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The Pre-Pandemic Growth in Online Public Education and the Factors that Predict It

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Abstract – While spring of 2020 introduced virtual instruction to all public schools, virtual schooling had already been growing in most states. We focus on pre-COVID-19 changes to full-time virtual school enrollment in public schools, and provide evidence on the relationship between virtual school enrollment, internet speed, community demographics, and traditional K-12 school achievement levels. We find negative associations between online enrollment and test achievement in brick-and-mortar schools, and low internet speeds. There is some evidence that students are less likely to enroll in virtual schools as the share of students of their own demographic in brick-and-mortar schools increases.

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1. Introduction

The spring of 2020 introduced virtual instruction to all public schools in the United States. But virtual public schooling had been growing in most states well before it became ubiquitous in the wake of the COVID-19 pandemic. Indeed, there has been a significant expansion in publicly provided online options. Florida Virtual School, for instance, was started in 1997 (Florida Department of Education, 2021). Since then, full-time virtual schooling options have been introduced in 35 states and the District of Columbia.[1] While precise national estimates are hard to come by, there is evidence that the number of public school students enrolled full-time in online K-12 public education programs increased by nearly 50% from 2010 to 2020 (Wicks, 2010; National Center for Education Statistics [NCES], 2021b).[2]

Despite this rapid increase in virtual schooling, relatively little is known about the factors that predict the decisions of students/families to choose this option. This is an important gap in knowledge given that virtual schools are likely to continue, even after the pandemic, to play an important role in the schooling landscape. A number of large school systems, such as Fairfax County Public Schools (DeVoe, 2021), Fulton County Schools of Atlanta (Singer, 2021), and Houston Independent School District (Carpenter, 2021) have announced plans to provide virtual school options in the fall of 2021.[3] Large districts are not alone. A recent RAND survey of school districts and charter management organizations finds that 20 % of survey respondents "were considering, planning to adopt, or had already adopted a virtual school or fully online option" (Schwartz et al., 2020, p. 11). And the recent passage of the 2021 Infrastructure and Jobs Act (H.R. 3684) included $63 billion to fund broadband development and access, reflecting needs identified given that many students have been online during the COVID-19 pandemic (McGill, 2021).

In this paper, we focus on *pre*-COVID-19 changes to full-time virtual school enrollment in public schools and the factors that predict enrollment. Specifically, we use data from the Common Core of Data to track the growth in online public enrollment over four years and

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[1] As described in Gemin et al. (2015), "Virtual schools are full-time online schools, sometimes referred to as cyber schools, which do not serve students at a physical facility. Teachers and students are geographically remote from one another, and all or most of the instruction is provided online. These may be virtual charter schools or non-charter virtual schools" (p. 6).

[2] There is no census of full-time virtual public school students before the first year of tracking within the Common Core of Data, 2014. Wicks (2010) bases his best estimate of 2010 full-time virtual school enrollments off of survey data, and classifies it as "somewhat conservative". Such comparisons are challenging because definitions of full-time virtual school may be different. For instance, if "primarily virtual" schools are considered full-time virtual schools in the CCD then enrollment increased 120% since 2010. Regardless, the rise in virtual school enrollments is much higher than increases in overall enrollment (three percent) (NCES, 2021a).

[3] On the other hand, some states, such as New Jersey will not allow school districts to offer virtual options in the 2021-22 school year (Tully, 2021).

describe the demographics of students participating in virtual schools. We use unique data from Stride, an education management organization that provides online education. Stride is one of the largest providers of online education (based on student enrollment) in the U.S., representing approximately 25% of all fully virtual student enrollment. Stride data is combined with American Communities Survey, the Stanford Education Data Archive of student achievement, and Federal Communications Commission data to provide descriptive evidence on the relationship between virtual school enrollment, broadband access and quality, community demographics, and traditional (brick-and-mortar, a.k.a. neighborhood schools) K-12 school achievement levels.[4] We seek to answer the following:

1. What were the pre-pandemic trends in full-time virtual school enrollment by different demographic groups?

2. What factors predict virtual school enrollments? Specifically does the racial composition, standardized achievement of neighborhood school districts, and/or internet access and quality, predict virtual school enrollments?

Ours study is one of only a handful of studies examining the predictors of online enrollment, the only study to use multi-state data, and one of the only to use panel data to determine how changes in these predictors lead to changes in enrollments.

We focus on *pre*-COVID-19 changes to full-time virtual school enrollment in public schools and the factors that predict enrollment. Relying on data from Stride, a large, virtual school education management organization, we provide descriptive evidence on the relationship between virtual school enrollment, broadband access and quality, community demographics, and traditional (brick-and-mortar) K-12 school achievement levels. We find negative associations between online enrollment and both income and test achievement in neighborhood brick-and-mortar schools. There is also evidence that enrollment rises nonlinearly with internet speed; in particular, internet speed appears to matter more for online enrollment at low speeds than for higher speeds. There is some evidence that virtual school enrollment depends on the demographics of neighborhood public schools, with students less likely to enroll in virtual schools as the share of students of their own demographic in neighborhood schools increases, but these results are not consistent across specifications.

[4] To be clear, we are not attempting to assess the quality of virtual K-12 education, rather whether achievement in brick-and-mortar schools predicts virtual school enrollment. For more on the limited evidence on the student achievement effects of online schooling, see Patrick and Powell (2009), Ahn and McEachin (2017), Molnar et al. (2019), and Sahni et al. (2021).

2. Background

Despite the growth in virtual schooling over the past decade, tracking virtual schooling, its prevalence, and who is participating is spotty. Virtual K-12 schooling began in the early 1990s with a few schools (Gemin et al., 2015), but estimates suggest that while 10 states allowed virtual K-12 schools in the 2001 school year (defined as Fall 2000 through Spring 2001) (Wicks, 2010), relatively few students utilized this option (Gulosino & Miron, 2017). Initially, virtual schooling started by providing online courses that were difficult to attain within students' neighborhood school districts. Some of the first courses offered online were Advanced Placement (AP) courses to students in rural or inner-city schools where no AP curriculum existed (Gemin et al., 2015).

The early 2000s witnessed ballooning of both state initiatives and law changes to permit virtual schooling (Revenaugh, 2005; Molnar et al., 2013), along with a significant increase in the number of students enrolled in virtual offerings (though not always entirely virtual according to the definition in footnote 1 above). For instance, between the 2000 and 2014 school years the best estimates[5] suggest full-time enrollment in virtual schools went from near zero to a quarter million students (Molnar et al., 2013).

Today virtual public schools can now, depending on the state, be operated by individual districts or schools (including charter schools), and not-for-profit as well as for-profit companies.[6] One of the largest providers of virtual and blended online learning is Stride, a for-profit education management organization. Launched in 2012 Stride has grown to cover roughly a quarter of the online enrollment in the U.S. Stride manages public, private, and charter schools, depending on the state, and are looking to continue their expansion of providing alternative learning options to traditional brick and mortar schools.[7]

Instruction in Stride schools, and virtual schools more generally, can be fully-remote (i.e., replacing a student's entire K-12 education), supplemental (offering additional classes online with the student attending some in-person schooling), or blended (a single course has an in-person and online portion) (Wicks, 2010). Prior to the 2013-14 school year when the Common Core of Data (CCD) began tracking student enrollment in virtual schools there was no standardized or centralized data collection informing national estimates of how many students were participating in virtual schools. Since 2013-14, the CCD asked whether or not a school identified as a virtual school, and offered the following definition:

> "A public school that offers only instruction in which students and teachers are separated by time and/or location, and interaction occurs via computers and/or

[5] Estimates come from the annual National Education Policy Center on virtual schools. During this time no national data was collected in a standardized way. Instead, the authors estimate enrollment figures from reports on education management organizations and an annual report, *Keeping Pace*, paid for by the K-12 virtual schooling industry.
[6] For a review of virtual charter enrollment by state see, Gill et al. (2015).
[7] This is noteworthy as Stride is proactive in growing its enrollment via recruitment and advertising, and as such is expansion process may affect the makeup of online enrollments.

telecommunications technologies. A virtual school generally does not have a physical facility that allows students to attend classes on site"

Beginning in the 2016-17 school year, more nuanced data on the type of online schooling was collected (e.g., is instruction fully virtual, primarily virtual, or supplemental (Keaton, 2021)). Gulosino and Miron (2017) used the CCD to produce a national snapshot of student enrollment in virtual schools. They report 261,449 students enrolled in 454 virtual schools in the 2014-15 school year, which represents about 0.5 % of total K-12 public school enrollments in that year. They also find significant disparities by race/ethnicity in the likelihood of virtual schooling; for instance, White students represented about 50% of public school students but nearly 70% of students enrolled in virtual schools. Ascertaining whether racial preferences are related to virtual schooling enrollment decisions is inherently speculative, but Gulosino and Miron suggest the "desire to evade racial integration" is partially responsible for the observed patterns.[8]

As we describe below, there is limited evidence about whether preferences for virtual schools are related to the demographics of neighborhood brick-and-mortar schools, but there is certainly broader evidence that demographics (and demographic change) influence schooling choices more generally. For example, research dating back to the 1970s (Clotfelter, 1976) finds that after school desegregation, neighborhood schools with high minority shares saw larger attrition of White students from public schools to private schools.[9] This issue also arises with other forms of school choice, such as charter schools and vouchers. For instance, charter schools have been found to increase segregation for Black and Hispanic students within a school district; though because charters draw students across district lines, they modestly decrease segregation across districts (Monarrez et al., 2019).

Prior studies disagree on the extent to which virtual school enrollment is related to the demographics of local brick-and-mortar public schools or whether they lead to changes in school segregation (Gulosino & Miron, 2017; Mann, 2019). However, these studies use absolute measures of school segregation, that is, they document how isolated or exposed students of one racial group are to other racial groups. Importantly, they do not account for how segregated the broader school system is and/or residential segregation. In other words, previous studies do not show that students attending virtual schools would have been exposed to more diverse settings

[8] Mann (2019) uses the 2015-16 CCD to examine racial segregation in online charter schools (not all of which are full-time virtual schools). He finds that 66% of students in virtual charter schools are White. Note that because of the difference in definitions between online schools and all online charter schools, it is impossible to tell if this four percent differential between Gulosino and Miron's study and Mann's reflects differences amongst virtual charter schools or differences in the definitions of virtual.

[9] Clotfelter finds that there are tipping points, that is, White attrition to private schools becomes much more marked after the proportion of the non-White share reaches a certain threshold; in the case of Mississippi in the late 60's that threshold was approximately 57%. More recent work suggests that such tipping points exist in neighborhood composition (as opposed to school composition at much lower thresholds. Using a regression discontinuity design, Card et al., (2008) find that, depending on the city, White residents are more likely to leave a neighborhood when the minority share reaches 5-20%. School segregation tends to track housing segregation and this relationship has only gotten stronger over the past few decades (Frankenberg, 2013).

had they not attended virtual schools. To fully understand this phenomenon, data linking the schools students would have attended had they not gone to virtual schools is needed.

Using data from Pennsylvania between the 2009 and 2012 school years, Kotok et al. (2017) examines the isolation index from neighborhood schools sending Black, White, and Hispanic students to virtual schools. They find that when Black and Latino students, and White students (depending on the geography of the school) leave neighborhood schools for virtual schools, the virtual schools are, on average, more racially isolated. One of the contributions of our work is to extend this type of analysis by examining over 25 states, 8 years later,[10] and to examine the decision to enroll in virtual schools across the distribution of neighborhood school district racial composition.

Another notable finding on virtual schooling is that there is considerable geographic variation in virtual school enrollment. Virtual schooling options exist within state-specific legal frameworks, leading to a diverse set of policies regulating virtual school. For instance, Oregon allows school districts to prohibit their students from enrolling in virtual schools if more than three percent of their students are enrolled (Oregon Department of Education, 2020), while Florida requires students to *take* one online course to earn a standard high school diploma (Hart et al., 2020). Even within states, variation in utilization exists. Rural students are more likely to take online courses (Mann, 2016; Ahn & McEachin, 2017), and one reason rural students are taking more online courses may be because specific courses are not offered at their in-person school (Hart et al., 2020).

To our knowledge, there is no large scale multi-state evidence about participation in fully virtual schools by urbanicity. But variation in virtual schooling by urbanicity might be expected given differences in course offerings for small districts as well as broadband infrastructure. On one hand, small rural schools often lack the capacity or demand, to offer more advanced courses (Mann et al., 2017), suggesting there may be greater rural demand for virtual options. On the other hand, the infrastructure needed to access and utilize virtual opportunities will be contingent on internet access and quality. As of 2015, roughly 39 % of students were judged to lack internet or devices at home (NCES, 2018). Concerns about the ability to engage with virtual schools due to technology constraints are framed around the availability and costs of high-speed internet in a student's neighborhood (Wheeler, 2020).

The Federal Communications Commission (FCC) estimates that 18 million people, primarily concentrated in rural areas, lack access to broadband (FCC, 2020). Because of the granularity of reporting for the FCC data, (i.e., the census block rather than individual addresses), other research suggests this figure could be an undercount, representing only half of the true number of Americans without access to broadband (Busby & Tanberk, 2020). Moreover, access to broadband is not evenly distributed: disparities in access to the internet vary significantly by race, where in 2015 93% of White students had some form of broadband in the home, compared to 81% and 73% for Black and American Indian/Alaskan Native students, respectively (NCES, 2018). Additional disparities in access to the internet relate to geography as there are more students without access for for students living in rural areas compared to suburban

[10] An important distinction considering the rate of change of information technology; for example, between the two periods of study, broadband access at home has climbed from 57% in 2008 to 70% in 2016 (Pew, 2021).

or urban areas (NCES, 2018). These disparities may, in part, be explained by differences in socio-economic status, with 50% of households without broadband citing cost as one of the main reasons for not having it (Anderson, 2019).

Several qualitative studies suggest the reasons for choosing virtual schools are extremely varied; for example, students may have disabilities that prohibit them from attending brick-and-mortar schools or parents might desire a higher degree of customizability (Ahn, 2011; Marsh et al., 2009). And there is a body of evidence exploring the influence of student achievement on enrollment decisions in the context of other schooling options. Murnane and Reardon (2018), for instance, find that 31% of parents report sending their child to private school because they believed private schools had better academics than their neighborhood school.[11] Similarly, parents report that a reason for electing to home school their child was a "dissatisfaction with academic instruction at other schools" (Kunzman & Gaither, 2013).

Experimental evidence of schools choice, as opposed to reported reasons for choices (in above studies), generally finds that the academic achievement of schools is a factor in parents' enrollment decisions,[12] but there is considerable heterogeneity in how much measures of school performance matters. Parents use proficiency rates on standardized tests to pick schools in a school choice model, but also exhibit preferences for schools with a higher percent of same-race students, and shorter distances from home (Glazerman & Dallas, 2017). Harris and Larsen (2015) find that non-academic preferences such as extracurricular activities and distance from home are "at least as [important] as academic quality", and that low-income families have diminished preferences for academic outcomes.

An under-studied potential predictor of virtual school enrollment is the performance of neighborhood schools. To our knowledge there is one existing study on how traditional school performance, as measured by state standardized tests, might influence the choice to utilize virtual schools.[13] Mann and Baker (2019) find that the percent of students meeting proficiency on state standardized tests in a neighborhood school district is inversely related to the percent of students attending virtual schools in Pennsylvania. Importantly, the predictive power of standardized test has increased over time, which the authors speculate is due to parents' increasing knowledge about the poor academic performance of virtual schools. Given that Pennsylvania was an early adopter of online schooling, it is unclear if these finding will hold in other states and policy contexts (Mann & Baker, 2019).

As we describe below, the data we utilize allows us to characterize changes in virtual school enrollment by different demographic groups and by geographic region, and to assess the degree

[11] Murnane and Reardon argue that declines in private school enrollment between 1990 and 2010 are due in part to a narrowing gap in student achievement between public and private schools

[12] There is limited evidence on the academic effects of attending virtual schools, but the existing evidence suggests that student performance is lower in a virtual setting; Fitzpatrick, Berends, Ferrare, and Waddington (2020), for instance, find that on average students who switched from traditional schools to virtual charter schools in Indiana experienced negative effects on mathematics and ELA achievement.

[13] There is limited evidence on the performance of students in virtual schools, but the available evidence shows that virtual schools had lower performance ratings and lower graduation rates than brick-and-mortar schools (Ahn & McEachin, 2017; Molnar et al., 2019); for instance, the graduation rate for virtual schools in 2019 was 50% compared to 84% for traditional public schools (Molnar et al., 2019).

to which enrollment is associated with internet access and quality, or the performance or student demographics of neighborhood public schools. All of this represents novel contributions to our knowledge of virtual schooling.

3. Data

The data used in this study come from several sources. Information on public school enrollment come from the Common Core of Data (CCD) maintained by the National Center for Education Statistics (NCES). The CCD provides information on the physical location of every public school in the United States, key school characteristics such as the number of students on Free or Reduced Priced Lunch (FRPL), the racial makeup of students, and flags for the extent to which schools operate virtually. In our primary analysis we categorize schools as being virtual if they are reported to be "Exclusively Virtual," but, below, we also show enrollment trends for more relaxed definitions of virtual schooling.[14]

The CCD began tracking virtual school status in the 2014 school year, but due to changes in how the data were reported starting in the 2017 school year, it is difficult to compare data across reporting periods. For this reason, and because data that we describe below were only available for the 2017 through 2020 school years, we focus our analysis on the 2017 through 2020 school years. The CCD school information are linked to district catchment zones that are maintained by the National Center for Education Statistics as part of the Education Demographics and Geographic Estimates database.

In **Figure 1**, we show how full-time virtual school enrollment as a percent of total K-12 enrollment varies across state and time. Over the past four years both the number of states offering full-time virtual school and virtual school enrollment as a percent of total enrollment has grown. For example, in 2017 31 states offered full-time virtual school, but by 2020 35 states offered virtual school. Virtual school enrollment rose over this period in 87% of states offering virtual school in 2017, rising nationally from 212,311 to 293,689 students.

We use the CCD data to provide a national picture of changes over time in virtual school enrollments and assess how the CCD compares to a subset of virtual schools for which we have more nuanced data; we supplement the CCD data with information on students enrolled in Stride K12 virtual schools. Stride K12 (henceforth "Stride") is an education management organization that supports several virtual schools providing online programs and curriculum, and state-

[14] Across the four years of this study the CCD records schools are coded as one of nine types: exclusively virtual, fully virtual, primarily virtual, supplemental virtual, virtual with face-to-face options, not virtual, no virtual instruction, missing, and not reported. Prior to the 2020 school year, "fully virtual" was used instead of "Exclusively Virtual", we code "fully virtual" schools in these earlier years as virtual schools. NCES collects data for a reference date of October 1st for a given school year, i.e., data reflect Fall enrollments. As such, all CCD utilized in this study predate potential COVID-19 induced enrollment pattern changes.

certified teachers for students wishing to enroll in online education.[15] While Stride supports online education for both public and private schools, the data we use includes only tuition-free public and public charter school enrollment. During the period of study, Stride made up 25% of all fully virtual school enrollments across the nation.[16]

The advantage of the Stride data is that it includes detailed information, not available in the school-level CCD data, on the attendance of students in virtual schools by their residential zip codes. Specifically, Stride provided us with an annual dataset for school years 2017 through 2020 containing the total enrollments at a specific Stride school (and race-specific enrollments) by student' residential zip code. Importantly, we have data on a student's residential zip code, so by using geolocation data students can be linked to the school district they would have likely attended had they not attended virtual school.

Eligibility for enrollment in Stride schools most often depends on a student's home address (i.e., does a student live in a county or state served by Stride schools). We constructed virtual school level catchment zones based on eligibility requirements for each Stride school and merged these catchment zones to the Stride enrollment data. In other words, if students living in a particular zip code were eligible to attend a particular Stride school then this zip code was included in the catchment zone for that particular school. For example, if any student in a state is eligible to attend a Stride school then all zip codes for that state are considered to be in the school's catchment zone (subject to the constraint that the zip code contained residential addresses and at least one child under 18 lived in the zip code).[17] Zip codes with no students enrolled in Stride schools, but within the catchment zone had their enrollment in Stride schools recorded as 0.[18]

We merge the Stride dataset to zip code level information from the American Community Survey (ACS) that includes data on the median income, total under 18 population, the percent of households with home computers, and the percent of households with broadband in the home (Manson et al., 2020), and we add data on zip codes' urbanicity.[19] To address the role of internet

[15] For more information on Stride K12 please visit https://www.k12.com/.
[16] The CCD classifies some Stride schools in some years as partially virtual. For comparison, we calculate the above statistic only from CCD fully virtual CCD schools and fully virtual, per the CCD, Stride schools. While most Stride schools are fully virtual, because Stride schools can be partially virtual we refer to Stride schools as Stride schools from here on, as opposed to fully virtual schools.
[17] Similarly, if students only from a single county are eligible to attend a Stride school, then all zip codes from that county constitute the catchment zone.
[18] Students attending Stride schools were linked to Common Core District data by merging U.S. Census Bureau TIGER/Line shapefiles of zip codes to the National Center for Education Statistic's Education Demographic and Geographic Estimates for district boundaries. When a zip code intersected multiple districts, the zip code was assigned to the district with the most overlapping area.
[19] Data on a zip code's urbanicity come from the 2010 Rural-Urban Commuting Area Codes (RUCA) maintained by the U.S. Department of Agriculture.

quality and access in virtual school enrollment, we merge the Stride data with information on Internet Service Provider (ISP) speeds available in different geographic locations.[20] This information is derived from the Federal Communications Commission (FCC) Fixed Broadband Deployment data. All ISPs submit a list of census blocks where they currently have or could have the ability to offer service to at least one location within each block (e.g., household or business), along with additional details pertaining to said service (e.g., minimum/maximum upload and download speeds).[21] The Fixed Broadband Deployment is collected every June and December of each year starting in June 2016 and continuing through June of 2020.[22] As of 2015, the FCC recommends a minimum download speed of 25 Megabits per second (Mbps) and a minimum upload speed of 5 Mbps (FCC, 2015). Different activities such as email, streaming online radio and social media require the lowest download speed, while activities like streaming ultra HD video and telecommuting require higher download speeds.

Finally, using students' residential zip codes[23] we link information about virtual school enrollments to achievement levels in local public schools derived from the Stanford Education Data Archive (SEDA) (Reardon et al., 2021).[24] SEDA data contains district by grade level standardized assessment scores for math and reading. To get one measure of standardized achievement per subject, the average across grades within a district weighted by grade-level enrollment was taken for math and reading. In our main models described below, we take the average of these math and reading scores to get a composite measure of achievement.[25] SEDA data cover the 2009 through 2018 school years, however, the period of study for this paper is the 2017 through 2020 school years. To avoid including potentially endogenous measures of neighborhood district performance, the most recent available year of achievement data prior to the period of study was used for each school district.[26]

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[20] FCC data was linked to Stride K12 data (described below) through a zip code to census track crosswalk maintained by the Department of Housing and Urban Development (HUD): the USPS Zip crosswalk file. Because many census tracts can be matched to the same zip code, the HUD data also contains the percent of residential addresses that a particular census tract comprises of a zip code's total residential addresses. To get one observation per zip code, we took the mean of download speeds offered across intersecting census tracts and weighted by the share of residential addresses. Stride K12 and FCC data were merged by zip codes and year.

[21] A note concerning these data from the FCC, "A provider that reports deployment of a particular technology and bandwidth in a census block may not necessarily offer that service everywhere in the block. Accordingly, a list of providers deployed in a census block does not necessarily reflect the number of choices available to any particular household or business location in that block, and the number of such providers in the census block does not purport to measure competition."

[22] For more information on the granularity of the data see: https://broadbandmap.fcc.gov/#/

[23] All analyses assume that students are not changing their residential zip codes so as to be able to enroll in online education. We believe that such changes are possible, but likely small because most online schools in this sample allow students from an entire state to enroll.

[24] Specifically, the district cohort standardized datafile was used. The most recent available year was used for each school district. SEDA data was standardized within the sample and merged to residential zip codes in the Stride data by first merging SEDA data to district catchment boundaries maintained by NCES, and then spatially merging SEDA and zip code data.

[25] The correlation between district level math and reading achievement was 0.89.

[26] The code used to build and model the data is available at https://github.com/gratzt/Online_education.

Table 1 provides summary statistics by school type and student demographics for the 2017 through 2020 school years. Statistics are provided for several different sub-groups of schools: all public K-12 schools, all schools with some virtual component (both partially and fully virtual schools), fully virtual schools, and Stride schools. The sample characteristics for the dataset we use for much of the analytic work, the "Stride dataset", are in column (4) of Table 1. Schools with some virtual component comprised about eleven percent of school and year observations, and students attending schools with at least some virtual component made up about nine percent of total enrollments, while fully virtual schools composed 0.5% of total enrollments. Fully virtual schools and Stride schools tend to enroll higher proportions of female students and White Students, and a lower proportion of Hispanic, Black, and Asian students. Stride schools often enroll students from anywhere in a state, whereas some fully virtual schools are district specific. Thus, it is not surprising that they tend to be much larger (approximately 3 times as large) compared to other fully virtual schools.[27] As we show in column (4), which is exclusive to the Stride data, there are only 73 schools representing 353,796 student-year observations (roughly 88,500 students per year) across 18,166 unique zip codes, but these 73 schools represent about a third of students enrolled in fully virtual schools.[28]

Both virtual and Stride schools saw considerable growth in enrollment over time: Using the 2017 school year as a baseline, **Figure 2** depicts percent changes in enrollment by different types of virtual schools. Over the four years during the period of study Stride school enrollment increased by just over 40%, roughly equal to the increase in other fully virtual schools, but a far higher increase than the roughly 10% increase in enrollment in partially virtual schools.

Table 2 provides summary statistics for students enrolled in Stride schools, and compares the demographics of Stride schools to the student demographics of neighborhood school districts students would likely have attended had they not attended Stride schools. (1) provides summary statistics for Stride students, column (2) for neighborhood school districts, and column (3) the differences between columns (1) and (2).[29]

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[27] This comports with prior research, who offer a descriptive snapshot of virtual schools in the 2014-15 school year (Gulosino & Miron, 2017).

[28] We say "likely" because there are some zip codes that intersect multiple school districts. In these cases, we assume the neighborhood school district is the one most overlapping in area with the zip code. The median zip code has 89% of its area covered by one neighborhood school district. Zip codes with 0 children under the age of 18 (per the ACS data), zip codes with too few residents to warrant data collection in the ACS, and/or zip codes that were recorded as having zero residential addresses in the USPS zip code crosswalk dataset maintained by the U.S. Housing and Urban Development were dropped.

[29] Statistical significance was calculated following equation 2.11 of Cameron et al., (2011) for testing the statistical significance of mean differences with clustered standard errors on more than one variable. For this analysis, observations were clustered at the Stride school and neighborhood school district level. All mean differences are weighted by the total enrollment of Stride schools or for particular student groups from the Stride schools.

On average Stride students attend a school that is about 16% Black, 8% Hispanic, 65% White, and 11% other races. These demographics are quite different from the composition of average neighborhood school districts where the Stride students live, as the districts from which Stride schools draw are far more likely to enroll Hispanic students and relatively less likely to enroll White students.[30]

4. Methods

The analytic dataset contains data on the total number of students living in a residential zip code for a given year linked to a specific Stride school, as well as a variety of demographic and geolocation based covariates. We aim to assess the relationships between virtual school enrollment and potential predictors of enrollment, by estimating the following Poisson model:[31]

$$\ln(E_{STZ}) = \beta_1 AIS_{(T-1)Z} + \beta_2 Test_Z + \beta_3 X_{TZ} + \theta_T + U_Z + \delta_S + 1 * \log(Child_z) + \epsilon_{STZ} \quad (1)$$

In Equation (1), E_{STZ} is the total enrollment in virtual school *S* in year *T*, coming from residential zip code *Z,* and in Poisson regression is natural log transformed. $AIS_{(T-1)Z}$ is the average available internet download speed in the prior school year in zip code *Z* and is parameterized as a set of 0/1 indictors for the quintile of internet speeds,[32] $Test_Z$ is the most recent standardized average achievement of math and reading test scores prior to the 2017 school year (the start of the study period) for the neighborhood school district that is linked to zip code *Z*, and X_{TZ} is a vector of controls in year *T* in zip code *Z*. X_{TZ} contains the neighborhood districts' race/ethnicity composition, indicators for whether or not the neighborhood district ran their own fully or partially virtual schools, and the median income of the zip code. θ_T is a year fixed effect. U_Z is a factor variable for the urbanicity of the zip code with different categories: urban, micropolitan, town, and rural; the omitted category is urban.[33] δ_S is a Stride school fixed effect, and in some models is replaced by Stride school by neighborhood school district fixed effects.[34] Recall, that total enrollment in a Stride school is linked by year and residential zip

[30] Stride data provided information on enrollment by race/ethnicity and students residential zip codes. For this reason, it is difficult to compare variables other than these between Stride schools and neighborhood school districts.
[31] We also estimate Equation (1) using ordinary least squares (OLS). Results are directionally consistent with those presented below, but we prefer the Poisson model given that OLS can produced biased estimates with low count data (Coxe et al., 2008); indeed we find the magnitudes of some key variables of interest to be significantly larger in OLS models than Poisson models. Lastly, we note that residual analysis suggests Poisson models fit the data substantially better than OLS. Results are available upon request.
[32] We also estimated estimate Equation (1) with a cubic in available internet speeds. Results are qualitatively similar and available upon request.
[33] Missing covariates were recorded as 0 and a missing dummy was added to the regression. Achievement data is missing for 1/16th of the sample and income data is missing for 1/50th of the sample. Models with listwise deletion are qualitatively similar and available upon request.
[34] We also estimate models without Stride school fixed effects, but prefer the models with Stride effects given that Stride schools can focus on particular grades (and school levels) and/or different sub-populations of students.

code, so a positive and significant coefficient on, say, available internet speed would mean that zip codes with better available internet represent a larger share of students in a particular Stride school than zip codes with slower internet speeds linked to that particular Stride school. The inclusion of a Stride school fixed effect ensures coefficients are identified by enrollment changes in existing schools, and not by the opening or closing of schools tied to zip codes.

Fixed effects models are estimated as conditional Poisson models. To account for the fact that student enrollment in online education is constrained by the number of children under 18 in a given zip code, the exposure parameter, $1 * \log(Child_z)$, is included, where $Child_z$ is the number of children under age 18 living in zip code z. ϵ_{STZ} is the error term and is clustered at the virtual school-zip code level.[35]

The coefficients from equation (1) describe the relationship between total enrollment and internet speeds, traditional brick-and-mortar neighborhood school district performance (judged by state assessments), and neighborhood school district racial composition. However, these coefficients may be biased by unobserved factors.[36] For example, areas with higher internet speeds may correlate with unobserved factors such as the ability of parents being able to stay in the home with children to facilitate online education.[37] Such a relationship would bias estimates of the coefficients for available internet speeds upwards. We address the potential for time-*invariant* unobserved heterogeneity by adding Stride school by zip code fixed effects to Equation (1) in place of $Test_Z$, the time-invariant components of X_{TZ} (e.g., median income), and urbanicity indicators. In this model, coefficients are identified by variation in total enrollment in Stride schools and zip code over-time.[38]

$$ln(E_{STZ}) = \beta_1 AIS_{(T-1)Z} + \beta_2 X^*_{TZ} + \theta_T + \pi_{SZ} + 1 * \log(Child_z) + \epsilon_{STZ} \qquad (2)$$

Models with state fixed effects are qualitatively similar to models with Stride school fixed effects and are available upon request.

[35] Conditional Fixed Effect Poisson regression models cannot directly estimate clustered standard errors. To account for this, we follow Allison (2009) and bootstrap our models by sampling at the cluster level 1,000 times with replacement and run each model. Reported standard errors are the standard deviations of coefficients across the 1,000 models, and significance tests come from constructing the 95% confidence intervals using the 2.5 and 97.5 percentiles of coefficient estimates.

[36] Unfortunately, school district panel student achievement data is not available for this period of study. Hence, no time series analyses were done using student achievement data.

[37] This assumes that the relationship between wealthy areas and online enrollment is not fully accounted for by the median income of the zip code.

[38] In some specifications we replace school by zip code fixed effects with zip code fixed effects. We might expect differences between these models if new virtual schools open up or existing schools close. That is, school by zip code models capture changes in enrollment for existing schools, while zip code fixed effects capture changes in enrollment for existing schools and the entry or exit of schools. Results are qualitatively similar and available upon request.

In Equation (2) E_{STZ} and $AIS_{(T-1)Z}$ are the same variables as in Equation (1), X^*_{TZ} includes only the time-variant variables of the original X_{TZ} vector (e.g., neighborhood district race compositions), and θ_T is a year fixed effect.[39] The virtual school by zip code fixed effects, π_{SZ}, remove time-invariant factors (but not dynamic) that might influencing the relationship between potential predictors and enrollment. As with available download speeds, we lag the neighborhood school district racial composition variables. The use of lags in equation (2) seeks to answer whether or not changes to the variables *precede* changes to total enrollment in the following year.

5. Results

Table 3 presents results from the Poisson models depicted by Equations (1) and (2) for all students enrolled in Stride schools, and **Table 4** provides the results separately by student race/ethnicity (for the largest subcategories of students). The different specifications (across the columns) in the table include different types of fixed effects. Column (1) includes Stride school fixed effects; in this specification coefficients are identified by within Stride school variation across zip codes, and within the same zip code over time. In column (2) these fixed effects are replaced by Stride school by neighborhood school district fixed effects, so the coefficients are identified by cross zip code variation within a Stride school and neighborhood school district, and within zip code variation over time.[40] In essence, these are neighborhood school district catchment effects. Finally, in column (3), neighborhood school district fixed effects are replaced by Stride school by zip code fixed effects. In this specification the coefficients are identified by variation overtime within a Stride school and a single zip code.

All coefficients are reported as the incident rate ratio. Thus, for instance, if the coefficient on the top quintile of internet speed was 1.1, this would indicate that we would expect to see 1.1 times more students enrolling in online education from zip codes in the top quintile of internet speeds relative to the lowest quintile (the omitted category).

5.1 Factors Predicting Change in Stride Virtual School Enrollments

Table 3 presents the Poisson regression coefficients from Equations (1) and (2), where the outcome is the total number of students from residential zip code Z enrolling in virtual school S. Prior to focusing on the coefficients of interest, it is worth noting that across the models the median income of a zip code is negatively associated with online enrollment in all specifications. In particular, a $1,000 increase in median income is associated with a 0.6-0.7% reduction in

[39] Within this period of study median income is time-invariant as it is only available at the zip code level through the American Community Survey's 5-year rolling average data.
[40] There are an average of 2.7 zip codes per neighborhood school district.

online enrollment. Rural zip codes enroll between 9-12% more students in online school than urban zip codes, after controlling for the under 18 population of the zip code. However, the inclusion of a Stride school by neighborhood school district fixed effect increases both the magnitude and standard error on the rural zip code indicators and is no longer statistically significant.[41] This is perhaps not surprising given that only 15% of neighborhood school districts contain at least 2 different urbanicity types.

As hypothesized, internet speed is highly positive and predictive of online enrollment in all specifications. Focusing on columns (1) and (2), it is worth noting that the additional effect of moving from the bottom quintile to a higher internet speed quintile flattens out after the second or third quintile. Put another way, generally internet speed appears to matter more for online enrollment at low speeds than for higher speeds. As a specific example, based on the coefficient estimates in column (1), if all zip codes with internet speeds in quartile 1 and 2, instead had internet speeds at par with quartile 3, we would expect to see 925 more students per year enrolled in online education, which constitutes about a 1% increase in annual enrollment, and accounts for 9% of the annual increase to online enrollment. The findings on broadband speed that include Stride school by neighborhood school district fixed effects ((2)) and Stride school by zip code fixed effects (column (3)) are qualitatively similar.

There is also evidence that enrollment is dependent on the average test achievement of students' neighborhood schools. Students are less likely to enroll in Stride schools when neighborhood school test achievement rises: a one standard deviation decrease in standardized test scores at neighborhood school districts is associated with a 17% increase in enrollment online.[42] This finding is consistent with Hanushek et al (2007), who find that students are more likely to leave charter schools if their local schools perform well on state standardized tests.[43]

Finally, turning to the demographics of neighborhood schools, we find inconsistent evidence that the percent of students who are Black, Hispanic, or other races is associated with fewer students enrolling in online education. In particular, column (1) shows a negative relationship, whereas columns (2) and (3) show a mostly positive relationship. Because columns (2) and (3) include neighborhood school district fixed effects, the coefficients on neighborhood school district racial composition are identified solely by changes within the neighborhood school

[41] Recall Poisson models control for the total number of students that could have enrolled in online school through the inclusion of the under 18 population as the exposure parameter. In raw differences, urban zip codes enroll more students in online education because the average number of children living in an urban zip code is higher than the number living in a rural zip code.

[42] Note that we elected not to estimate the model with Stride school by neighborhood school district fixed effects because the SEDA data only runs through the 2017-18 school years, and are incomplete.

[43] We also ran a model replacing average test achievement of students' neighborhood schools with the change in students' average test achievement between their most recent pre-study year and their second most recent pre-study year. The coefficient on the change in standardized test achievement is positive, but not statistically significant. Results are available upon request.

district overtime. Hence, these should be interpreted as, for example using column (2), a 1 percentage point increase to the Hispanic percent composition, results in a 0.6% increase in online enrollment. That being said, there is little variation in neighborhood district-wide racial composition over time. For instance, the average change between the percent of a district that is Black across two consecutive years is 0.05%. Because of this we choose to focus on the columns with Stride school fixed effects.

5.2 Do the Results Differ by Race/Ethnicity?

A Chow test confirms that the predictors of total enrollment vary by students race and ethnicity. Hence to ascertain the extent to which there are differential preferences for virtual schools by race and ethnicity, we estimate equation (1) and (2), but replaces E_{STZ} with E^*_{STZG}, the enrollment of racial group G in virtual school S in year T, coming from residential zip code Z. We also replace the overall neighborhood school district standardized test scores with race specific scores and replace the exposure parameter (the under 18 population) with the race specific under 18 population.[44] This analysis is focused on the three most populous racial sub-groups: Black, Hispanic, and White students. The results of this exercise are reported in **Table 4**.

Before turning to the regression models depicted in equations (1) and (2) we offer a descriptive picture of the racial composition of students leaving neighborhood school districts for virtual schools compared to the racial composition of the neighborhood school district they are leaving. The panels of **Figure 3** separately plot the proportion of Black, Hispanic, and White students enrolled in virtual schools compared to the proportion of Black, Hispanic, and White students in neighborhood school districts.[45] The red line represents the marginal effects from a regression of the racial composition of Stride schools on a cubic of the racial composition of neighborhood school districts.[46] The green line represents a hypothetical case where the students leaving for virtual schools were perfectly representative of the neighborhood school district racial composition (i.e., the y=x line).

Starting in Panel A, when neighborhood school districts are between 0-20% Black the virtual school enrollments from these districts are reflective of the neighborhood school district demographics, that is, the red line mirrors the green line. However, as the share of neighborhood school districts' enrollment of Black students increases, the share of Black students enrolled in

[44] Note these under 18 population counts come from the American Communities Survey, which does not disaggregate data by race (and age). Instead, we use the zip codes overall racial composition to estimate the race specific under 18 population.
[45] For visual clarity in the scatter plot, neighborhood school district compositions were averaged over 1% increments, however, the cubic regression is based off of the un-collapsed data.
[46] The data was collapsed to the neighborhood school district level and all regressions include the same set of controls present in column (2) of Table (3).

virtual schools increases at a lower rate. In other words, the red line drops below the green. Panel B and C is an analogous figure for Hispanic and White students, respectively. Regardless of the demographic composition of the neighborhood school district, Hispanic students are underrepresented in virtual schools. White students tend to be overrepresented in virtual schools when the neighborhood school district is more non-White. While Figure 3 offers a descriptive picture of the differing racial compositions between virtual and neighborhood schools, it does not depict how changes in racial compositions are associated with changes in enrollment nor does it communicate the magnitude of these differences.

Table 4 presents the Poisson models depicted by equations (1) and (2) where the dependent variable, total enrollments in virtual schools, has been replaced by race specific enrollments. Median income is differentially predictive for Black, Hispanic, and White students; the relationship is positive and sometimes statistically significant for Black students, mixed for Hispanic students, and consistently negative and statistically significant for White students. More rural zip codes tend to have lower online Black enrollment (and sometimes statistically significant). Conversely, more rural zip codes have lower Hispanic and White enrollment in models without fixed effects, but higher (albeit not statistically significant) enrollment in models with fixed effects.

Internet speed is generally highly predictive of Black student enrollment in online school. For instance, in models with Stride school fixed effects, Black student enrollment in online education rises by 21% between zip codes with the slowest internet and those with the fastest. Similarly, internet speed is positive (in all models) and statistically significant (in models with Stride school by neighborhood school district fixed effects) in predicting Hispanic student enrollment in online school. Internet speed is positive, and sometimes statistically significant in predicting online enrollment for White students. Lastly, recall that coefficients in models with Stride school by zip code fixed effects are identified solely by variation within a zip code over time. Hence, the interpretation here for columns (3), (6), and (9) is that online enrollments increase *following* increases to internet speeds.

The findings on the relationship between neighborhood school district standardized achievement and Black student enrollment is negative, but insignificant, whereas Hispanic and White student enrollment is negatively associated with the standardized test scores of neighborhood school districts and statistically significant. While all coefficients on standardized achievement are negative, the magnitude of the coefficients differs substantially. For instance, in the models with Stride school fixed effects, if the neighborhood school district achievement decreases by one standard deviation Black, Hispanic, and White student online enrollment increases by 4%, 29%, and 48%, respectively.

The findings on the racial composition of students' peers in their neighborhood school district are not terribly consistent across model specification. That said, we focus on the findings with the models with Stride school by neighborhood fixed effects and Stride school by zip code fixed effects as these models are identified by within neighborhood school district racial composition change.[47] These models suggest that there are small effects of neighborhood school demographics on the likelihood of online enrollment of various student subgroups, with the high-level finding that students of color are less likely to enroll in online education as the proportion of students of color rise in local districts whereas White students are more likely to enroll in online education as the proportion of students of color increases.

7. Discussion and Conclusion

Simple analyses of families' willingness to enroll in online education can mask the myriad factors that are related to and/or influence their decision-making process. Understanding the predictors of online enrollment will become increasingly important as enrollment in online settings surges as a consequence of families' experiences with online schooling during the COVID-19 pandemic.

After controlling for a rich suite of covariates, internet speed significantly predicts online enrollment, and higher speeds are associated with a 2-10% increase in online enrollment. Moreover, the magnitude of the association flattens out by the second or third quintile of internet speed. This suggests that lower speeds act as a constraint on enrolling in online education, but that higher speeds do not tend to encourage enrollment once the speed constraint is passed. And, slow internet speeds may not only act as a constraint on the demand side for virtual schooling, but on the supply side as well. Patrick et al. (2021) finds that during the pandemic more rural districts with slower internet speeds provided fewer online education opportunities for their students. These findings suggest that the expressed desire of many districts to offer their own virtual school curriculum (Belsha, 2021; Singer, 2021) may be curtailed by poor internet infrastructure. And if districts do successfully start their own online curriculum they will still need to compete with well-established online schools (Mann, 2020).

Whether internet speeds act as a constraint on online education enrollment today may say little about whether they will act as a constraint in the future. Due to changes in behavior and technological advancements, over time the speeds required to maintain an acceptable connection have increased. For instance, up until 2010 the FCC considered download speeds of 4 Mbps to be broadband, whereas today the FCC considers speeds of 25 Mbps or more to be broadband

[47] While the number of students of a particular race enrolled in online schools is mechanically related to the percent of students from that race going to the neighborhood school districts, in practice Stride school enrollments are roughly 0.3% of the total neighborhood school district enrollments and likely do not strongly influence the coefficients on the racial composition of neighborhood school districts.

(FCC, 2015). To maintain the same level of operability for online schooling, speeds will likely need to increase to match these technological changes.

When a neighborhood's internet infrastructure does improve, we find that online enrollment increases by 5-17% the following year. During the period of study available internet speed was rapidly expanding; the average available internet speed rose from 35 Mbps to 123 Mbps. However, since large jumps in the availability and quality of internet speed are potentially accompanied by other infrastructural changes, it is possible that these jumps in enrollment are picking up on other changes to infrastructure aside from changes to internet speed.

That being said, the $63 billion passed in the Infrastructure and Jobs Act (H.R. 3684) act to improve internet speeds and access has the potential to facilitate enrollment in online education (McGill, 2021). This is particularly relevant as nearly all students have now had some experience with online education due to the COVID-19 pandemic and are more familiar with online schooling.

The potential of more students enrolling in online education begs for an understanding of how these online schools perform. While we do not assess this here, we find that enrollment in online education is highly associated with the standardized achievement of neighborhood school districts. That is, lower academic performance in neighborhood school districts is associated with higher enrollment in online education. Parents and students may be leveraging information on districts' performance to make informed decision about enrolling in online education (Dougherty et al., 2009; Mann & Baker, 2019), though it is also possible that it reflects unobserved differences in preferences for different aspects of public schooling.

What is clear is that the relationship between the achievement levels of brick-and-mortar schools and online school enrollment varies by student race/ethnicity, with a substantially stronger relationship between the two for White students than students of color. The reasons for this finding merit more investigation as the differential enrollment response portends greater school segregation by race as the online education sector grows. This issue also arises in terms of the finding of heterogeneous impacts on enrollment attributable to racial and ethnic composition of a student's local school district. Consistent prior research (Gulosino & Miron, 2017), we find that online enrollment is positively associated with the White student population. For instance, if the percent of White students in a neighborhood school district increases by 10 percentage points, online enrollment increases by 6.5%.[48]

At first glance this may appear inconsistent with prior research. Prior research has documented that as the share of minority students in local public schools rises, White student

[48]Results are from a model similar to Column (1) of Table 3, where the neighborhood school district percent Black, Hispanic, and Other have been replaced by percent White.

enrollment in alternative schooling environments, e.g., private schools, increases (Clotfelter, 1976; Card et al., 2008). It is possible that White students' have an overall higher propensity for enrolling in online school, but when the brick-and-mortar school demographics start to change (i.e. the non-White percent share increases), enrollment in online schools for White students increases, and there is some evidence of this in the models that look at enrollment trends for different student subgroups.

Examining stated racial preferences, Hailey (2021) confirms this finding; White students prefer schools with more White students and fewer Black and/or Hispanic students. Hailey also finds that Black families prefer schools with more Black students and fewer White students, and Hispanic families prefer schools with more Hispanic students and fewer Black students. Using observed preferences (rather than expressed), our results broadly bear this out. Black students enroll in online school less if there are more Black and Hispanic students in the local school district relative to White students, Hispanic students enroll less often in online schools if there are more Hispanic students in the local school district, and White students are more likely to enroll in online education if there are more Black students in the local school district.

However, while these findings are statistically significant, the magnitudes could be considered modest. At most, we observe that if Black student enrollment in the neighborhood school district increases by 10 percentage points, then White student enrollment in online school increases by two percent. Given that the average school district is roughly 15% Black, a 10 percentage point increase in the Black student population in a neighborhood school district represents 2/3rds of the average. To be clear, we are not arguing that White Flight does or does not exist, but rather that enrollment in online education does not appear to be a large and salient avenue of White Flight.

While many school systems have returned to in-person instruction (Burbio, 2021), there is evidence to suggest that online education will be an important policy issue in the future. Recent surveys suggest that a sizable share of parents, upwards of 75%, support more online learning in the future (Laird, 2020). Indeed, due to parental demands, a number of school systems have decided to make online schools an option going forward. Our findings suggest that low internet speed is an important constraint on the likelihood that students utilize online options.

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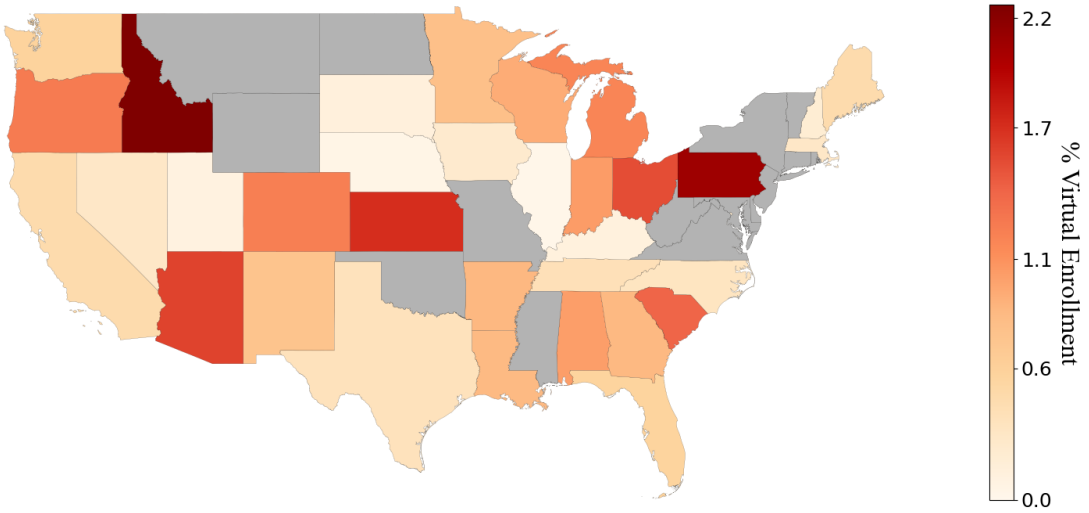
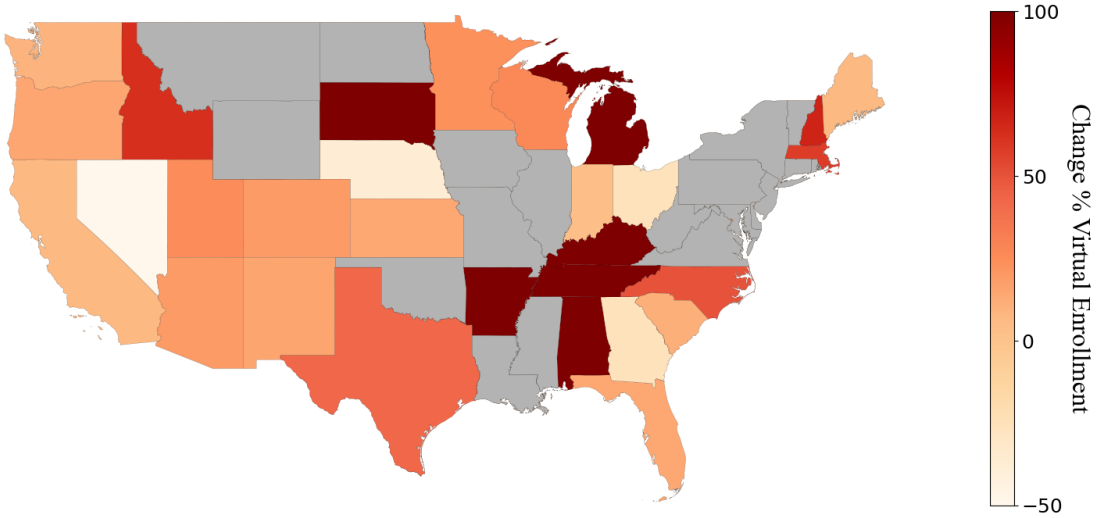
Figures

Figure 1: Growth in Virtual School Enrollment by State

Panel A: 2020 Virtual School Enrollemnt as a Percent of Total Public School Enrollment



Panel B: Percent Change in Virtual School Enrollment Between 2017 and 2020



Notes: Grey indicates no data in 2020 and/or 2017, depending on the panel.

Figure 2: Percent Changes in School Enrollment: Baseline 2017

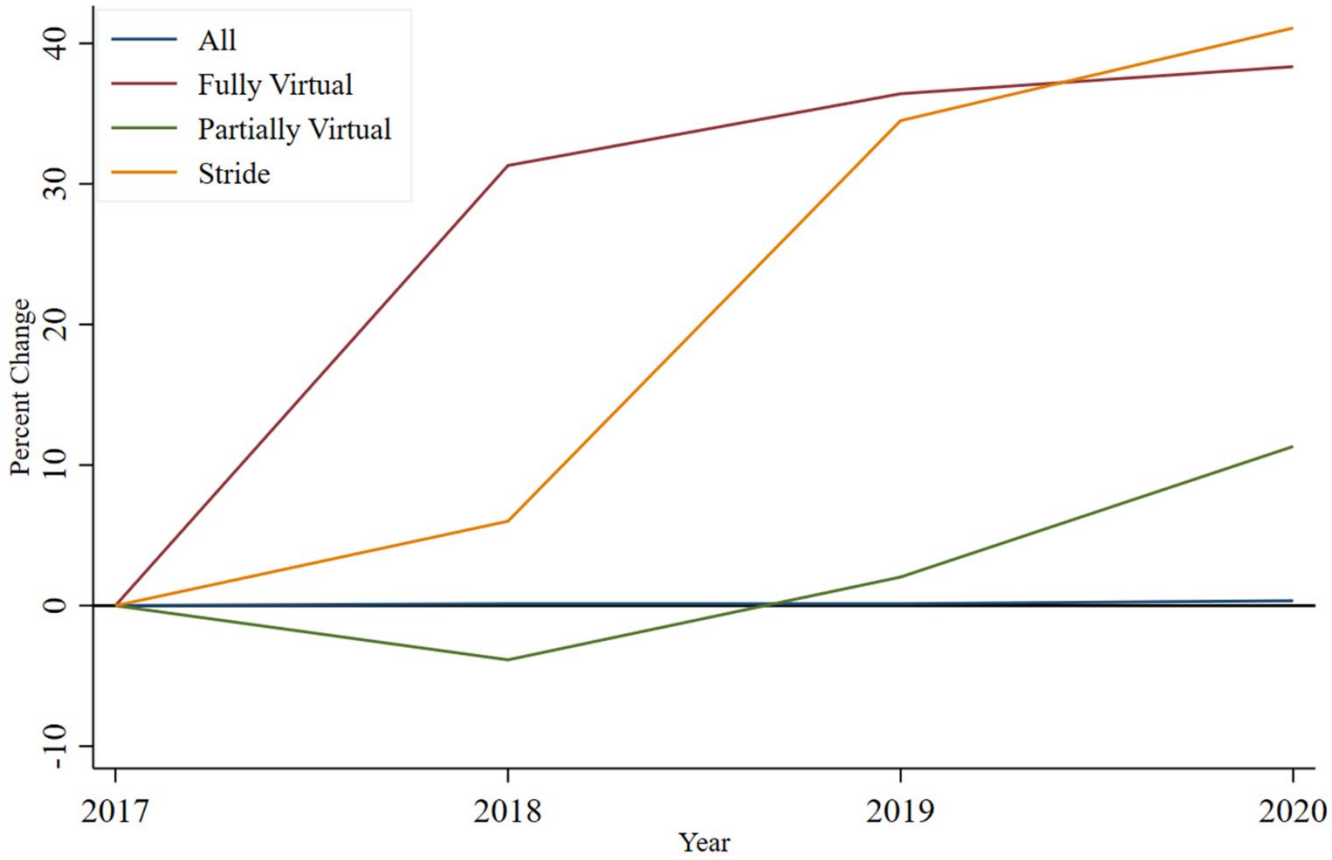
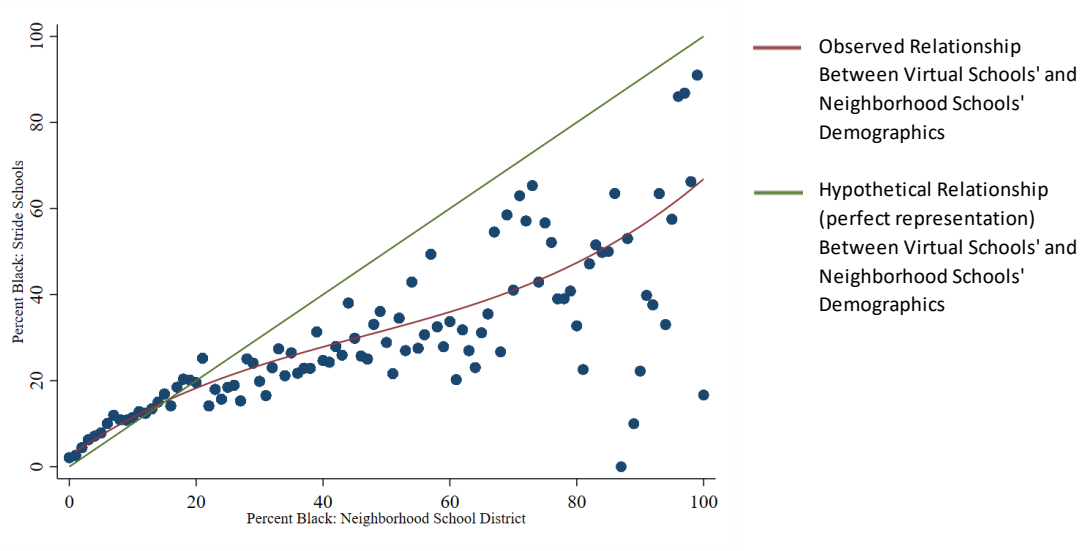
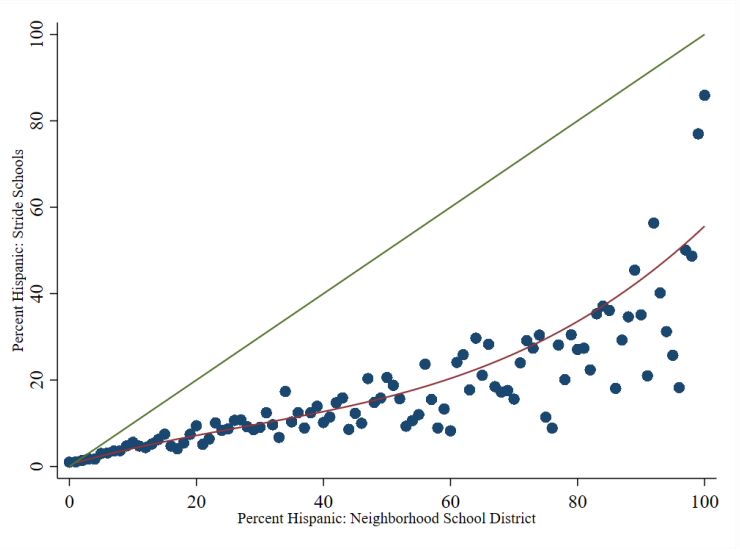


Figure 3: Neighborhood and virtual school racial compositions

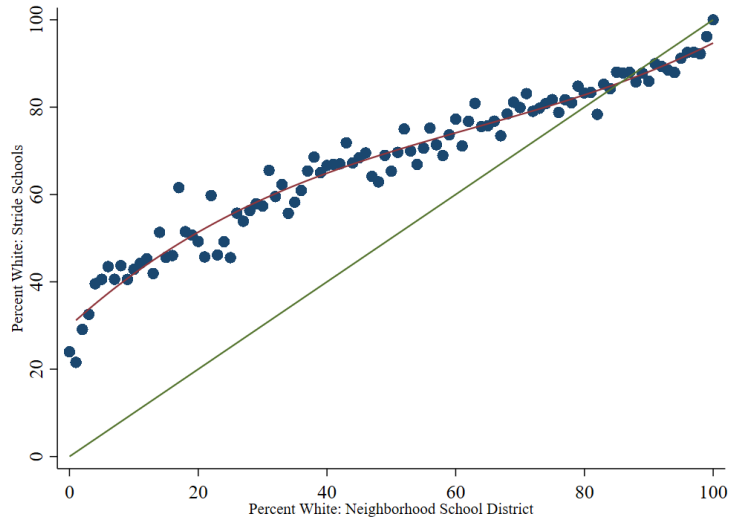
Panel A: Percent Black



Panel B: Percent Hispanic



Panel C: Percent White



Tables

Table 1: Public School Summary Statistics

	2017-2020			
	All	Any Virtual Instruction	Fully Virtual	Stride
	(1)	(2)	(3)	(4)
School Average Enrollment	518	555	418	1361
	(454)	(579)	(1169)	(1743)
Percent				
Female	47.8%	47.8%	54.6%	53.0%
Native American	1.7%	2.0%	1.3%	1.7%
Asian	3.8%	3.2%	1.5%	2.4%
Black	14.9%	12.1%	8.8%	13.4%
Hispanic	23.9%	17.1%	16.6%	15.9%
Native Hawaiian/Pacific Islander	0.3%	0.3%	0.2%	0.5%
Multi-racial	4.0%	4.0%	4.9%	6.5%
White	51.3%	61.3%	66.6%	59.6%
Number of Schools	104053	11233	844	73
Students-Year Observations	201375072	18551735	1074436	353796
Percent of Observations		9.2%	0.5%	0.2%

Table 2: Summary Statistics of Stride Sample

	Stride Schools	Neighborhood SDs	Difference	
Percent Black	16.14	15.09	1.04	
	(8.13)	(20.30)		
Percent Hispanic	8.24	24.10	-15.85	***
	(7.48)	(23.03)		
Percent White	65.19	50.64	14.55	***
	(13.21)	(28.56)		
Percent Other	10.43	10.17	0.26	
	(10.53)	(9.28)		
N	353796			

Table 3: Factors Predicting Enrollment in Virtual Schools

	(1)		(2)		(3)	
Median Income (Per $1,000)	0.993	*	0.994	*		
	(0.000)		(0.000)			
Zip Code Urbanicity						
Micropolitan	1.003		1.004			
	(0.023)		(0.058)			
Town	0.970		0.983			
	(0.022)		(0.064)			
Rural	1.091	*	1.123			
	(0.044)		(0.076)			
Available Download Speeds Quintiles						
Quintile 2	1.073	*	1.017		1.047	*
	(0.020)		(0.015)		(0.015)	
Quintile 3	1.100	*	1.086	*	1.148	*
	(0.022)		(0.020)		(0.019)	
Quintile 4	1.096	*	1.056	*	1.145	*
	(0.025)		(0.022)		(0.022)	
Quintile 5	1.088	*	1.051	*	1.173	*
	(0.027)		(0.025)		(0.025)	
Neighborhood District Std.	0.831	*				
Achievement Score	(0.008)					
Neighborhood SD Percent						
Black	0.997	*	0.996		1.000	
	(0.000)		(0.005)		(0.005)	
Hispanic	0.988	*	1.006		1.010	*
	(0.001)		(0.005)		(0.005)	
Other	0.993	*	1.001		1.002	
	(0.001)		(0.004)		(0.003)	
Fixed Effects						
Stride School	X					
Stride School by Neighborhood SD			X			
Stride School By Zip					X	
Year	X		X		X	
Observations	160,136		123,357		89,927	

Note: *p <= 0.05

Total enrollment models are estimated with Poisson regression according to Equations (1) and (2) and include exposure parameters for the under 18 population in a given zip code. All errors are clustered at the school-zip code level.

Table 4: Differential Associations between Factors Predicting Enrollment in Virtual Schools by Race and Ethnicity

	Black Enrollment			Hispanic Enrollment			White Enrollment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Median Income (Per $1,000)	1.000	1.002 *		1.001	1.004 *		0.990 *	0.987 *	
	(0.001)	(0.001)		(0.001)	(0.001)		(0.000)	(0.000)	
Zip Code Urbanicity									
Micropolitan	0.873 *	0.782		0.984	0.894		0.988	1.051	
	(0.039)	(0.112)		(0.048)	(0.193)		(0.023)	(0.063)	
Town	0.813 *	0.774		0.933	0.994		0.982	0.994	
	(0.052)	(0.162)		(0.063)	(0.344)		(0.023)	(0.070)	
Rural	0.876	0.588 *		1.049	1.127		1.054	1.122	
	(0.148)	(0.158)		(0.096)	(0.463)		(0.036)	(0.079)	
Available Download Speeds Quintiles									
Quintile 2	1.054	1.060	1.040	0.984	1.135 *	1.146 *	1.045 *	1.019	1.067 *
	(0.050)	(0.042)	(0.040)	(0.056)	(0.059)	(0.056)	(0.020)	(0.016)	(0.015)
Quintile 3	1.241 *	1.263 *	1.240 *	1.098	1.353 *	1.405 *	1.067 *	1.067 *	1.148 *
	(0.059)	(0.054)	(0.053)	(0.065)	(0.078)	(0.078)	(0.022)	(0.020)	(0.019)
Quintile 4	1.200 *	1.233 *	1.212 *	1.020	1.225 *	1.274 *	1.041	1.026	1.146 *
	(0.062)	(0.059)	(0.058)	(0.066)	(0.079)	(0.078)	(0.025)	(0.022)	(0.022)
Quintile 5	1.208 *	1.248 *	1.210 *	1.009	1.207 *	1.276 *	1.031	1.016	1.184 *
	(0.069)	(0.069)	(0.066)	(0.068)	(0.086)	(0.088)	(0.027)	(0.027)	(0.027)
Race Specific Neighborhood	0.963			0.706 *			0.515 *		
District Std. Achievement Score	(0.060)			(0.050)			(0.014)		
Neighborhood SD Percent									
Black	0.997 *	1.008	1.010	1.001	1.088 *	1.105 *	1.002 *	0.997	1.001
	(0.001)	(0.009)	(0.009)	(0.001)	(0.021)	(0.019)	(0.000)	(0.006)	(0.006)
Hispanic	0.995 *	1.018	1.026 *	0.989 *	1.009	1.007	0.999	1.004	1.011 *
	(0.001)	(0.011)	(0.012)	(0.001)	(0.011)	(0.011)	(0.001)	(0.004)	(0.004)
Other	0.991 *	1.005	1.007	0.993 *	0.987	1.006	0.997 *	1.001	1.001
	(0.002)	(0.010)	(0.009)	(0.002)	(0.012)	(0.009)	(0.001)	(0.004)	(0.004)
Fixed Effects									
Stride School	X			X			X		
Stride School by Neighborhood SD		X			X			X	
Stride School By Zip			X			X			X
Year	X	X	X	X	X	X	X	X	X
Observations	116,298	55,942	30,817	144,003	56,217	27,277	159,918	117,558	80,579

Note: *p <= 0.05 Dependent variables are the number of Black, Hispanic, and White students enrolled in virtual schools, columns (1-3), (4-6), and (7-9) respectively. All models additionally control for the race-specific under 18 population at the zip code level through the exposure parameter. All errors are clustered at the school-zip code level