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Do virtual schools deliver in rural areas? A longitudinal analysis of academic outcomes

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ABSTRACT

Enrollments in full-time virtual schools have surged in recent years. One of the main arguments for virtual schools is that they extend school choice to rural areas where educational options are limited. In this study, we investigated the academic performance of virtual school students from rural areas by drawing on four years (2016–2019) of data from the US state of Oklahoma. Results show large negative associations with academic achievement for students who attend virtual schools in the overall sample ($n = 836{,}250$) and for a subsample of rural students ($n = 371{,}503$). Negative associations for virtual school students were also larger during elementary and middle school than in high school. This study's overall findings contribute to a growing evidence base indicating poor academic performance for virtual school students. Future research may be needed to identify conditions that foster student learning in virtual schools.

1. Introduction

Full-time virtual schools are a growing segment of the global K-12 educational landscape (Barbour, 2018; Molnar & Boninger, 2021). During the COVID-19 pandemic, enrollments in these schools surged while many brick-and-mortar public schools established permanent virtual academies to provide students with full-time remote options (Dee & Murphy, 2021; McCoy, 2021). Although the pandemic may have accelerated the expansion of virtual schools (Miron, Barbour, et al., 2021), their growth is not a pandemic-era development alone. Full-time virtual school enrollments were on the rise for over two decades before the pandemic (National Center for Education Statistics, 2020).

The steady expansion of full-time online schooling among K-12 students raises important questions about the effects of this model on learning outcomes (Mann et al., 2016). Proponents argue that virtual schools are a revolutionary force in public education, providing customized learning that meets individual needs at a lower cost than that of brick-and-mortar schools (Greenway & Vanourek, 2006). Yet, critics assert that virtual schools are likely to be ineffective because they require consistently high levels of parent monitoring and engagement as well as an atypical ability for a student to learn independently (Barbour & Reeves, 2009; Borup et al., 2015; Gill et al., 2015). Virtual schools might also struggle to replicate collaborative work and peer interactions that are thought to foster learning in traditional classrooms (Gill et al., 2015; Quinn et al., 2019; Rice & Ortiz, 2020). In the empirical literature, an accumulating body of research indicates poor academic performance for students attending full-time virtual schools (Ahn & McEachin, 2017; Center for Research on Education Outcomes [CREDO], 2019c; Fitzpatrick et al., 2020).

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The evidence base on virtual schools is expanding, but few studies test whether heterogeneity exists among key subgroups within the sector. For example, virtual schools have been promoted as a way of extending school choice to rural areas where brick-and-mortar school options tend to be constrained by low population densities, long commutes, and limited resources (Beck et al., 2016; Denice & Gross, 2016; Hamlin & Cheng, 2020). Rural students may have the most to gain from virtual schools (Ahn, 2011), and they are more likely than students in urban and suburban areas to enroll in virtual schools (Mann & Baker, 2019; Mann et al., 2016). Nonetheless, previous research offers little insight into how virtual school students from rural areas are performing academically.

In this study, we investigated the academic performance of full-time virtual school students from rural areas by drawing on four years (2016–2019) of student test score ($n = 836{,}250$) and administrative data from the US state of Oklahoma. The study setting has both a large rural student population and rapidly growing virtual school enrollments (Westapher et al., 2021), so the findings are derived from a robust sample spanning several years. We first analyze the full sample to compare our overall results with those of previous studies. We then specifically examine the academic performance of rural students. Because virtual school students tend to have high rates of school mobility (Westapher et al., 2021), our statistical models also provide results for students who have relatively consistent virtual school experiences as well as those who switch in and out of the virtual sector. For the analyses, the following questions are addressed:

Research question 1. Is there a difference in academic performance (i.e., math and English language arts) between virtual school students and their peers in brick-and-mortar public schools?

Research question 2. Do virtual school students in rural areas outperform their rural peers in brick-and-mortar public schools?

Our study uses the term *virtual school* to refer to online K-12 schools that students attend on a full-time basis (Molnar et al., 2019; National Center for Education Statistics, 2016). Virtual schools in this study's sample do not include blended schools or brick-and-mortar schools that allow students to do some coursework online. By analyzing the academic performance of key subgroups being served by virtual schools, this study makes valuable contributions to the literature on a form of schooling that is growing steadily (National Center for Education Statistics, 2020).

2. Research and theory on virtual schools

2.1. Theoretical mechanisms underlying student learning in virtual schools

In the literature, common theoretical perspectives make different predictions for student learning in virtual schools. One of these lines of reasoning focuses on how school choice processes may lead to improved academic outcomes for virtual school students (Campos & Kearns, 2022; Deming et al., 2014). As a school of choice, virtual schools create an expanded set of school options, which hypothetically allows families to pursue the most academically successful schools among the choices available to them (Marsh et al., 2009). This notion is relevant for rural students because virtual schools are less constrained by geographic barriers that tend to prevent brick-and-mortar schools of choice from operating in rural locales (Hamlin & Cheng, 2020; Denice & Gross, 2016). In addition, virtual schools can theoretically unleash competitive mechanisms, incentivizing schools to provide a high-quality education or risk losing student enrollments to competitors (Barbour, 2018; JabbarAlkubaisi, Al-Saifi, Al-Shidi, & Al-Shukaili, 2021). In the K-12 public education system, full-time virtual schools are most prevalent in the United States, and many are publicly funded charter schools that operate independent of local governance structures for traditional public schools (Molnar et al., 2019). This operational autonomy could, in theory, give virtual schools the flexibility to develop innovative instructional strategies that help to raise student achievement (Buckley & Schneider, 2009; Huerta et al., 2006; Maranto & Ritter, 2014). In the virtual school sector, technology could be leveraged to offer scheduling flexibility, personalized instruction, and access to a wide range of content (Bradley-Dorsey et al., 2022; Marsh et al., 2009).

In contrast to the positive outlook for academic achievement indicated by school choice assumptions, social learning theories underscore how daily learning processes in virtual school environments can impede learning (Hill et al., 2009; Rice & Ortiz, 2020). Reciprocal interactions and direct feedback that occur in classrooms among peers and teachers are thought to spur student engagement, socioemotional development, and deep learning, but such exchanges may be less common for students attending full-time virtual schools (Bradley-Dorsey et al., 2022; Gill et al., 2015). Student-teacher ratios are also markedly higher in virtual schools compared to brick-and-mortar schools (Gill et al., 2015). The potential for limited student-teacher interactions in full-time virtual schools could greatly reduce the well-documented effects teachers have on student achievement (Barbour & Reeves, 2009; Chetty et al., 2014; Cowan & Goldhaber, 2018). Furthermore, teacher preparation programs often train teachers for in-person instruction in brick-mortar schools, but teaching online may require different training (Barbour, 2011). For virtual schools that offer entirely asynchronous instruction, this challenge could be exacerbated (Bradley-Dorsey et al., 2022).

The nature of full-time online learning itself might present barriers to academic success for some students. Younger students, in particular, may struggle with navigating virtual learning platforms and organizing their learning independently. Parents may have to assume highly active roles each school day by monitoring their children, holding them accountable for class work, and providing direct instruction when needed (Borup et al., 2015; Huerta et al., 2006; Molnar et al., 2019). For some families, this high level of parental engagement could be difficult to sustain, possibly resulting in poor outcomes for virtual school students (Hamlin, 2023; Gill et al., 2015).

2.2. Achievement differences between virtual and brick-and-mortar schools

An emerging body of research indicates that virtual school students are underperforming academically (Ahn & McEachin, 2017; Fitzpatrick et al., 2020; Miron, Barbour, et al., 2021; Zimmer et al., 2009). Most of these existing studies are analyses of public virtual charter schools in the United States that operate independent of local public school governance structures. With a large sample from the US state of Ohio, Ahn and McEachin (2017) found strong negative academic performance for virtual school students. Elementary and middle virtual school students scored −0.37 SD lower in math and −0.19 SD lower in reading than traditional public-school students. In high school, patterns are similar with virtual school students scoring lower in math (−0.23 SD) and reading (−0.13 SD) than their brick-and mortar public school counterparts.

Other recent studies relying on matching techniques find similarly large negative academic outcomes for virtual school students. Fitzpatrick et al. (2020) used a matching approach to compare how students perform in a virtual charter school over a three-year period. The authors report substantial declines in student learning (i.e., −0.41 SD in math and −0.29 SD in ELA) that are concentrated in the first year that a student attends a virtual school. This learning loss in the first year is sustained in the second and third years at a virtual school. Another matching study showed large losses in the first year, but found that initial losses dissipated and even became positive in subsequent years of attending a virtual school. However, this study's analyses draw from a relatively small matched sample (Leuken et al., 2015).

CREDO also performed a series of studies using matching techniques (Center for Research on Education Outcomes CREDO, 2015; 2019a; 2019b; 2019c). In an analysis of 18 US states, CREDO reported losses of −0.25 SD in math and −0.10 SD in reading for virtual school students. Researchers from CREDO showed persistent negative results in separate reports in the US state of Pennsylvania, suggesting little improvement in the virtual school sector over time (Centerfor Research on Education Outcomes CREDO, 2015; 2019c). While offering credible evidence, matching techniques used in previous research are non-causal and contain certain limitations (Barbour, 2015). For example, these studies match students across school sectors on student characteristics available in state administrative data, which may mask substantive differences between virtual school students and their peers or result in students being removed from analyses when they do not have cross-sector matches (Davies & Aurini, 2011; Greene & Paul, 2022). Moreover, matching studies offer an overall estimate of virtual school performance that provides little information on how subgroups (e.g., mobile and non-mobile students) within the sector are performing academically.

Among key subgroups within the virtual school sector, student enrollment patterns show that rural students disproportionately attend virtual schools (Beck et al., 2016; Mann & Baker, 2019; Mann et al., 2016). In rural areas where school choice is limited, virtual schools might provide an alternative that delivers personalized learning and increased access to academic content (Ryan & Hill, 2017). On the other hand, rural students who are dissatisfied with their local public school may opt for a virtual school because it is the only option available (Mann & Baker, 2019). This circumstance may not necessarily create conditions that contribute to improved academic achievement. Even though full-time virtual schooling tends to be more of a rural phenomenon than it is in suburban and urban locales, empirical analysis is lacking on the academic performance of rural students in virtual schools.

3. Materials and method

3.1. Study setting

In the United States, enrollments in full-time virtual school have been increasing in the K-12 education sector (Black et al., 2021; McElrath, 2020). Before the pandemic, the sector had grown to 330,000 students in nearly 500 virtual charter and district-run public schools over the span of more than two decades (National Center for Education Statistics, 2020). Some states have experienced particularly sharp rises. In Oklahoma, virtual school enrollments increased by 90%, rising from 8722 students in 2016 to 16,606 students in 2019 (Westapher, 2021). Full-time virtual schools in the state are non-fee-paying public charter schools that operate independent of the school districts that govern most American public schools. Educational management organizations (EMOs) operate these virtual schools (Miron, Barbour, et al., 2021). Approximately 80% of virtual school students in Oklahoma were enrolled in one virtual school during the period of analysis. The other 20% of virtual school students were enrolled in three other virtual school networks. The performance of large full-time virtual school networks in states like Oklahoma is significant because these large operators account for a substantial share of students in the broader virtual school sector (Miron, Barbour, et al., 2021). Over 50% of the state's students reside in rural areas, so it is also an important setting for testing the performance of rural students attending virtual schools (Westapher et al., 2021).

3.2. Data

Student-level administrative data maintained by the Oklahoma State Department of Education (OSDE) from 2016 to 2019 were used for the analyses. These records contain ELA and math test scores for the state's virtual, brick-and-mortar charter, and brick-and-mortar public school students. These data also contain student level sociodemographic information on gender, racial background (i.e. Hispanic, Black, White, Asian, Native, or other race/multiracial), English language learner status (ELL), special education status (IEP), free/reduced priced lunch (FRL) status, attendance, grade level, and school of enrollment. Starting in 2017, the state began using a new standardized assessment, and the COVID-19 pandemic led the cancellation of standardized examinations in 2020. Data from the older 2016 assessment are thus used to control for prior student achievement.

3.3. Variables

Dependent variables. The dependent variables were math and ELA test scores in grades 3 to 8 and math and ELA test scores in grade 11. Math and ELA test scores were generated from the Oklahoma School Testing Program. These assessments are state mandated, criterion referenced exams that are administered by the Oklahoma State Department of Education to students in grades 3 to 8 (Oklahoma State Department of Education, 2021). The assessments do not track achievement growth across grades but use the same scale for each grade level. In Oklahoma, the American College Testing (ACT) assessment is typically administered to 10th and 11th grade students and broken down into math and ELA scales. Test scores for grades 3 to 8 and grade 11 were standardized for analysis.

Table 1 provides a descriptive breakdown for each of the variables of analysis for virtual schools, brick-and-mortar charter schools, and brick-and-mortar public schools for students in grades 3–12. For virtual schools, average math and ELA scores are lower than those of charter and brick-and-mortar public schools. For student background characteristics, there are descriptive differences across school types. Only 1% of virtual school students are English language learners, whereas 17% of brick-and-mortar charter school students and 7% of brick-and-mortar run public school students are English language learners. In virtual schools, 64% of students are White. In brick-and-mortar charter schools, 27% of students are White and 49% of students are White in brick-and-mortar public schools.

Virtual schools have a mobile student population. Approximately 33% of virtual school students switch schools within the academic year but only 17% do so in brick-and-mortar charter schools and 9% do so in brick-and-mortar public schools do so. On average, students in Oklahoma's two large cities (i.e., Tulsa and Oklahoma City) are less likely to attend virtual schools. For virtual schools, 61% of students switched into a virtual school from a brick-and-mortar public school located in a rural area. Virtual schools seem to be more likely to serve White students and students from rural areas, and they have proportionally higher enrollments in high school grades. For example, nearly 60% of virtual school enrollments are in grades 9–12 but only 36% of brick-and-mortar public school enrollments are in grades 9–12.

Table 1
Summary statistics for each variable of analysis by school sector (2017–2019).

	Virtual	Brick-and-mortar charter	Brick-and-mortar public
Dependent variables			
ELA	−0.33 (1.00)	−0.16 (0.97)	0.01 (0.99)
Math	−0.57 (0.98)	−0.19 (1.01)	0.02 (0.99)
ACT (Composite)	16.64 (4.07)	17.31 (4.61)	18.18 (4.73)
ELA (ACT)	−0.25 (0.94)	−0.05 (1.00)	0.01 (1.00)
Math (ACT)	−0.43 (0.84)	−0.09 (0.96)	0.02 (1.00)
Independent variables			
Female	0.55 (0.49)	0.51 (0.49)	0.49 (0.49)
FRL	0.65 (0.48)	0.74 (0.48)	0.62 (0.49)
ELL	0.01 (0.11)	0.17 (0.38)	0.07 (0.25)
IEP	0.12 (0.32)	0.11 (0.31)	0.17 (0.38)
White	0.64 (0.48)	0.27 (0.44)	0.49 (0.49)
Hispanic	0.09 (0.29)	0.40 (0.49)	0.17 (0.37)
Black	0.06 (0.24)	0.24 (0.43)	0.09 (0.29)
Asian/Pac. Islander	0.01 (0.09)	0.02 (0.13)	0.02 (0.15)
Multiracial	0.03 (0.18)	0.02 (0.15)	0.09 (0.29)
Native	0.16 (0.37)	0.05 (0.22)	0.14 (0.35)
Mobility	0.33 (0.47)	0.17 (0.38)	0.09 (0.29)
High Mobility	0.06 (0.23)	0.04 (0.19)	0.03 (0.16)
Large City	0.13 (0.34) [1]	0.98 (0.15)	0.19 (0.39)
Midsize City	0.04 (0.19)	0.01 (0.04)	0.03 (0.17)
Small City	0.08 (0.27)	0.00 (0.00)	0.08 (0.27)
Suburb	0.15 (0.35)	0.00 (0.00)	0.20 (0.40)
Rural	0.61 (0.49)	0.02 (0.15)	0.49 (0.49)
Grade 3	0.05 (0.23)	0.06 (0.25)	0.11 (0.31)
Grade 4	0.05 (0.27)	0.07 (0.25)	0.11 (0.31)
Grade 5	0.06 (0.24)	0.08 (0.28)	0.11 (0.31)
Grade 6	0.07 (0.26)	0.11 (0.31)	0.10 (0.30)
Grade 7	0.09 (0.29)	0.11 (0.32)	0.09 (0.29)
Grade 8	0.10 (0.30)	0.10 (0.31)	0.09 (0.29)
Grade 9	0.18 (0.38)	0.14 (0.34)	0.10 (0.30)
Grade 10	0.16 (0.36)	0.12 (0.33)	0.09 (0.30)
Grade 11	0.13 (0.33)	0.10 (0.31)	0.09 (0.29)
Grade 12	0.11 (0.31)	0.10 (0.29)	0.08 (0.29)
Schools	4	33	1613
Student Observations	53,442	45,123	1,563,970

Note. Data exclude PK to Grade 2 students who do take the state assessment. For virtual school observations, geographic locale is identified by determining the locale of a student attending a brick-and-mortar charter or district-run public school in 2016 who then switched into a virtual school. *Mobility* denotes students who switched schools once during the academic year and High Mobility denotes students who switched schools more than one time within the academic year.

3.4. Empirical strategy

Determining the effect of full-time virtual schooling on student achievement presents a methodological challenge because of selection bias concerns. Although academic considerations are reportedly a major priority for those opting for virtual schools (Greenway et al., 2006; Marsh et al., 2009), families identify additional reasons for choosing virtual schools that range from mental and physical health challenges to bullying and safety problems at previous schools (Beck et al., 2016; Greene & Paul, 2022; Prosser, 2011; Tonks et al., 2021). Students who opt for a virtual school may represent a distinctive subgroup with learning needs and circumstances that are not captured by standard control variables (Greene & Paul, 2022). Random assignment methods resolve this methodological problem, but no random assignment mechanism (e.g. school admission lotteries) exists for virtual schools that could be used to derive truly causal estimates (Abdulkadiroglu et al., 2009; Cheng et al., 2017). Therefore, to generate credible estimates that help to build on existing research, we use a series of fixed and random effects models. The fixed effects models provide estimates for virtual school students who switch between brick-and-mortar public and virtual schools between academic years while the random effects models offer estimates of students who stay in the virtual school sector for several years. The combination of these two statistical approaches presents evidence on the academic performance of virtual school students who move in and out of the sector as well as those who have a more consistent school experiences across years.

In the first set of analyses, we estimated student fixed effects over a three-year period, analyzing test score differences in math and ELA for the same students when they are in a brick-and-mortar public school versus when they are in a virtual school. This approach reduces selection bias by controlling for unobserved time invariant student characteristics that may confound the relationship between virtual school attendance and academic achievement. Grade and year fixed effects were included in the model along with potentially time varying control variables listed in the equation below. By clustering at the student level, we estimated the following model for both math and ELA test scores,

$$\mathrm{Y}_{\mathrm{it}} = \alpha_{\mathrm{i}} + \beta0 + \beta_1\mathrm{Virtual\_Charter}_{\mathrm{it}} + \beta_2\mathrm{BM\_Charter}_{\mathrm{it}} + \beta_3\mathrm{FRL}_{\mathrm{it}} + \beta_4\mathrm{ELL}_{\mathrm{it}} + \beta_5\mathrm{IEP}_{\mathrm{it}} + \beta_6\mathrm{Grade}_{\mathrm{it}} + \beta_7\mathrm{School\_Year}_{\mathrm{it}} + \mathrm{u}_{\mathrm{it}}, \tag{1}$$

where Y_{it} is the test score for student *i* at time *t.* The term αi is a student fixed effect that accounts for time-invariant student characteristics. The main variable of interest is *Virtual_Charter,* which is a binary variable indicating whether student *i* attended a virtual school student in time *t. BM_Charter* is a binary variable denoting whether student *i* attended a brick-and-mortar charter school at time *t.* The variables *ELL* (English language learner)*, IEP* (Individualized Education Program), and *FRL* (Free/Reduced Priced Lunch) are binary control variables. *Grade* is a vector of six binary variables indicating whether a student is in grade 3, grade 4, grade 5, or grade 6, grade 7, or grade 8. *Year* is a vector of three binary variables for 2017, 2018, and 2019. The error term is u_{it}.

In sub-analyses, we used this same model but restricted the sample to students who attended brick-and-mortar charter and brick-and-mortar public schools in rural areas in 2016. This restriction allows us to observe students who switched into virtual schools from brick-and-mortar schools located in rural areas. It must be noted that we cannot be certain that switching students remained living in rural areas. We reasonably assume that most students remained in rural areas given the very low rates of movement out of rural areas observed for brick-and-mortar public schools in Oklahoma (Westapher et al., 2021). To test the robustness of the main models, we restricted the sample to students with three years of consecutive test scores (Appendix Table 2A). We also performed the same models by adding a control for prior achievement in 2016 (Appendix Table 3A). Results across these models were consistent with those of the main models.

Even though fixed effects analysis can yield useful estimates of school sector differences, these models are dependent on the results of students who move between virtual and brick-and-mortar schools between years so that within-student heterogeneity can be observed. One issue is that the act of switching to a virtual school could coincide with physical health problems, mental health challenges, family disruption, or other shocks in the life of a student (Davis & Raymond, 2012). Fixed effects results might yield narrow estimates driven by school switchers but exclude students who remain in virtual schools throughout the period of analysis. Students who remain in virtual schools without switching may have greater consistency both in and out of school that could support stronger achievement. To understand the performance of students who have a steady virtual school experience over a long duration, random effects models are estimated for students in grades 3–8 who remain in the same school for all three years of analysis and have four consecutive years of test scores. In these models, we cluster at the student level to account for the correlation of test scores for the same student across academic years. To reduce selection bias, we also control for baseline student achievement in 2016. Within-study comparisons have shown that controls for prior achievement play a large role in replicating random assignment results with non-experimental data (Bifulco, 2012). The random effects models also control for gender, FRL status, IEP status, ELL status, race/-ethnicity, grade level, and school year. The following model was estimated for both ELA and math test scores:

$$\mathrm{Y}_{\mathrm{it}} = \beta_0 + \beta_1\mathrm{Virtual\_Charter}_{\mathrm{it}} + \beta_2\mathrm{BM\_Charter}_{\mathrm{it}} + \beta_3\mathrm{Baseline\_Achievement}_{\mathrm{it}} + \beta_4\mathrm{Race}_{\mathrm{it}} + \beta_5\mathrm{Gender}_{\mathrm{it}} + \beta_6\mathrm{FRL}_{\mathrm{it}} + \beta_7\mathrm{ELL}_{\mathrm{it}} + \beta_8\mathrm{IEP}_{\mathrm{it}} + \beta_9\mathrm{Grade}_{\mathrm{it}} + \beta_{10}\mathrm{School\_Year}_{\mathrm{it}} + \mu_{\mathrm{it}} + e_{\mathrm{it}}, \tag{2}$$

Where Y_{it} is the test score for student *I* in grade *g* at time *t.* The between-student error term is μ, while the within-student error term is e_{it}. Along with these models, we specified random effects models that include students who switched schools within the academic year. In these models, we control for high mobility (i.e. students who switched schools more than once within the academic year) and mobility (i.e. students who switched schools once within the academic year). In sub-analyses, we used this same model but restricted the sample to students who attended brick-and-mortar charter and district-run public schools in rural areas in 2016. We tested the robustness of these results by restricting the sample to students with four consecutive years of test scores (Appendix Table 5A) and by removing the baseline achievement control (Appendix Table 6A). Estimates across models were largely consistent with those of the main models. In separate regressions, we also found that associations in math were similar whether the student was in the first, second, or third year of attending a virtual charter school. In ELA, negative results were stronger in Year 1 than in Years 2 and 3 though still considerably negative in magnitude.

To assess math and ELA achievement during high school, we examine test score records from grade 11 when high school students are tested in Oklahoma. Because high school students are usually tested in 10th grade, we use 10th grade achievement as a control for prior achievement. For this analysis, we estimated the following OLS regression model accounting for student-level clustering:

$$Y_i = \beta_0 + \beta_1 \text{Virtual\_Charter}_i + \beta_2 \text{BM\_Charter}_i + \beta_3 \text{High\_Mobility}_i + \beta_3 \text{Mobility}_i + \beta_3 \text{Grade10\_Score}_i + \beta_4 \text{Race}_i + \beta_5 \text{Gender}_i + \beta_6 \text{FRL}_i + \beta_7 \text{ELL}_i + \beta_8 \text{IEP}_i + \beta_{10} \text{School\_Year}_i + e_i, \quad (3)$$

where Y_i is the test score result in 11th grade for student *i*.

Overall robustness checks generated negative associations between virtual school students and academic achievement that were similar in magnitude to those presented in the main models. Supplementary analyses were run to probe the issue of negative selection into virtual schools (Appendix Table 7A). Students scoring in the 75th percentile or higher in 2016 were identified. Then, those who switched into virtual schools in 2017 were compared to other students scoring in the 75th percentile of higher who remained in brick-and-mortar public schools. These supplementary analyses also indicated negative associations for virtual school students that were similar in magnitude to those of the main models. Furthermore, we performed sub-analyses of schools within the virtual sector because approximately 80% of virtual school students in the study setting are enrolled in a single virtual school. Based on these sub-analyses, the three other virtual schools underperform similarly with two exceptions. In Grades 3–8, students in one virtual school perform statistically higher in reading, and students at another virtual school statistically outperform those in the large virtual school at the high school level. As a caution, student samples in these two virtual schools are relatively small and do not influence overall patterns observed in the main models.

A limitation to this study's analyses is that they present non-causal estimates, which is a limitation that runs through existing research on virtual schools. The main methodological concern with non-causal studies is that students who opt for virtual schools may represent a particular type of struggling student whose achievement levels may not necessarily reflect the effectiveness of virtual school models.

4. Results

Table 2 presents student fixed effects estimates over a three-year period in ELA and math for virtual school students in grades 3 to 8. In the years when students attend virtual schools, they exhibit large negative associations when compared to years when these same students attend brick-and-mortar public schools. Virtual school attendance is associated with a large drop in scores in both ELA (−0.21 SD) and math (−0.30 SD) in the full sample in Models 1 and 3. These negative associations correspond to two-thirds of an academic year of learning in ELA and slightly more than two-thirds of an academic year in math (see Hill et al., 2008). In Models 2 and 4, the sample is restricted to students from rural areas. Virtual school students from rural areas also show large negative statistical associations in ELA (−0.22 SD) and math (−0.41 SD). These negative associations amount to a little over two-thirds of an academic year of learning in ELA and nearly an entire academic year in math. In the Appendix, Table 2A shows estimates that are consistent with the main models when the sample is restricted to students who have three consecutive years of test scores. Table 3A demonstrates consistent estimates when a control for baseline achievement in 2016 is added to these same models.

Table 2
Estimates of student fixed effects for virtual school students (Grades 3–8).

Variables	ELA	ELA Rural	Math	Math Rural
Virtual	−0.21***	−0.22***	−0.30***	−0.41***
	(0.01)	(0.02)	(0.01)	(0.02)
Brick & mortar charter	0.10***	−0.08	0.16***	−0.13**
	(0.01)	(0.05)	(0.01)	(0.05)
Time-invariant student characteristics[1]	Y	Y	Y	Y
Student, grade, and year controls	Y	Y	Y	Y
Virtual observations	11,596	2995	11,598	2996
Total Observations	836,250	371,503	836,297	371,275

***p < 0.001, **p < 0.01, *p < 0.05. Robust standard errors in parentheses. Notes. 1. Fixed effects models control for time invariant student characteristics. Student, grade, and year controls are FRL, IEP, ELL, grade level, and school year.

Table 3 presents random effects estimates in ELA and math for students in grades 3–8 who attend the same school (whether virtual, brick-and-mortar charter, or brick-and-mortar public) for three consecutive years. These estimates are consistent with those of the fixed effects models, indicating that students who move in and out of the virtual school sector as well as those who attend the same virtual school for three years show similarly low achievement relative to their brick-and-mortar public school peers. In Table 3, virtual school students show large negative associations in ELA (−0.22 SD) and math (−0.41 SD). These estimates correspond to nearly three quarters of an academic year of learning in ELA and an entire academic year of learning in math. In the Appendix, Table 4A demonstrates that results remain negative (though they are stronger in magnitude) when controls for baseline student achievement are removed and when the sample is not restricted to students who have four consecutive years of test scores. In addition to these analyses, we tested if virtual school students improved after their first year in a virtual school by performing separate regressions for each year of

Table 3
Random effects estimates for virtual school students who attend the same school for three consecutive years (Grades 3–8).

Variables	ELA 3-yr	Math 3-yr
Virtual	−0.22***	−0.41***
	(0.04)	(0.05)
Brick-and-mortar charter	0.13***	0.17***
	(0.02)	(0.03)
Student, grade, baseline achievement, and year controls	Y	Y
Sample restriction – four consecutive test scores	Y	Y
Virtual obs.	431	430
Total obs.	107,193	107,311

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors in parentheses. Notes. Student, grade, baseline achievement, and school year controls are FRL, race/ethnicity, IEP, ELL, baseline achievement in 2016, grade level, and school year. The analytic sample restricted to students who do not switch schools within the academic year and to students with four years of consecutive test scores.

Table 4
Random effects estimates for virtual school students (including within-year school switchers) (Grades 3–8).

Variables	ELA	ELA Rural	Math	Math Rural
Virtual	−0.24***	−0.28***	−0.36***	−0.46***
	(0.01)	(0.01)	(0.01)	(0.01)
Brick-and-mortar charter	0.05***	−0.28***	0.06***	−0.30***
	(0.01)	(0.03)	(0.01)	(0.03)
High mobility	−0.26***	−0.21***	−0.32***	−0.27***
	(0.01)	(0.02)	(0.01)	(0.02)
Mobility	−0.15***	−0.13***	−0.19***	−0.15***
	(0.01)	(0.01)	(0.01)	(0.01)
Student, grade, baseline achievement, and year controls	Y	Y	Y	Y
Virtual obs.	10,052	3742	10,030	3736
Total obs.	661,594	308,824	660,528	308,547

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors in parentheses. Notes. Student, grade, baseline achievement, and school year controls are FRL, race/ethnicity, IEP, ELL, baseline achievement, grade level, and school year. *Mobility* refers to students who switched schools once during the academic year while *High Mobility* denotes students who switched schools more than one time within the academic year.

Table 5
OLS regression estimates for virtual school students in Grade 11.

Variables	ELA	ELA Rural	Math	Math Rural
Virtual	−0.04	−0.06	−0.12***	−0.12***
	(0.02)	(0.03)	(0.02)	(0.03)
Brick-and-mortar charter	0.04	−0.12	0.02	−0.11
	(0.02)	(0.10)	(0.02)	(0.09)
High mobility	−0.17	−0.12	−0.08	−0.08
	(0.12)	(0.22)	(0.09)	(0.17)
Mobility	−0.14***	−0.17***	−0.06**	−0.07*
	(0.02)	(0.03)	(0.02)	(0.03)
Student, prior achievement, school year controls	Y	Y	Y	Y
Virtual obs.	761	318	763	319
Total obs.	37,266	18,348	37,267	18,314

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors in parentheses. Notes. Student, prior achievement, school year controls are FRL, race/ethnicity, IEP, ELL, 10th grade achievement, grade level, and school year. *Mobility* refers to students who switched schools once during the academic year while *High Mobility* denotes students who switched schools more than one time within the academic year.

analysis among students who remained in the same school for three consecutive years. However, these analyses show negative associations for virtual school students that are similar in magnitude whether the student is in the first, second, or third year of attendance at the same virtual school.

In Table 4, random effects models are presented that include students in the sample who switch schools within the academic year. In these models, student mobility within the school year is negatively associated with academic achievement for both students who switch schools once within the year and those who switch schools more than once within the year. Attendance in a virtual school remains negatively associated with ELA (−0.24 SD) and math (−0.36 SD) achievement in Models 1 and 3 in the full sample. In Models 2 and 4, with the sample restricted to students from rural areas, virtual school students from rural areas show large negative statistical associations in ELA (−0.28 SD) and math (−0.46 SD). In the Appendix, Table 5A shows consistent patterns when the sample is restricted to virtual school students who have four years of consecutive test scores.

In the final set of analyses, we examined results for virtual school students during high school. Table 5 presents OLS regression estimates in math and ELA for eleventh grade students. In the first model, there is a negative association between attendance in a virtual school and ELA, but this result is not statistically significant. In Model 2, with the sample restricted to students from rural areas, a negative association is observed but it is not statistically significant. Because academic gains are smaller in high school (Hill et al., 2008), these two estimates correspond to approximately one-fifth of an academic year of learning in eleventh grade. For math, a statistically significant negative association is observed for virtual school students in the full sample in Model 3 (−0.12 SD) and for those from rural areas in Model 4 (−0.12 SD). These estimates correspond to about 85% of a year of learning in math during eleventh grade.

5. Discussion

One of the main arguments for virtual schools is that they can help to increase student achievement by creating educational options in rural areas where school choice is limited (Ahn, 2011; Beck et al., 2016; Marsh et al., 2009). In the literature, previous studies show strong negative academic outcomes for students who attend full-time virtual schools (Ahn & McEachin, 2017; Fitzpatrick et al., 2020; Zimmer et al., 2009), but little research has investigated the academic performance of virtual school students from rural areas. By using longitudinal data, we analyzed the academic performance of virtual school students in a setting with a large number of rural students (Westapher et al., 2021). We found that rural virtual school students in Grades 3–8 showed substantially lower academic performance than their rural peers in brick-and-mortar public schools. Virtual school students in Grades 3–8 in the overall sample also exhibited similarly lower academic performance. In high school, negative academic performance was found for virtual school students in both the rural and full samples though negative associations were not as strong as those observed for virtual school students in Grades 3–8. We found little difference based on the consistency of virtual school experiences. Students who moved in and out of the virtual school sector between academic years and those who remained in the same virtual school over time exhibited mostly the same levels of low academic performance relative to their counterparts in brick-and-mortar public schools.

The overall estimates in this study build on an evidence base that generally paints a dismal picture for student learning in virtual schools (Ahn & McEachin, 2017; Fitzpatrick et al., 2020; Zimmer et al., 2009). Several recent studies using matching techniques report academic underperformance for virtual school students that range from −0.10 SD to −0.29 SD in ELA and −0.25 SD to −0.41 SD in math (Center for Research on Education Outcomes CREDO, 2015; Fitzpatrick et al., 2020). Our results using different analytical techniques show very similar estimates (i.e., −0.21 to 0.24 SD in ELA and −0.25 to 0.41 SD in math). In addition, we advance current research by showing similarly negative estimates for virtual school students from rural areas who disproportionately attend full-time virtual schools (Beck et al., 2016; Mann & Baker, 2019; Mann et al., 2016). At the high school level, there is less previous scholarship. We observe negative learning patterns for virtual high school students that align with findings from prior research but our negative estimates are smaller in magnitude (see Ahn & McEachin, 2017). More scholarly work is needed at the high school level. It is possible that high school students who require less monitoring and direct assistance organizing their learning could perform better in full-time virtual environments than younger students do (Borup et al., 2015).

This study's analyses contribute to existing research by generating results for mobile and comparatively stable students within the virtual school sector. Virtual school students tend to have greater school mobility, (Westpaher, 2021), which can be an obstacle to continuity that might support academic success (Mehana & Reynolds, 2004). In this study, students who switch in and out of the virtual school sector and those who remain in the same virtual school for several years show similar negative associations with achievement. When considering the learning trajectories of students who stay in the virtual school sector over time, findings are mixed (Fitzpatrick et al., 2020; Lueken et al., 2015). With a small matched-sample, Lueken et al. (2015) demonstrated that initial learning losses for virtual school students eventually became positive, whereas in a larger matched sample, Fitzpatrick et al. (2020) showed that initial losses were sustained over time. Consistent with Fitzpatrick et al. (2020)'s results, our estimates indicate that negative associations are sustained.

This study does not make causal claims. However, mounting empirical analyses across study settings, statistical models, and subgroups offer considerable evidence suggesting that students underperform academically when attending full-time virtual schools. Because purely causal designs that can rule out selection bias concerns are likely to remain elusive, scholars should pose new questions about virtual schools that can improve understanding of the mechanisms behind academic underperformance within them and shed light on how to improve fully virtual models of education. For example, researchers have identified high student-teacher ratios, infrequent peer-peer interactions, lack of instructor presence, poor student engagement, and low-quality virtual learning platforms as potential reasons for low achievement in virtual schools (Bradley-Dorsey, 2022; GarrettDikkers, Whiteside, & Lewis, 2013; Molnar et al., 2019). Future work is needed to ascertain the conditions that can support learning in virtual schools.

Existing research also underscores a seemingly counterintuitive pattern – virtual school enrollments are rising but academic outcomes in them are routinely poor (Molnar & Boninger, 2021). Education departments tend to caution families who are considering full-time virtual options, stating that virtual schools are not for every student and that they require both student independence and regular parental monitoring (OSDE, 2023). It is not clear whether such guidance reaches most families or if it adequately prepares them for what to expect. Yet, families may have non-academic motives in mind when choosing a virtual school. Researchers report that non-academic factors can drive students to the virtual school sector (Beck et al., 2014; Greene & Paul, 2022; Prosser, 2011). Students encountering severe bullying at school, physical and mental health challenges, and adverse family disruptions could choose virtual schools when academics are less of a priority (Prosser, 2011; Tonks et al., 2021). Future research is thus needed to determine whether students benefit from virtual schools in ways that have not been explored.

Finally, the broader virtual learning arena is transforming and continuously presenting new opportunities for students (Villena-Taranilla et al., 2022). Educational technologies that supplement in-person instruction, such as augmented reality and virtual gaming, appear to be beneficial complements to in-person instruction in certain cases (Kuznetcova et al., 2023). New types of online credit recovery and supplementary courses also demonstrate more positive learning outcomes than full-time virtual schools do (Chingos & Schwerdt, 2014; Darling-Aduana & Heinrich, 2020; Hart et al., 2019; Viano, 2021). In future work, it may be essential for researchers to draw clear distinctions between full-time virtual schooling and forms of virtual learning that complement in-person instruction.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Appendix

Table 1A
Enrollment patterns by school type[1]

	2017			2018			2019		
Grade	Virtual	Charter	TPS	Virtual	Charter	TPS	Virtual	Charter	TPS
PK	408	445	42,068	315	709	42,237	587	997	41,945
K	527	597	48,779	436	950	48,539	680	1096	48,823
1	578	646	50,112	471	906	48,881	660	1145	48,292
2	608	477	49,886	527	914	48,278	756	1059	46,904
3	598	470	50,443	532	800	50,051	806	1118	47,917
4	586	535	49,160	512	866	49,020	795	1080	48,414
5	628	734	47,116	533	1080	48,658	847	1292	48,501
6	638	978	44,425	689	1287	46,561	936	1606	47,737
7	861	1011	45,245	701	1377	43,897	1226	1762	45,399
8	894	876	45,168	893	1333	45,034	1247	1555	43,277
9	1584	1009	46,636	1561	1490	46,215	2339	1915	45,400
10	1416	976	44,725	1355	1437	44,058	2141	1707	43,985
11	1333	850	42,411	1182	1338	41,846	1632	1374	41,104
12	1135	898	41,414	1213	1275	41,587	1954	1568	41,167
Total	11,794	10,502	647,588	10,920	15,762	644,862	16,606	19,274	638,865

Notes. Data exclude students who switch schools within the academic year.

Table 2A
Estimates of student fixed effects for virtual school students (Grades 3–8)

Variables	ELA	ELA Rural	Math	Math Rural
Virtual	−0.18***	−0.19***	−0.27***	−0.37***
	(0.01)	(0.02)	(0.02)	(0.02)
Brick & mortar charter	0.14***	−0.05	0.23***	−0.10
	(0.01)	(0.07)	(0.01)	(0.06)
Time-invariant student characteristics[1]	Y	Y	Y	Y
Student, grade, and year controls	Y	Y	Y	Y
Sample restriction – three consecutive test scores	Y	Y	Y	Y
Virtual observations	4232	1101	4227	1100
Total Observations	417,628	198,174	418,004	198,047

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors in parentheses. Notes. 1. Fixed effects models control for time invariant student characteristics. Student, grade, and year controls are FRL, IEP, ELL, grade level, and school year. The analytic sample was restricted to students who have three years of consecutive test scores.

Table 3A
Estimates of student fixed effects for virtual school students (Grades 3–8)

Variables	ELA	ELA Rural	Math	Math Rural
Virtual	−0.17***	−0.17***	−0.26***	−0.35***
	(0.02)	(0.02)	(0.02)	(0.03)
Brick & mortar charter	0.14***	−0.06	0.25***	−0.09
	(0.01)	(0.07)	(0.01)	(0.07)
Time-invariant student characteristics[1]	Y	Y	Y	Y
Student, grade, and year controls (including baseline achievement in 2016)	Y	Y	Y	Y
Sample restriction – four consecutive test scores	Y	Y	Y	Y
Virtual obs.	3640	1044	3636	1043
Total obs.	413,998	197,130	414,368	197,043

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors in parentheses. Notes. 1. Fixed effects models automatically control for time invariant student characteristics. Student, grade, and year controls are baseline achievement in 2016, FRL, IEP, ELL, grade level, and school year. The analytic sample was restricted to students who have four years of consecutive test scores.

Table 4A
Random effects estimates for virtual school students who attend the same school for three consecutive years without a baseline achievement control and with/without sample restriction of four consecutive years of test scores (Grades 3–8)

Variables	ELA 3-yr	ELA 3-yr	Math 3-yr	Math 3-yr
Virtual	−0.46***	−0.48***	−0.61***	−0.62***
	(0.06)	(0.06)	(0.06)	(0.05)
Brick-and-mortar charter	0.16***	0.17***	0.22***	0.22***
	(0.03)	(0.03)	(0.04)	(0.04)
Student, grade, and year controls (excluding baseline achievement)	Y	Y	Y	Y
Sample restriction – four consecutive test scores	Y		Y	
Virtual obs.	612	671	612	671
Total obs.	135,549	136,936	134,696	137,660

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors in parentheses. Notes. Student, grade, and school year controls are FRL, race/ethnicity, IEP, ELL, grade level, and school year. The analytic sample restricted to students who do not switch schools within the academic year.

Table 5A
Random effects estimates for virtual school students including within-year school switchers (Grades 3–8)

Variables	ELA	ELA Rural	Math	Math Rural
Virtual	−0.24***	−0.28***	−0.38***	−0.47***
	(0.01)	(0.01)	(0.01)	(0.02)
Brick-and-mortar charter	0.07***	−0.25***	0.09***	−0.32***
	(0.01)	(0.04)	(0.01)	(0.04)
High mobility	−0.24***	−0.21***	−0.31***	−0.25***
	(0.02)	(0.02)	(0.02)	(0.02)
Mobility	−0.15***	−0.13***	−0.19***	−0.16***
	(0.00)	(0.01)	(0.01)	(0.01)
Student, grade, baseline achievement, and year controls	Y	Y	Y	Y
Sample restriction – four consecutive test scores	Y	Y	Y	Y
Virtual obs.	6291	2583	6271	2576
Total obs.	464,586	218,777	464,809	218,570

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors in parentheses. Notes. Student, grade, baseline achievement, and school year controls are FRL, race/ethnicity, IEP, ELL, baseline achievement, grade level, and school year. *Mobility* refers to students who switched schools once during the academic year while *High Mobility* denotes students who switched schools more than one time within the academic year.

Table 6A
Random effects estimates for virtual school students including within-year school switchers (Grades 3–8)

Variables	ELA	ELA Rural	Math	Math Rural
Virtual	−0.29***	−0.29***	−0.41***	−0.47***
	(0.01)	(0.01)	(0.01)	(0.01)
Brick-and-mortar charter	0.07***	−0.22***	0.11***	−0.30***
	(0.01)	(0.04)	(0.01)	(0.04)
High mobility	−0.18***	−0.18***	−0.23***	−0.19***
	(0.01)	(0.02)	(0.01)	(0.02)
Mobility	−0.10***	−0.10***	−0.12***	−0.10***
	(0.00)	(0.01)	(0.00)	(0.01)
Student, grade, and year controls (excluding baseline achievement)	Y	Y	Y	Y
Sample restriction – three consecutive test scores	Y	Y	Y	Y
Virtual obs.	8149	3301	8132	3296
Total obs.	544,917	251,455	545,019	251,145

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors in parentheses. Notes. Student, grade, and school year controls are FRL, race/ethnicity, IEP, ELL, grade level, and school year. *Mobility* refers to students who switched schools once during the academic year while *High Mobility* denotes students who switched schools more than one time within the academic year.

Table 7A
Random effects estimates for students achieving in the 75th percentile or higher when attending a brick-and-mortar public or charter schools in 2016

Variables	High Read	High Read	High Math	High Math
Virtual	−0.20***	−0.18***	−0.34***	−0.36***
	(0.02)	(0.02)	(0.02)	(0.02)
Brick-and-mortar charter	0.06***	0.08***	0.07***	0.08***
	(0.02)	(0.02)	(0.02)	(0.02)
High mobility	−0.16***	−0.12***	−0.21***	−0.18***
	(0.03)	(0.04)	(0.03)	(0.03)
Mobility	−0.11***	−0.11***	−0.13***	−0.11***
	(0.01)	(0.01)	(0.01)	(0.01)
Student, grade, and year controls	Y	Y	Y	Y
Sample restriction – four consecutive test scores		Y		Y
Virtual obs.	1721	1102	1706	1121
Total obs.	136,014	102,393	157,442	118,479

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors in parentheses. Notes. Student, grade, and school year controls are FRL, race/ethnicity, IEP, ELL, grade level, and school year. *Mobility* refers to students who switched schools once during the academic year while *High Mobility* denotes students who switched schools more than one time within the academic year. Students who were in the 75th percentile or higher in math/ELA in 2016 but switched into a virtual school in 2017 are compared to their high achieving peers (i.e. 75th percentile or higher) in brick-and-mortar public schools.

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