other alternatives to traditional public schools. First, prior to the pandemic, many virtual schools, particularly those operated by local school districts and state education agencies, specialized in supplemental courses (i.e., advanced courses or credit-recovery coursework) and thus served as a complement to brick-and-mortar public schools (Digital Learning Collaborative 2019). Second, while voucher-supported private schools and brick-and-mortar charters primarily attracted students previously attending local neighborhood schools, full-time virtual schools are often seen as an alternative (or support) for homeschooling, as they provide a structured environment and/or curriculum for students at home. The pandemic has led to increased interest and discussions around this topic (Brenan 2020; Schultz 2020; Patrick et al 2021). Nationwide, 35 states have recently proposed legislation relating to charter schools and school vouchers showing that the school privatization movement may be stronger than ever, with numerous companies petitioning to have a piece of the growing market for private virtual learning (Flannery 2020; Strauss 2021).

When examining the impact of fully virtual schools specifically, most studies have identified large negative associations with student achievement in aggregate, despite being a better fit for some individual students (CREDO 2015; Woodworth et al 2015; Ahn and McEachin 2017; Bueno 2020; Fitzpatrick et al 2020; Molnar 2021). This may be due, at least in part, to the fact that pre-pandemic, virtual charter schools tended to serve more lower-performing students; virtual charter schools also tended to serve fewer ELL students, more female students, and more students identifying as White (CREDO 2015; Ahn and McEachen 2017; Bueno 2020; Molnar 2021). Specific to the COVID-19 pandemic, schools that began the school year virtual saw lower than normal enrollments, with slightly higher enrollment observed among private schools and districts with pre-established virtual schools (Flanders 2020; Kelly 2021).

2.2 The Current Study

Building on the prior literature related to equity and choice in virtual learning, this study examines preferences, engagement, and learning during the COVID-19 pandemic. More specifically, we examine which families opted into virtual learning; associations between virtual learning, student engagement, and achievement; and interactions between the learning environment and student characteristics, experience, and outcomes. While there is a large extant literature on school choice and student characteristics relating to academic achievement, there is much less evidence on virtual learning more generally and family preferences for virtual instruction more specifically. Accordingly, the findings from this study have the potential to establish baseline data on family expectations and student experiences with virtual learning, especially for students belonging to groups not often targeted for virtual learning prior to the current pandemic. This evidence is of critical importance as we move into a future that is likely to include greater demand for, and reliance on, virtual learning.

3. Methods

3.1 Setting

This study is part of a larger Research-Practice Partnership (RPP) where the research topics studied emerged through joint-agenda setting in response to shared priorities among district administrators and the research team. Our district partner is a large school district in the Southeast that serves a predominately minoritized, mixed-income student population across rural, urban, and suburban communities. In response to the COVID-19 pandemic, this district -

along with most other school districts in the United States - was forced to close their physical schools and switch to virtual learning. In the school district studied, all content was delivered virtually beginning in mid-March 2020, which included teachers delivering lectures and giving assignments online. The district reported that devices were made available to students who needed them to aid with virtual learning. In fall 2020, this district continued a virtual learning approach to start the semester but began to bring students back into the classroom as the semester progressed, first with a hybrid program and then a fully face-to-face learning option.

3.2 Data

Our partner school district provided administrative, virtual learning system, and family learning mode survey data for the fall 2020 semester. The administrative data we received from the school district included information on student learning mode by day, test scores, grades, attendance, racial-ethnic identity, English-learner status, free or reduced-price meal (FRPM) status, and special education status. Using the test score and sociodemographic variables provided, we estimate student achievement growth by calculating the difference between each student's fall and winter SY 2020-21 scores on the iReady formative assessments in math and reading. As such, the resulting student achievement growth measures captures test score gains in math and reading for the approximately five months from the beginning of the fall SY 2020-21 test administration through the test scores collected during the winter SY 2020-21 administration. We subsequently divided this growth measure by the number of weeks between when the student took fall and winter iReady tests during the 2020-21 school year to calculate weekly student achievement growth in each subject.

In addition, the district provided student-by-month usage information from two virtual learning-based platforms: Microsoft Teams and iReady. Teams is the learning management program used by the district during the study period through which students could access a plethora of online tools, programs, and software. The most common tools accessed through the platform included those facilitating synchronous meetings, assignments, communication, and the Microsoft suite (i.e., Word, PowerPoint, Excel). iReady is a self-contained learning and assessment tool that can also be used to support blended instruction and teacher-directed interventions that all students were required to use throughout the district.

This analysis focuses on fourth through eighth grade students in the district during the fall 2020 semester due to low reliability in lower grade test scores (Curriculum Associates 2021a; Sass and Goldring 2021). High school grades were excluded due to the use of a different formative assessment that could not be nationally normed or linked to the exam used in K-8.

3.3 Sample

Among students in the sample, 43 percent identified as Black, 25 percent as White, 17 percent as Hispanic, 12 percent as Asian, and three percent as "other" (see Table 1). In addition, 36 percent of students qualified for FRPM during SY 2019-20. We used FRPM status from the prior school year as information on FRPM status was not reported during SY 2020-21.

During fall 2020, students logged around 17 hours a week virtually on average. Students assigned the entire semester to virtual mode logged approximately 23 hours a week virtually compared to an average of 16 hours a week among students assigned to virtual mode for 50-99 percent of days, and an average of 14 hours a week among students assigned to virtual mode for fewer than 50 percent of days. The variability by proportion of days in virtual mode is to be expected, as students attending face-to-face could receive instruction outside the virtual learning system. However, we also know that many students who attended face-to-face continued to learn in classrooms that made use of the virtual learning system to deliver instruction, facilitate collaboration, and complete assignments at least part of the time. Thus, while not a true measure of instructional time for students attending face-to-face, this information provides a useful check (and potentially additional information) compared to solely examining days attended. It is important to note than even the average of 23 hours a week logged by students assigned to virtual mode one hundred percent of the time was still substantially lower than the over 30 hours a week students would have attended school during a pre-pandemic traditional school schedule.

Additionally, results from the family survey indicated that approximately 38 percent of families in the sample preferred to remain virtual when face-to-face instruction was offered. The surveys were administered prior to the beginning of fall 2020 with a smaller second wave administered later in the semester to families who did not complete the initial survey. Families' initial preference was strongly associated with subsequent instructional mode assignment. Among students who attended 100 percent of days virtually, 84 percent indicated a desire to remain virtual when face-to-face instruction was offered compared to only four percent of families who indicated the same desire among the students that attended fewer than 50 percent of days virtually. Discrepancies between initial preference and subsequent attendance patterns are likely due in large part to school (or classroom closures) triggered by neighborhood infections. Regardless of preference, however, due to the first portion of the school year beginning entirely virtually, the modal student attended 69 percent of the fall 2020 semester virtually.

The proportion of days assigned to virtual mode was also influenced by the proportion of positive cases and quarantines within each students' school. On average, the student-weighted modal school quarantine rate during fall 2020 was approximately nine percent. In other words, on average, nine percent of students at any given school were required to learn virtually at one point during the semester due to a potential COVID-19 exposure.

3.4 Empirical Strategy

Family preference to have their child learn virtually is a decision comprised of many factors. Equation 1 conceptualizes the choice for student i to engage in virtual learning at time t in school s. We postulate that this choice is a function of the expected achievement growth $(A_{ist+1} - A_{ist})$ and health $(H_{ist+1} - H_{ist})$ a student will experience conditional on the virtual learning choice in the current period, and we assume that families (including the students themselves) have positive preferences for both achievement and health. In other words, families would be more likely to have their children engage in virtual learning if they expect it to increase achievement growth and/or decrease the chance of contracting COVID-19.[1]

Furthermore, this decision is also a function of time-invariant student characteristics (x_i) like comorbidities or learning needs (such as likelihood the student will benefit from face-to-face accommodations due to not fully developed self-regulation skills, emerging English language proficiency, special education needs etc.); time-invariant family preferences (f_i), which may be shaped by factors such as familial resources, constraints, and political beliefs; and school characteristics (c_s) such as digital infrastructure and COVID-19 cases. Our empirical analyses isolate each of these factors in turn. Despite the time-series element of the learning mode choice function (equation (1)), our primary empirical specifications are estimated as cross-sections, given that structural limitations imposed by the district resulted in minimal week-to-week variation in instructional mode for a student.

$$P(V_{ist} = 1) = f[E(A_{ist+1}, H_{ist+1} | V_{ist}), x_i, f_i, c_s, \varepsilon_{ist}] \tag{1}$$

[1] Ideally, families would have been able to make an educated guess about expected differences in learning based on test score growth between winter and spring 2020 when the district transitioned to virtual learning. However, district test policy resulted in only approximately two percent of students taking spring assessments. For this reason, families were forced to rely on potentially weaker signals to determine expected differences in learning, and we were not able to estimate the impact of spring 2020 test score growth on familial learning mode preferences.

Understanding family preference. To examine family learning mode preference during COVID-19, we first estimated associations between student and school characteristics and preference for continuing virtual learning when face-to-face instruction was initially offered during the summer of 2020. Using learning mode choice data from the family survey, we estimated a linear probability model predicting opting on the family survey to remain virtual when face-to-face instruction was offered (y_{is}), as shown in Equation (2) below.

$$y_{is} = \beta_0 + \boldsymbol{X_i\beta_1} + \boldsymbol{A_{is}\beta_2} + \varepsilon_{is} \tag{2}$$

In reference to our model of the virtual learning decision (Equation 1), this model estimates the roles of student (x_i) and school (c_s) characteristics. At the student level, we controlled for grade-level, gender, race, disability status, English learner status, and days enrolled ($\boldsymbol{X_i\beta_1}$). Other demographic information was not collected during SY 2020-21, and so we used SY 2019-20 data instead to control for prior-year FRPM, homelessness, disciplinary referrals, suspension, and an indicator variable for whether the student was enrolled in the district during the prior year. Although captured at the student-level, many of these covariates also provide insight into family characteristics likely to influence fixed preferences (f_i). For instance, students who qualified for FRPM likely faced greater familial constraints when it came to providing alternative learning opportunities at home (virtually). Similarly, student race provided insights into likely familial political affiliation in the district studied, with national surveys finding that families identifying as Democrats (versus Republican) were substantially more likely to prefer remaining virtual. At the school level ($\boldsymbol{A_{is}\beta_2}$), we controlled for the region within the district in which the school was located,[2] school-level proportion of COVID-19 positive cases and the proportion of students quarantined at the school, as well as the mean proportion of days assigned to virtual mode across

[2] Each region in the district studied had distinct socio-demographic characteristics.

all students attending the same school during fall 2020. We used robust standard errors clustered at the school level in all analyses.

Understanding student engagement and outcomes. After investigating patterns in family learning mode preference, we set out to determine how much student attendance, engagement (i.e., weekly hours logged virtually), and learning (i.e., average weekly student achievement growth) varied by instructional mode. For our base model, we estimated the same covariate-rich OLS regression model described above with the proportion of days assigned to virtual mode during fall 2020[3] included as the independent variable ($prop\_virtual_{is}$), as shown in Equation 3. We ran separate models examining each of the outcome variables described above as dependent variables in the model.

$$y_{is} = \beta_0 + \beta_1 prop\_virtual_{is} + \boldsymbol{X_i}\boldsymbol{\beta_1} + \boldsymbol{A_{is}}\boldsymbol{\beta_2} + \varepsilon_{is} \tag{3}$$

School fixed effect approach. Next, we estimated models (see Equation 4) comparing each student to other students at the same school (versus all students within the district) by adding school fixed effects (δ_s) in place of the time-invariant school-level covariates in Equation 3.

$$y_{is} = \beta_0 + \beta_1 prop\_virtual_{is} + \boldsymbol{X_i}\boldsymbol{\beta_1} + \delta_s + \varepsilon_{is} \tag{4}$$

This approach allowed us to remove all endogenous variation associated with school characteristics that were fixed over time within the school. For instance, this approach removed variation due to school-level resources, support, and leadership as well as any consistent neighborhood or student characteristics (including aggregate infection rates) during the study

[3] Given the discrete decision points during the semester, this variable was not normally distributed. To account for this, we estimated alternative models that included quantile indicators in the regression. Each quartile centered around different spikes in the distribution. As results were qualitatively similar between the estimates produced by these models and linear specification (with one exception explained in greater detail below), we reported only estimates from the more easily interpretable linear specification.

period. Further, it removed variance associated with school characteristics that affect the virtual learning decision for all students in the school, as given by c_s in Equation 1. Thus, by examining differences within the same school, we controlled for many of the structural differences in schools – and the neighborhoods they served. Nonetheless, these estimates should still be interpreted as descriptive, rather than causal, as the proportion of days assigned to virtual mode could still be correlated with unobserved time-varying factors associated with student outcomes.

Despite differential attendance rates being a part of the impact of instructional mode and thus appropriately included when evaluating impacts on achievement, we were also interested in measuring what proportion of any overall association was due to each mechanism. To disentangle these elements, we estimated the above model including days attended as an additional covariate.[4] To the extent that any differential outcomes persisted (or emerged) after conditioning on days attended, we could be more confident that those associations were due to variation in rates of learning per day (versus variation in attendance) by mode. Conversely, if any differential outcomes became non-significant after conditioning on days attended, we would expect that previously identified associations were more likely due to variation in attendance (versus learning per day) by instructional mode. Lastly, we added the time logged by virtual program (i.e., synchronous meetings, Microsoft Word, iReady) to the version of Equation 4 that conditioned on days attended to ascertain whether learning varied by time logged in each virtual program.

Instrumental variable approach. We next estimated a 2SLS instrumental variables (IV) model to mitigate potential bias from unmeasured factors that might drive both instructional

[4] An important caveat to the inclusion of days attended is that for a period in fall of SY 2020-21, the district measured attendance differently in different learning modes. During this period, virtual attendance was based on log data versus teacher-taken attendance in homeroom.

mode preference and student outcomes (Angrist and Pischke 2009). Ultimately, we are interested in variance associated with differences in the school-level decisions about how to implement virtual instruction (i.e., digital program used, professional development provided on teaching virtually, technology-specific infrastructure and assistance) and differential experiences among students in neighborhoods served by different schools. By excluding school fixed effects and instead leveraging excluded variables to remove bias from our estimates, we were able to examine both within and across-school trends. Examining estimates in conjunction with those from models employing a school fixed effect strategy, therefore, can help parse out sources of variance, while also serving as a sensitivity test.

To implement our IV approach, the first-stage equation predicted the proportion of days assigned to virtual mode during fall 2020 based on a vector of the same student (χ) and school characteristics (A) included in the OLS regression models. The 2SLS model (Equation 5) leveraged as excluded instruments differences in family preference for remaining virtual when face-to-face instruction resumed as well as plans to use the school bus for transportation or walk to school, which provided insight into familial resources and confidence in being in close contact with students outside the students' own class.

$$prop\_virtual_{is} = \gamma_0 + \gamma_1 preference_{is} + \gamma_2 bus_{is} + \boldsymbol{X_i \gamma_1} + \boldsymbol{A_{is} \gamma_2} + r \tag{5}$$

In the models predicting attendance and engagement (weekly hours logged virtually), we removed learning mode preference as an excluded instrument as the Sargan overidentification test indicated that learning mode preference indicated on the family survey was correlated with the error term and thus should not be excluded from the estimated equation. We then used the predicted value of the proportion of days assigned to virtual mode generated from each first stage model to predict each dependent variable of interest, controlling for the same vectors of student and school characteristics, as shown in Equation 6 below.

$$y_{is} = \beta_0 + \beta_1 \widehat{prop\_virtual}_{is} + \boldsymbol{X_i \beta_1} + \boldsymbol{A_{is} \beta_2} + \varepsilon_{is} \tag{6}$$

By leveraging learning mode and transportation preferences indicated on the family survey, we aimed to remove endogenous variation related to subsequent COVID-19-related incidents and circumstances that might also have influence students' attendance, engagement, and achievement. Equation 1 indicated that the virtual learning decision was a function of several factors that could also affect a student's achievement growth, like health, student characteristics, and school characteristics. The goal of using these excluded variables was to remove bias not associated with family preference, although we acknowledge that family preference might still be shaped by confounding characteristics and the differential structural impacts of COVID-19. Consistency between estimates produced by the instrumental variable and OLS regression models would minimize concern regarding many (although not all) potential sources of bias in the base model.

Post-estimation tests, summarized in Table 2, demonstrated that the excluded variables predicted assignment into treatment. More specifically, the first-stage statistics demonstrate that the excluded variables explained a sizable proportion of variance in the proportion of days assigned to virtual mode. The Sargan Overidentification test examined the null hypothesis that the excluded instruments should be included in Equation 6 and thus would not represent valid instruments.[5] In all but one case, we fail to reject the null that the overidentifying restrictions are valid. For the model predicting total weekly hours logged virtually we reject the null at better

[5] Although all estimated models included robust standard errors clustered at the school level, the Sargan Overidentification test is incompatible with clustered standard errors. So, for the purpose of this test, we only used robust standard errors without clustering.

than a 98 percent confidence level. For this reason, we are less confident in, and place less weight on, estimates produced from the 2SLS models predicting time logged virtually.[6]

Student fixed effect approach. As our last sensitivity test, we employed a student-fixed-effect approach that examines month-to-month variation in days attended and time logged virtually among students who switched from or to fully virtual learning during the fall 2020 semester. Because we could only measure student achievement growth at the semester level, we could not estimate achievement models with student fixed effects.

The use of a student fixed effect approach - as shown in Equation 7 - mitigated potential bias from endogenous learning mode choice by accounting for time-invariant characteristics of a student (α_i) and, by extension, their family background that may be correlated with both learning mode choice and student outcomes. Likewise, the month fixed effect (δ_t) controlled for changes common to all students in each month.

$$y_{it} = \beta_0 + \beta_1 prop\_virtual_{it} + + \boldsymbol{X_{it}\beta_1} + \alpha_i + \delta_t + \varepsilon_{it} \tag{7}$$

We also controlled for the all covariates included in prior models where there was month-to-month variation ($\boldsymbol{X_{it}\beta_1}$), including the number of days each student was expected to attend school each month (i.e., the total number of instructional days in the month) as well as the proportion of positive cases and students quarantined in each school by month. If these estimates (that are only examining within-student changes in engagement) are qualitatively similar with estimates from our other models, we can be more confident that our main cross-sectional models were not biased by any unobserved time-invariant factors. Consistency of estimates across each of these separate models would provide evidence that our estimates were unlikely to be biased by

[6] We also conducted a Hausman test that showed that the difference between the OLS and 2SLS estimates was statistically significant, indicating bias in the OLS estimates of the proportion of days assigned to virtual mode.

remaining confounders, while inconsistent estimates would provide key insights into potential remaining sources of bias that should be considered.

Heterogeneous effects. Lastly, we examined the extent to which student characteristics were associated with differential responses to learning mode. To do so, we separately estimate associations between the proportion of days assigned to virtual mode and achievement, attendance, and engagement after limiting the analytic sample to each subgroup of interest. These associations were separately estimated using the school fixed effect and 2SLS models described above by gender race/ethnicity, special education status, ELL status and FRPM status.

4. Findings

4.1 Learning Mode Preference

We first examined the relationship between preference for virtual schooling when face-to-face schooling was offered (as indicated on the family survey) and student and school characteristics. Overall, we found that a student's preference for remaining virtual when face-to-face was offered had a reasonably strong association with several of our covariates (see Table 3). We identified a large, significant relationship between family preference and the school-level proportion of days assigned to virtual mode (β=0.612, ρ<0.001). Students who attended a school where 75 (versus 25) percent of classmates attended virtually were 31 percent more likely to remain virtual themselves, which likely reflects some combination of peer effects and neighborhood characteristics. We also identified a large, significant association between student's preference for remaining virtual and the proportion of positive cases in the students' school (β=1.797, ρ<0.01). The families of students attending schools with the modal proportion of positive cases (equivalent to approximately one percent of enrollment) were around two percent more likely to prefer virtual learning when face-to-face instruction was offered than families of students attending schools with no positive cases.

Furthermore, we identified clear differences in preference for virtual learning based on sociodemographic characteristics. Students who identified as Black were 10 percentage points more likely to want to remain in virtual learning mode, holding all else equal, while students who identified as ELL were five percentage points *less* likely to want to remain virtual. The latter might indicate that communicating and comprehending language on a virtual learning platform is particularly difficult for students with still-developing English skills. Finally, students who received special education services as well as those with past disciplinary infractions were slightly less likely to prefer to remain virtual, whereas students identified as female and qualifying for FRPM were slightly more likely to prefer to remain virtual. Lastly, students attending schools in the more affluent region of the district were eight percent less likely to prefer virtual learning when face-to-face instruction was offered, which might be in response to lower infection rates and/or a higher prevalence of families identifying as Republican in this region.

4.2 Engagement and Achievement

Estimates of the relationship between the proportion of days assigned to virtual mode and achievement growth, days of school attended, and weekly hours logged on virtual platforms are presented in Table 4. We found generally negative associations between the proportion of days a student assigned to virtual mode and scale-score growth per week in math and reading, although only some model specifications identified significant, negative associations.[7] For instance, we

[7] We were concerned that associations with student achievement growth might be a function of which students took assessments during the study period. To test the likelihood that differential rates of test taking might be biasing estimates, we predicted whether students had student achievement growth scores. In the base model, we identified a

found that students achieved 0.20 scale score points lower weekly reading growth when estimating models with school fixed effects. This difference translates into an effect size of -0.08, which is considered moderate in magnitude compared to studies employing Randomized Control Trials (RCTs) of education interventions with standardized achievement outcomes (Kraft, 2020).[8] In math, we identified a significant, negative association between the proportion of days students were assigned to virtual learning and weekly test score growth only after conditioning on days of school attended, which further increased in magnitude when conditioning on virtual program usage, indicating that not just how much time was spent online, but how the time was used matters. Estimates remain comparable in direction and magnitude (if not significance) between the models employing OLS, school fixed effects, and IV approaches.[9]

When examining associations with days of school attended, we found that students attending entirely virtually (versus students who attended 50 percent of days face-to-face), attended 1.5 to 2 more days of school a semester depending on model specification. When examining within-student variation from month-to-month, students attended approximately half a day more school on average when they switched from being assigned to attend school entirely virtually from face-to-face mode. However, it should be noted that when examining associations with hours logged when using categorical variables to measure each quartile of the proportion of days assigned to virtual mode, the highest associations were observed among students in the fourth quartile (assigned to virtual mode for 90-100 percent of days) followed by students in the

significant, positive association (β=0.057, $\rho < 0.001$) between proportion of days assigned to virtual mode and not having student achievement growth data. However, this association was no longer significant after controlling for school fixed effects.

[8] However, despite the comparable effect size observed in our study, this should be placed in the context that correlational studies (such as this one) often report larger magnitude associations than RCTs (Kraft, 2020).

[9] Additionally, we provide evidence in Appendix A that estimates are consistent (if smaller in magnitude) when substituting the primary excluded instrument (family preference for virtual learning when face-to-face instruction was offered) entirely for the proportion of days assigned to virtual mode.

first quartile (assigned to virtual mode for fewer than 40 percent of days). Similarly, students attending entirely virtually logged 8.5 to 10.5 more weekly hours virtually than students who attended 50 percent of days face-to-face according to the same OLS and 2SLS models. When examining within-student changes, the modal student who switched from attending school entirely virtually to entirely face-to-face, logged 17 more hours virtually per month. The comparability of estimates across model specifications demonstrates robustness to the varied assumptions of each model, minimizing concern regarding the influence of substantial omitted variable or selection bias in any one of these estimates.

To provide insight on potential mechanisms, we reported associations between virtual learning usage by program and weekly differentials in student achievement growth. These estimates, shown in Table 5, are identical to those reported in the "+Usage" columns of Table 4. The separate table was created to share coefficients for additional covariates. When examining associations with specific virtual learning program and applications, we generally found higher rates of student achievement growth the more time students logged in programs (apart from a few non-significant negative associations). Most notably, each additional hour per week that students spent on the iReady platform was associated with scoring approximately 0.3 scale score points higher in math (and 0.5 scale score points higher in reading) per week. Those gains translate into effect sizes of 0.19 in each math and reading, which are considered moderate to large in magnitude within educational research (Kraft, 2020). Although this should be interpreted cautiously, as at least part of the strength of the relationship is likely due to high alignment between content covered in iReady and the iReady-developed standardized tests used to measure learning compounded by the identification of larger effect sizes in correlational (versus causal) studies (Kraft, 2020). Across subjects, applications that supported visualizations such as PDF viewer and image apps were also significantly associated with positive gains.

Beyond aggregate associations, it is likely that the efficacy of virtual learning varied based on student characteristics associated with structural inequities that both proceeded and were exacerbated by COVID-19. To this end, we also examine subgroup variation by estimating models limited to only students belonging to each subgroup of interest, as shown in Table 6. We estimated four models when examining student achievement growth, our base model with school fixed effects, a second model accounting for days attended also with school fixed effects, our 2SLS model, and our 2SLS model accounting for days attended. As expected, based on findings from the full sample, OLS and 2SLS estimates are qualitatively similar with minimal variation depending on whether we controlled for days attended virtually.

Across subgroups, students assigned to a higher proportion of days in virtual mode attended more days of school and logged more weekly instructional hours virtually. Students who identified as Black and qualified for FRPM experienced the largest positive associations between the proportion of days assigned to virtual mode and days of school attended. When examining associations with math and reading test score growth, the identification of significant, negative associations with proportion of days assigned to virtual mode appear to be concentrated primarily among students identified as male, Black, and FRPM.

4.3 Limitations

Throughout our analysis we strove to mitigate potential bias in a variety of ways, including through the inclusion of controls for observable student characteristics, the use of school, grade and student fixed effects, and the application of two-stage-least-squares estimation techniques. Nonetheless, there remain potential threats to the reliability of our estimates. For example, the pandemic exacerbated existing inequities throughout society, including within the education system. Technology usage and achievement outcomes are likely associated with differences in family characteristics and resources, including but not limited to, the ability for families to provide (or pay for) supervision and academic support during the school day. Similarly, we cannot fully account for differences in students' motivation or self-regulation that may affect both the activities that teachers assigned to their students and student outcomes. However, the fact that a wide variety of empirical models yielded similar results suggests that any omitted variable bias is likely small.

Another possible concern is the representativeness of the analytic sample and external validity. While the district studied is diverse and overall achievement is close to nationwide averages, our study is based on a single district and may not extrapolate to other settings. Further, while our sample should, theoretically, contain all fourth through eighth grade students in the participating school district, certain parts of our analyses include only a subset of students for whom we have key data, such as responses to the family survey used to control for family preferences or student test scores used to measure student achievement growth.

5. Discussion

The COVID-19 pandemic necessitated widespread changes in the way that students engaged in education, particularly a shift from face-to-face to virtual instruction. Such a shift has not been previously seen on this scale, and because of this, knowledge is scarce regarding implementation, outcomes, and preferences for virtual learning at this magnitude. Our analysis uncovered notable variation in both the preferences for and benefits of virtual learning among the students attending the school district studied.

We used two metrics to measure preferences for virtual learning. The first was a survey administered to families asking whether they would prefer virtual or face-to-face learning for their child, and the second was the proportion of days assigned to virtual mode. This second measure reflected initial family preference as expressed on the survey as well as forced assignment to virtual mode (i.e., in response to being quarantined). Our results indicated that the largest correlate of a family's virtual preference was associated with COVID-19 infection rates and the virtual preferences of other families at their school. It is unclear to what extent within-school associations were due to peer effects, variation in local COVID-19 infection rates, and/or correlated familial characteristics within neighborhoods. Regardless, it implies that much of the variation in family preference for virtual learning occurred between, rather than within, schools. We also found that students identified as Black or female were 10 and one percent, respectively, more likely to prefer virtual instruction than their non-Black or male peers, while students residing in the more affluent region of the district, receiving ELL or SPED services, or with prior behavioral referrals were each two to eight percent less likely to prefer virtual instruction.

When examining student attendance and weekly hours logged virtually by mode, we identified generally positive associations with the proportion of days assigned to virtual mode. Specifically, students who attended 100 (versus 50) percent of days virtually attended 1.5 to 2 more day of school during the fall semester and logged between 8.5 to 10.5 more hours a week virtually (depending on model specification). Findings were comparable when estimating models examining month-to-month within-student changes. While at least some of this increased time might be a result of students attending face-to-face receiving some instruction outside of the virtual learning system used by the district, the discrepancy in time logged nonetheless supports the finding of additional attendance among students assigned to a higher proportion of days in virtual mode and reassures the reader that this attendance was unlike to be associated with fewer instructional hours per day. However, it should be also noted that part of the positive association with proportion of days assigned to virtual mode might be due to the inherent stress or challenges to learning in a face-to-face environment during COVID-19 restrictions, including increased likelihood of infection and quarantine as well as many teachers being expected to continue accommodating virtual learners even once they had students back physically in their classrooms.

In contrast, we identified a significant, negative associations between student achievement growth and the proportion of days assigned to virtual mode. The negative association in math (but not reading) only appeared after conditioning on the generally higher rates of attendance observed among students assigned to a greater proportion of days virtually. These findings are consistent with those identified in contemporaneous research within different educational settings, which have generally found null or negative associations between virtual instruction and student learning (Kuhfeld et al 2020; Curriculum Associates 2021a; Kogan and Lavertu 2021; Renaissance 2021; Pier et al 2021). When examining associations between time logged in specific virtual applications and student achievement growth, time logged in iReady was the most strongly associated with student achievement growth, potentially due to the highly structured, standards targeted, and personalized practice facilitated by the system.

Beyond average treatment effects, we also observed some notable variation across subgroups. Being assigned to a greater proportion of days in virtual mode was associated with the largest increases in days attended among students who identified as Black or received FRPM. These findings stand in contradiction to research conducted earlier during the COVID-19 pandemic that identified lower rates of engagement and assignment completion among students belonging to marginalized groups (Besecker and Thomas 2020; Thompson 2021). One potential reason for divergent findings might be that earlier in the pandemic there was evidence that differential access to digital devices and infrastructure (i.e., the digital divide) resulted in limited access to educational content and experiences for many students belonging to marginalized groups (Gonzales, Calarco, and Lynch 2020; Kim and Padilla 2020). Alternatively, our partner district may have provided more equitable access to devices during the entire pandemic (in part because they had been doing some virtual instruction pre-pandemic and already had devices in the hands of students). However, the finding that students identified as Black or received FRPM attended more school the greater the proportion of days assigned to virtual mode provides evidence that district attempts to mitigate this divide by providing access to devices and broadband were likely largely successful during the fall 2020 semester. Although particularly salient in the COVID-19 era, the greater ease of school attendance virtual learning affords is a key advantage to the mode, particular for students with multiple competing demands on their time and who possess sufficient self-regulation (or family regulation) at home to keep up with virtual coursework (Jacob et al 2016; Darling-Aduana 2019; Heinrich et al 2019; St. George et al 2021).

In contrast, when examining associations with student achievement growth by subgroup, students identified as male, Black, and FRPL-eligible were most likely to experience significantly lower achievement growth the greater the proportion of days assigned to virtual mode. These discrepancies likely reflect differences in family resources at home which became exacerbated by the virtual environment. From an equity perspective, it is concerning that many of the students who made the smallest gains when assigned to a higher proportion of days in virtual mode belonged to marginalized groups, which has the potential to exacerbate existing educational opportunity gaps.

Interestingly, when examining preference for virtual learning in conjunction with associated student achievement growth, we see that greater preference for virtual learning for a given group did not consistently align with the sign of our measured efficacy. Although preferences for instructional mode could be shaped by a host of factors including health and political concerns, prior research indicated that families primarily optimize with respect to their child's educational outcomes although non-academic factors, such as the availability of extracurricular activities also play a large role in school choice (Kleitz et al 2000; VanderHoff 2008; Lincove, Cowen, and Imbrogno 2018; Prieto et al 2019). In contrast to findings from the broader family choice literature, the greater preference among students identified as Black to remain virtual was associated with higher rates of attendance but negative associations with student achievement growth. One plausible explanation for the greater preference for virtual learning among this group might be that the families of students identified as Black were forced to make decisions based on more immediate health (versus academic) concerns (Golann, Debs, and Weiss 2019), due to greater likelihood of knowing someone who died from COVID-19 (The COVID Tracking Project 2021). Similarly, while students who received FRPM tended to prefer virtual learning, we observed lower rates of weekly student achievement growth across subjects the larger the proportion of days assigned to virtual mode for these students.

This calls to mind broader questions about the ways in which families navigated the difficult and multifaceted choice of instructional mode during the COVID-19 pandemic. The strong relationship between a student's preferences for virtual learning and the preferences of their schoolmates, combined with the variety of responses to virtual learning we measured by subgroup, could suggest several elements at play. The first is that family preferences were less shaped by their child's educational needs than we expected, compared to other preferences like health, or that those preferences were not expressed. The second is that families were attempting to optimize their child's education modality with imperfect information. Perhaps families had distorted perceptions regarding the benefits of virtual (or face-to-face) learning for their child; on the other hand, it could be the case that they did not foresee the difficulties virtual (or face-to-face) learning could entail, whether that be language, technology, motivation, or otherwise. Another explanation for the within-school correlation of modality choice could be beliefs about the ability of their school to successfully carry out virtual instruction.

6. Conclusion

The COVID-19 pandemic has brought about widespread changes in how students and families engage with the education system and has necessitated a shift to virtual learning on a scale that has not been seen previously. During fall 2020, students and their families had to choose between face-to-face and virtual learning, which had the potential to lead to more personalized educational experiences and/or exacerbate educational inequity. Given the novelty of full-time virtual instruction, there is little prior research on the determinants and effects of the choice of instructional mode. We found significant variation in preference for virtual learning among students in our sample, and we demonstrated that observable characteristics of students and schools were strong predictors of this choice. Some of the strongest correlate of a student's virtual learning decision were school-level infection rates and the decisions made by other students at their school. In general, it is not clear that the students most likely to benefit academically from virtual learning were the students most likely to opt-in to virtual learning when face-to-face instruction was offered. Instead, other factors such as health or political considerations (or imperfect information) appeared more likely influences.

Nonetheless, under the confines of crisis-schooling studied, students appeared on average to attend more school and log more virtual hours the higher the proportion of days they were assigned to attend school virtually. Further, students belonging to advantaged groups achieved similar rates of student achievement growth regardless of instructional mode despite negative associations with achievement growth identified among students identified as male, Black, or receiving FRPM. These findings suggest that virtual learning as implemented during fall 2020 in the district studied might be most viable as an alternative learning mode for students identified as female and/or belonging to historically advantaged groups. In turn, this might allow for spillover benefits for students who remain in a more comprehensive, traditional, face-to-face instructional environment (Darling-Aduana 2019, 2021; Hart et al 2019). Further, continuing to offer virtual learning options where feasible might be a helpful option to provide students likely to benefit from anytime, anywhere access (i.e., students who possess sufficient self-regulation skills and/or out-of-school resources to monitor their own engagement) (Darling-Aduana 2019).

Although the state of virtual learning is likely to continue evolving and society will (hopefully) soon move past the current era of COVID-19 triggered crisis-schooling, this study provides a nuanced look at preferences, engagement, and achievement during this unique era. Certain outcomes (most notably attendance) and subgroup-specific trends demonstrate the potential for virtual learning to enhance educational experiences when appropriately targeted to students most likely to benefit, while also expanding opportunities for choice within educational institutions. However, families may need additional assistance navigating and understanding the ramifications of these new educational modes, while policymakers and practitioners must continue to investigate critically and refine educational offerings to ensure equitable, quality educational opportunities for all students.

References

Ahn, J., & McEachin, A. (2017). Student Enrollment Patterns and Achievement in Ohio's Online Charter Schools. *Educational Researcher, 46*(1), 44–57. doi:10.3102/0013189X17692999

Angrist, J. D., & Pischke, J. S. (2009). *Mostly harmless econometrics.* Princeton University Press.

Besecker, M., & Thomas, A. (2020). Student engagement online during school facilities closures: An analysis of students' Schoolology activity from March 16 to May 22, 2020. *Los Angeles Unified School District.* Retrieved from http://laschoolboard.org/sites/default/files/IAU%20Report%202020%200707%20-%20Student%20Engagement%20Online%20During%20Closures.pdf

Brenan, M. (2020, August 25). K-12 parents' satisfaction with child's education slips. *Gallup.* https://news.gallup.com/poll/317852/parents-satisfaction-child-education-slips.aspx

Carter, P. L., & Welner, K. G. (Eds.). (2013). *Closing the opportunity gap: What America must do to give every child an even chance.* Oxford University Press.

Center for Research on Educational Outcomes (CREDO). (2015). *Online charter school study.* Stanford, CA: Stanford University. Retrieved from https://credo.stanford.edu/sites/g/files/sbiybj6481/f/online_charter_study_final.pdf

Curriculum Associates. (2021a). What we've learned about unfinished learning: Insights from midyear diagnostic assessments. Retrieved from https://www.curriculumassociates.com/-/media/mainsite/files/i-ready/iready-understanding-student-needs-paper-winter-results-2021.pdf

Curriculum Associates. (2021b). Academic achievement at the end of the 2020-2021 School Year: Insights after more than a year of disrupted teaching and learning. Retrieved from https://www.curriculumassociates.com/-/media/mainsite/files/i-ready/iready-understanding-student-needs-paper-spring-results-2021.pdf

Curriculum Associates. (2021c). Understanding student learning: Insights from Fall 2021. Retrieved from https://www.curriculumassociates.com/-/media/mainsite/files/i-ready/iready-understanding-student-learning-paper-fall-results-2021.pdf

Darling-Aduana, J. (2019). Behavioral engagement patterns among high school students enrolled in online courses. *AERA Open, 5*(4). doi:10.1177/2332858419887736

Darling-Aduana, J. (2021). High school student experiences and outcomes in online courses: Implications for educational equity and the future of learning. Paper presented at the annual meeting of the *American Educational Research Association*.

Darling-Aduana, J., Good, A., & Heinrich, C. J. (2019). Mapping the inequity implications of help-seeking in online credit-recovery classrooms. *Teachers College Record, 121*(11), 1-40.

Digital Learning Collaborative. (2019). Snapshot 2019: A review of K-12 online, blended, and digital learning. Retrieved from DLC-KP-Snapshot2019.pdf (squarespace.com).

Fitzpatrick, B., Berends, M., Ferrare, J. J., Waddington, R. J. (2020). Virtual illusion: Comparing student achievement and teacher characteristics in online and brick-and-mortar charter schools in Indiana. *Educational Researcher, 29*(3), 161-175.

Flanders, W. (2020). Opting out: Enrollment trends in response to continued public school shutdowns. *Wisconsin Institute for Law and Liberty.*

Flannery, M. E. (2020, May 22). With pandemic, privatization advocates smell a big opportunity. *National Education Association.* Retrieved from https://www.nea.org/advocating-for-change/new-from-nea/pandemic-privatization-advocates-smell-big-opportunity

Gaias, L. M., Duong, M. T., Pullmann, M. D., Brewer, S. K., Smilansky, M., Halbert, M., Carey, C. M., & Jones, J. (2020). Race and ethnicity in educational intervention research: A systematic review and recommendations for sampling, reporting, and analysis. *Educational Research Review, 31*. doi:10.1016/j.edurev.2020.100356

Goldstein, D., Popescu, A., & Hannah-Jones, N. (2020). As school moves online, many students stay logged out. *New York Times.* Retrieved from https://www.nytimes.com/2020/04/06/us/coronavirus-schools-attendance-absent.html

Golann, J. W., Debs, M., & Weiss, A. L. (2019). “To be strict on your own”: Black and Latinx parents evaluate discipline in urban choice schools. *American Educational Research Journal, 56*(5), 1896–1929.

Gonzales, A. L., Calarco, J. M., & Lynch, T. (2020). Technology Problems and Student Achievement Gaps: A Validation and Extension of the Technology Maintenance Construct. *Communication Research, 47*(5), 750–770. doi:10.1177/0093650218796366

Hart, C. M., Berger, D., Jacob, B., Loeb, S., & Hill, M. (2019). Online learning, offline outcomes: Online course taking and high school student performance. *AERA Open, 5*(1). doi:10.1177/2332858419832852

Heinrich, C. J., Darling-Aduana, J., Good, A. G., & Cheng, H. (2019). A look inside online educational settings in high school: Promise and pitfalls for improving educational opportunities and outcomes. *American Educational Research Journal, 56*(6), 2147–2188.

Heinrich, C.J., Darling-Aduana, J., & Good, A. (2020). *Equity and quality in digital learning: Realizing the promise in K-12 education.* Boston, MA: Harvard Education Press.

Jacob, B., Berger, D., Hart, C., & Loeb, S. (2016). Can technology help promote equality of educational opportunities? *Russell Sage Foundation Journal of the Social Sciences, 2*, 242–271. doi:10.7758/RSF.2016.2.5.12

Jones, T. M., Fleming, C., & Williford, A. (2020). Racial equity in academic success: The role of school climate and social emotional learning. *Children and Youth Services Review, 119*. doi:10.1016/j.childyouth.2020.105623

Kaufman, J. H., & Diliberti, M. K. (2021). Divergent and inequitable teaching and learning pathways during (and perhaps beyond) the pandemic: Key findings from the American Educator Panels Spring 2021 COVID-19 Surveys. *RAND Corporations.*

Kelly, S. M. (2021, July 16). Some parents are seeking out permanent virtual school for the fall. *CNN.* Retrieved from https://www.cnn.com/2021/07/16/tech/online-school-permanent/index.html

Kim, C. J. H., & Padilla, A. M. (2020). Technology for Educational Purposes Among Low-Income Latino Children Living in a Mobile Park in Silicon Valley: A Case Study Before and During COVID-19. *Hispanic Journal of Behavioral Sciences, 42*(4), 497–514. doi:10.1177/0739986320959764

Kleitz, B., Weiher, G. R., Tedin, K., & Matland, R. (2000). Choice, charter schools, and household preferences. *Social Science Quarterly, 81*(3), 846–854.

Kogan, V., & Lavertu, S. (2021). The COVID-19 pandemic and student achievement on Ohio's third-grade English Language Arts assessment. Report prepared for the *Ohio Department of Education.*

Kraft, M. A. (2020). Interpreting effect sizes of education interventions. *Educational Researcher, 49*(4), 241-253.

Kuhfeld, M., Tarasawa, B., Johnson, A., Ruzek, E., & Lewis, K. (2020). Learning during COVID-19: Initial findings on students' reading and math achievement and growth. *NWEA Brief.* Retrieved from https://www.nwea.org/content/uploads/2020/11/Collaborative-brief-Learning-duringCOVID-19.NOV2020.pdf

Lewis, K., Kuhfeld, M., Ruzek, E., McEachin, A. (2021). Learning during COVID-19: Reading and math achievement in the 2020-21 school year. NWEA. Retrieved from https://www.nwea.org/content/uploads/2021/07/Learning-during-COVID-19-Reading-and-math-achievement-in-the-2020-2021-school-year.research-brief-1.pdf

Lincove, J. A., Cowen, J. M., & Imbrogno, J. P. (2018). What's in your portfolio? How parents rank traditional public, private, and charter schools in post-Katrina New Orleans' citywide system of school choice. *Education Finance and Policy*, *13*(2), 194-226.

Molnar, A. (2021). Virtual schools in the U.S. 2021 (p. 119). *National Education Policy Center.* Retrieved from https://nepc.colorado.edu/sites/default/files/publications/RB%20Virtual%20Schools%202021.pdf

Patrick, S. K., Woods, S. C., Bala, N., & Santelli, F. A. (2021). *Schooling during COVID-19: Fall semester trends from six Tennessee districts.* Nashville, TN: Tennessee Education Research Alliance.

Pier, L., Christian, M., Tymeson, H., & Meyer, R. H. (2021). COVID-19 impacts on student learning: Evidence from interim assessments in California. *Policy Analysis for California Education.* Retrieved from https://edpolicyinca.org/publications/covid-19-impacts-student-learning

Prieto, L. M., Aguero-Valverde, J., Zarrate-Cardenas, G., & Van Maarseveen, M. (2019). Parental Preferences in the Choice for a Specialty School. *Journal of School Choice, 13*(2), 198–227.

Renaissance Learning. (2021a). How kids Are performing: Tracking the midyear impact of COVID-19 on reading and mathematics achievement. *Renaissance Special Report Series, Winter 2020-2021 Edition.* Retrieved from https://www.renaissance.com/how-kids-are-performing/.

Renaissance Learning. (2021b). How kids are performing: Tracking the impact of COVID-19 on reading and mathematics achievement. *Renaissance Special Report Series, Spring 2021 Edition.* Retrieved from https://www.renaissance.com/how-kids-are-performing/.

Roche, D. (2020). In continued rise more than 60% of U.S. K-12 public school students starting school "virtually" this fall. *Burbio.* Retrieved from https://info.burbio.com/press/

Sass, T. R., & Goldring, T. (2021). *Student achievement growth during the COVID-19 pandemic: Insights from Metro-Atlanta School Districts.* Atlanta, GA: Metro Atlanta Policy Lab for Education (MAPLE).

Schultz, T. (2020, May 14). National Poll: 40% of Families More Likely to Homeschool After Lockdowns End. *American Federation for Children.* Retrieved from https://www.federationforchildren.org/national-poll-40-of-families-more-likely-to-homeschool-after-lockdowns-end/

St. George, D., Strauss, V., Meckler, L., Heim, J., & Natanson, H. (2021, March 15). How the pandemic is reshaping education. *Washington Post.* Retrieved from https://www.washingtonpost.com/education/2021/03/15/pandemic-school-year-changes/

Strauss, V. (2021, May 20). The movement to privatize public schools marches on during coronavirus pandemic. *Washington Post.* Retrieved from https://www.washingtonpost.com/education/2021/05/20/school-privatization-movement-marches-on-during-pandemic/

The COVID Tracking Project. (2021). COVID-19 is affecting Black, Indigenous, Latinx, and other people of color the most. Retrieved from https://covidtracking.com/race.

Thompson, C. (2021, April 20). Schools confront "off the rails" numbers of failing grades. *AP NEWS.* Retrieved from https://apnews.com/article/distance-learning-coronavirus-pandemic-oregon-7fde612c3dbfd2e21fab9673ca49ad89

Torre, D. (2013). Virtual Charter Schools: Realities and Unknowns. International Journal of E-*Learning & Distance Education, 27*(1).

VanderHoff, J. (2008). Parental Valuation of Charter Schools and Student Performance. *CATO Journal, 28*(3), 479–493.

Table 1. Sample Characteristics, Overall and by Proportion Virtual

	All Students	By Proportion Virtual		
		< 50%	50-99%	100%
Female	0.492	0.476	0.501	0.504
	(0.500)	(0.499)	(0.500)	(0.500)
Asian	0.118	0.050	0.101	0.253
	(0.323)	(0.217)	(0.301)	(0.435)
Black	0.434	0.286	0.557	0.508
	(0.496)	(0.452)	(0.497)	(0.500)
Hispanic	0.165	0.221	0.153	0.091
	(0.371)	(0.415)	(0.360)	(0.287)
White	0.249	0.410	0.157	0.114
	(0.433)	(0.492)	(0.364)	(0.317)
Received Special Education Services	0.115	0.131	0.113	0.091
	(0.319)	(0.337)	(0.317)	(0.288)
Current English Language Learner	0.052	0.079	0.042	0.023
	(0.223)	(0.270)	(0.200)	(0.151)
FRPM (in 2019-20)	0.360	0.315	0.430	0.336
	(0.480)	(0.465)	(0.495)	(0.472)
Homeless (in 2019-20)	0.010	0.009	0.012	0.008
	(0.098)	(0.094)	(0.108)	(0.090)
Any Behavioral Incident (in 2019-20)	0.883	0.889	0.879	0.881
	(0.321)	(0.315)	(0.326)	(0.323)
Suspended (in 2019-20)	0.031	0.034	0.034	0.021
	(0.254)	(0.274)	(0.262)	(0.207)
Did Not Attend District in 2019-20	0.035	0.035	0.037	0.033
	(0.185)	(0.185)	(0.188)	(0.180)
No Parent Preference Survey Completed	0.185	0.143	0.269	0.141
	(0.389)	(0.350)	(0.444)	(0.348)
More Affluent Region	0.688	0.754	0.621	0.673
	(0.463)	(0.431)	(0.485)	(0.469)
Achievement School in Region	0.822	0.842	0.786	0.837
	(0.383)	(0.364)	(0.410)	(0.370)
School-level Proportion Days Assigned to Virtual Mode	0.680	0.623	0.711	0.729
	(0.121)	(0.092)	(0.121)	(0.126)
Days of School Attended (in F20)	84.662	84.102	83.475	87.184
	(14.259)	(14.571)	(14.524)	(13.021)
Days of School Expected to Attend (in F20)	91.404	91.187	91.663	91.404
	(9.574)	(9.714)	(8.854)	(10.255)
Total Weekly Hours Logged Virtually (in F20)	17.153	13.961	16.373	23.399
	(12.506)	(7.935)	(12.446)	(15.936)
Preferred Virtual When F2F Offered	0.380	0.041	0.444	0.843
	(0.485)	(0.198)	(0.497)	(0.364)
Proportion of Days Assigned to Virtual Mode (in F20)	0.686	0.390	0.807	1.000
	(0.273)	(0.049)	(0.153)	(0.000)
Proportion of Positive Cases at School (in F20)	0.011	0.014	0.010	0.010
	(0.012)	(0.012)	(0.012)	(0.010)
Proportion of Quarantines at School (in F20)	0.092	0.121	0.073	0.069
	(0.119)	(0.130)	(0.113)	(0.098)
Observations	32740	13356	11165	8219

Standard deviations in parentheses.

Table 2. Tests of the Exclusion Restriction for Instrumental Variable Analysis

	First-stage R-squared	First-stage F-statistic	Sargan Overid Test
Math Std. Test (Weekly S.S. Points)	0.676	1708.650***	0.841 (0.657)
Reading Std. Test (Weekly S.S. Points)	0.675	1700.540***	1.935 (0.380)
Math Std. Test (Controlling for Attendance)	0.679	1680.900***	0.795 (0.672)
Reading Std. Test (Controlling for Attendance)	0.678	2409.370***	0.094 (0.759)
Days Attended	0.419	340.599***	0.782 (0.377)
Total Weekly Hours Logged Virtually	0.419	340.599***	5.989 (0.014)

P-values in parenthesis. Dependent Variable = Proportion of days assigned to virtual mode; Excluded variables for student achievement growth on math and reading tests == preference for attending school virtually when face-to-face instruction was offered, intention to use the school bus for transportation to school, and intention to walk to school; Excluded variables for engagement measures == intention to use the school bus for transportation to school and intention to walk to school

Table 3. Associations between Opting to Remain Virtual when Face-to-Face Was Offered and Student/Family/School Characteristics

	Preferred Virtual During F2F
Female	0.013**
	(0.005)
Hispanic	-0.005
	(0.021)
Black	0.102***
	(0.023)
Received Special Education Services	-0.022*
	(0.010)
Current English Language Learner	-0.050**
	(0.016)
FRPM (in 2019-20)	0.016*
	(0.007)
Homeless (in 2019-20)	0.023
	(0.026)
Any Behavioral Incident (in 2019-20)	-0.030*
	(0.012)
Suspended (in 2019-20)	-0.019
	(0.010)
Days of School Expected to Attend (in F20)	0.000
	(0.000)
Did Not Attend District in 2019-20	-0.015
	(0.016)
No Parent Preference Survey Completed	-0.565***
	(0.024)
More Affluent Region	-0.080***
	(0.019)
Achievement School in Region	0.020
	(0.014)
School-level Proportion Days Assigned to Virtual Mode (in F20)	0.612***
	(0.108)
School-level Proportion of Positive Cases (in F20)	1.797**
	(0.616)
School-level Proportion of Quarantines (in F20)	-0.253***
	(0.073)
Grade Fixed Effect	Y
N	32658
R-sq	0.212

Standard errors in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 4. Associations between the Proportion of Instructional Days in Virtual Mode and Average Weekly Student Achievement Growth during the Fall 2020 Semester

	Dependent Variable: Math Std. Test Growth (Weekly Scale Score Points)						
	Base	+Sch FE	+ Attend	+ Usage	IV	+ Attend	S/M FE
Proportion Virtual	-0.109	-0.114	-0.140*	-0.237*	-0.086	-0.107	----
	(0.061)	(0.063)	(0.063)	(0.104)	(0.071)	(0.070)	
N	24594	24594	24594	24594	24594	24594	
R-sq	0.009	0.006	0.007	0.012	0.009	0.010	
	Dependent Variable: Reading Std. Test Growth (Weekly Scale Score Points)						
	Base	+Sch FE	+ Attend	+ Usage	IV	+ Attend	S/M FE
Proportion Virtual	-0.169	-0.201*	-0.228*	-0.181	-0.141	-0.163	----
	(0.094)	(0.096)	(0.096)	(0.146)	(0.111)	(0.111)	
N	24823	24823	24823	24793	24823	24823	
R-sq	0.012	0.002	0.003	0.006	0.012	0.013	
	Days of School Attended (in Fall 2020)						
	Base	+Sch FE	+ Attend	+ Usage	IV	+ Attend	S/M FE
Proportion Virtual	4.078***	3.737***	----	----	3.036***	----	0.519***
	(0.725)	(0.684)			(0.669)		(0.125)
N	32651	32651			32651		161007
R-sq	0.527	0.481			0.527		0.837
	Weekly Hours Logged Virtually (in Fall 2020)						
	Base	+Sch FE	+ Attend	+ Usage	IV	+ Attend	S/M FE
Proportion Virtual	16.915***	17.489***	----	----	21.099***	----	17.367***
	(1.245)	(1.163)			(1.741)		(2.540)
N	32651	32651			32651		161007
R-sq	0.329	0.298			0.322		0.511
Grade FE	Y	Y	Y	Y	Y	Y	
Student Cov.	Y	Y	Y	Y	Y	Y	Y
Region Cov.	Y	Y	Y	Y	Y	Y	
School FE		Y	Y	Y			
Attendance			Y	Y		Y	
Program Usage				Y			
Student FE							Y
Month FE							Y

Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table 5. Associations between 4th through 8th Virtual Learning Usage and Weekly Differential in Student Achievement Growth during the Fall 2020 Semester

	Math Std. Test Growth (Weekly S.S. Points)	Reading Std. Test Growth (Weekly S.S. Points)
Proportion of Days Assigned to Virtual Mode	-0.237*	-0.181
	(0.104)	(0.146)
Days of School Attended (in F20)	0.003	0.004
	(0.003)	(0.003)
Weekly Hours Logged In:		
- Meeting Apps	0.006	-0.006
	(0.006)	(0.009)
- Assignment Apps	0.008	0.016
	(0.026)	(0.035)
- Communication Apps	0.000	-0.000
	(0.002)	(0.003)
- Microsoft Word	0.021	0.009
	(0.014)	(0.013)
- Microsoft PowerPoint	0.014	0.050**
	(0.019)	(0.018)
- Microsoft Excel	0.201	-0.041
	(0.240)	(0.207)
- PDF Viewers	0.096*	0.144*
	(0.038)	(0.061)
- Media Apps	0.570*	0.319
	(0.222)	(0.288)
- Image Apps	0.146*	0.281**
	(0.062)	(0.088)
- Other Apps	-0.023	-0.034
	(0.015)	(0.025)
- iReady	0.307***	0.464***
	(0.057)	(0.100)
Grade Fixed Effect	Y	Y
Student Covariates	Y	Y
Region Covariates	Y	Y
School Fixed Effect	Y	Y
Attendance	Y	Y
N	24594	24823
R-sq	0.012	0.006

Table 6. Associations by Subgroup between Proportion Virtual and Attendance, Engagement, and Achievement

	Math Std. Test Growth (Weekly S.S. Points)				Reading Std. Test Growth (Weekly S.S. Points)				Days Attended		Hours Logged	
	Sch FE	FE + Attend	IV	IV + Attend	Sch FE	FE + Attend	IV	IV + Attend	Sch FE	IV	Sch FE	IV
Female	0.024	-0.010	0.095	0.072	0.043	0.023	0.041	0.027	4.171***	3.617***	17.960***	21.590***
	(0.057)	(0.055)	(0.073)	(0.071)	(0.112)	(0.115)	(0.116)	(0.115)	(0.774)	(0.850)	(1.214)	(1.836)
Male	-0.262**	-0.280**	-0.267**	-0.285**	-0.456***	-0.486***	-0.317*	-0.348*	3.309***	2.718***	16.979***	19.999***
	(0.089)	(0.091)	(0.100)	(0.100)	(0.118)	(0.120)	(0.146)	(0.148)	(0.655)	(0.739)	(1.149)	(1.735)
Black	-0.266**	-0.299**	-0.294*	-0.319**	-0.357*	-0.389*	-0.392*	-0.420*	4.921***	4.193***	12.003***	12.676***
	(0.100)	(0.098)	(0.120)	(0.117)	(0.156)	(0.158)	(0.187)	(0.186)	(1.131)	(1.176)	(0.767)	(0.946)
Hispanic	-0.025	-0.052	0.019	0.005	-0.358	-0.358	-0.297	-0.299	4.311***	1.932*	14.833***	16.083***
	(0.129)	(0.129)	(0.181)	(0.183)	(0.188)	(0.188)	(0.262)	(0.262)	(0.915)	(0.923)	(0.753)	(1.384)
White	-0.034	-0.052	-0.100	-0.121	0.046	0.019	0.040	0.013	2.135***	1.664	19.666***	19.969***
	(0.093)	(0.094)	(0.100)	(0.098)	(0.121)	(0.126)	(0.130)	(0.131)	(0.379)	(0.938)	(0.940)	(1.684)
SPED	-0.016	-0.042	0.052	0.035	0.133	0.078	0.111	0.066	2.709**	3.089*	15.057***	16.792***
	(0.165)	(0.161)	(0.180)	(0.178)	(0.280)	(0.279)	(0.372)	(0.369)	(0.891)	(1.445)	(0.924)	(1.770)
Not SPED	-0.119	-0.146*	-0.095	-0.116	-0.241*	-0.261*	-0.162	-0.179	3.871***	3.124***	17.762***	21.190***
	(0.064)	(0.064)	(0.076)	(0.075)	(0.105)	(0.104)	(0.120)	(0.119)	(0.743)	(0.723)	(1.226)	(1.777)
ELL	-0.112	-0.122	-0.097	-0.102	-0.546	-0.572	-0.163	-0.165	2.936*	1.508	16.051***	18.321***
	(0.242)	(0.244)	(0.333)	(0.333)	(0.357)	(0.351)	(0.447)	(0.442)	(1.183)	(1.717)	(1.300)	(2.091)
Not ELL	-0.117	-0.144*	-0.094	-0.115	-0.191*	-0.216*	-0.147	-0.168	3.776***	3.230***	17.531***	20.638***
	(0.063)	(0.063)	(0.071)	(0.070)	(0.094)	(0.094)	(0.113)	(0.114)	(0.692)	(0.629)	(1.188)	(1.697)
FRPM	-0.292**	-0.329**	-0.282*	-0.309**	-0.376*	-0.393**	-0.454**	-0.480**	5.698***	3.509***	12.892***	14.124***
	(0.099)	(0.097)	(0.121)	(0.120)	(0.150)	(0.149)	(0.175)	(0.175)	(1.139)	(1.079)	(0.826)	(1.449)
Not FRPM	-0.010	-0.034	0.013	-0.008	-0.123	-0.157	0.002	-0.025	2.765***	3.112***	19.897***	24.171***
	(0.062)	(0.063)	(0.076)	(0.075)	(0.109)	(0.108)	(0.119)	(0.117)	(0.495)	(0.610)	(1.217)	(1.548)
Grade FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Student Cov.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
School Cov.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
School FE	Y	Y			Y	Y			Y		Y	
Attendance		Y		Y		Y		Y				

Each cell represents a separate model estimated by limiting the sample to the subgroup indicated.
All models employ robust standard errors, clustered at the school level.
Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Appendix A: Associations between Family Survey Preference for Report and Weekly Differential in Student Achievement Growth during the Fall 2020 Semester

	Dependent Variable: Math Std. Test Growth (Weekly S.S. Points)			
	Base	+Sch FE	+ Attend	+ Usage
Preference for Virtual During F2F	-0.038	-0.039	-0.047	-0.059
	(0.031)	(0.031)	(0.031)	(0.035)
N	24594	24594	24594	24567
R-sq	0.009	0.006	0.010	0.012
	Dependent Variable: Reading Std. Test Growth (Weekly S.S. Points)			
	Base	+Sch FE	+ Attend	+ Usage
Preference for Virtual During F2F	-0.061	-0.074	-0.071	-0.035
	(0.049)	(0.049)	(0.048)	(0.060)
N	24823	24823	24823	24823
R-sq	0.012	0.002	0.012	0.006
	Days of School Attended (in Fall 2020)			
	Base	+Sch FE	+ Attend	+ Usage
Preference for Virtual During F2F	0.966***	1.102***	----	----
	(0.267)	(0.285)		
N	32658	32658		
R-sq	0.512	0.477		
	Weekly Hours Logged Virtually (in Fall 2020)			
	Base	+Sch FE	+ Attend	+ Usage
Preference for Virtual During F2F	9.685***	7.996***	----	----
	(0.836)	(0.618)		
N	32658	32658		
R-sq	0.335	0.230		
Grade FE	Y	Y	Y	Y
Student Cov.	Y	Y	Y	Y
Region Cov.	Y	Y	Y	Y
School FE		Y	Y	Y
Attendance			Y	Y
Program Usage				Y

Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001