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The Impact of Statewide Virtual Charter Schools on District Segregation

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The Impact of Statewide Virtual Charter Schools on District Segregation*

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Abstract

Enrollment patterns in K-12 online ("virtual") charter schools have the potential to influence segregation in traditional brick-and-mortar public schools. Yet, research has largely ignored how online schooling options impact racial segregation and poverty concentration within district schools. To address this gap, I conduct two complementary studies: In the first study, I exploit variation in the share of district students enrolling in virtual charter schools across the state, while in the second, I leverage the sudden and unexpected closure of a large statewide virtual charter school. Using a matched event study difference-in-differences approach, I find that the introduction of virtual charter schools reduced the gap in the likelihood of minority and non-minority students being exposed to minority peers (i.e., racial imbalance) by 45–75%, particularly in urban districts. However, virtual charter schools also led to 10-24% increase in the concentration of high-poverty students, again driven by effects in urban districts. I further find that the closure reduced racial imbalance in urban districts by 27% while increasing racial unevenness in rural districts by 38%. Potential mechanism analyses reveal selective exit of high-poverty students following introduction and selective or concentrated re-entry of minority students after closure as key channels shaping segregation outcomes in traditional district schools. These findings suggest that although racial imbalance declines following both the introduction and closure, particularly in urban districts, these changes largely reflect compositional sorting rather than meaningful integration, as students remain concentrated along racial and poverty lines.

Keywords: charter schools, virtual, segregation, inequality, enrollment, school districts
JEL Codes: H11, I21, I24, I26, I28, I29

*Note: I have no conflicts to declare.

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1. Introduction

The availability of K-12 online ("virtual") schooling options has expanded substantially over the last twenty five years (e.g., see Gulosino and Miron, 2017; Horn and Staker, 2011; Watson et al., 2012). This trend saw an even greater surge in online enrollment following the COVID-19 pandemic (Dee and Murphy, 2021; Flanders, 2021; Kamenetz and Korth, 2020; Lehrer-Small, 2022). The increasing enrollment in virtual schools has the potential to influence enrollment patterns in brick-and-mortar public schools. Despite the rapid increase in enrollment in online schools, such as virtual charter schools, we still do not know about their impact on segregation in traditional public schools. Empirical research is needed to understand whether virtual charter schools may or may not be segregating students in local public schools to an even greater extent than brick-and-mortar charter schools. In this paper, I examine segregation patterns within Ohio school districts following the introduction of statewide virtual charter schools and the closure of a large statewide virtual charter school.

Research estimating the impact of charter schools on racial segregation in public schools has largely focused on the opening of brick-and-mortar charter schools (see, e.g., Cohodes and Parham, 2021; Epple et al., 2016), with findings generally indicating that these schools modestly increase racial segregation in public schools (Alcaino and Jennings, 2020; Denice et al., 2021; Monarrez et al., 2022; Sorensen and Holt, 2021). However, this focus overlooks virtual charter schools, which are growing in popularity and enroll a different racial mix of students compared to brick-and-mortar charter schools. Studies show that virtual charter schools enroll a higher percentage of White students and a lower percentage of minority students (Ahn and McEachin, 2017; Kotok et al., 2017; Nowicki, 2022), potentially leading to different segregation effects in district schools. Unlike brick-and-mortar charters, which primarily attract students from high-density, diverse urban districts, virtual charter schools also draw students from low-density, relatively homogeneous rural districts, which may influence sorting behaviors differently.

Another limitation of existing research on charter schools and segregation is that it focuses primarily on the impact of opening charter schools (see, e.g., Alcaino and Jennings, 2020; Bifulco and Ladd, 2007; Bifulco et al., 2009; Booker et al., 2005; Cordes and Laurito, 2022; Denice et al., 2021; Ladd and Turaeva, 2020; Monarrez et al., 2022; Ritter et al., 2016). The implicit assumption in many such studies is that the elimination or closure of charter schools would reverse or undo segregation effects. However, it is not clear whether this would hold, especially because there is no guarantee that students attending charter schools would enroll in traditional public schools if charters were no longer an option. Families of students enrolled in charter schools might send their children to private schools, opt for homeschooling, or leave the district altogether. Similarly, merely closing one charter school option—such as a virtual charter school—might lead students to attend brick-and-mortar charter schools (or vice versa) as opposed to traditional public schools.

Given these considerations, I conduct two studies. The first examines segregation patterns within school districts following the introduction of statewide virtual charter schools. I estimate the impact of introducing statewide virtual charter schools on racial and poverty segregation of students within districts. I leverage variation in the proportion of district students enrolling in virtual charter schools across Ohio during the 2001–02 school year (baseline year), the year virtual charter schools were first introduced in the state. The second study estimates the impact of closing a large virtual charter school on racial segregation within districts. I take advantage of the sudden and unexpected closure of the Electronic Classroom of Tomorrow (ECOT), which was the largest virtual charter school in Ohio at the time. Here, I leverage variation in the proportion of district students enrolling in ECOT during the 2015–16 school year (baseline year). I strategically chose the 2015–16 school year as the baseline year for the closure analysis because, although ECOT officially closed in January 2018, data and news articles indicate that its financial controversies became public in early 2016. This was also the same year that the state Department of Education launched an investigation into ECOT's student attendance claims (Bush, 2018; Ohio Auditor of State, 2018; Smyth, 2018), prompting students to begin disenrolling immediately after the 2015–16 school year.

To create racial segregation measures, I use grade-level school enrollment data by race and ethnicity from 1999 through 2019. For both studies, I use three measures of segregation: 1) a relative exposure index (imbalance), 2) an isolation index (concentration), and 3) a dissimilarity index (unevenness). A relative exposure to minority index, which I will refer to as racial imbalance, captures the difference in expected exposure to minority students between minority and non-minority students (see Owens et al., 2022). An isolation index measures the expected exposure of a certain group to itself (i.e., the concentration of minority students), and a dissimilarity index measures how evenly two groups are distributed across schools within districts. For poverty segregation measures, I rely on school-level data on free- or reduced-price lunch (FRPL) from 1999 through 2013. I limit poverty segregation analysis to 2013 because Ohio implemented the Community Eligibility Provision (CEP) program in the 2012-13 school year, which allowed all schools in high-poverty communities to provide free lunches and breakfasts to all students.[1] This universal provision would complicate reliable differentiation of students from disadvantaged backgrounds to those from advantaged backgrounds. Consequently, in the second study, I do not analyze the impact of the closure on poverty segregation measures because this analysis takes place between the 2012-13 and 2018-19 school years.

To conduct the analyses on the introduction of virtual charter schools, I implement a matched event study difference-in-differences strategy to compare changes in racial and poverty segregation between observationally similar districts that had high and low enrollment in virtual charter schools at the baseline (2002). I repeat the analysis for the closure of ECOT and compare changes in racial segregation between observationally similar districts that had high and low enrollment in ECOT at the baseline (2016). A key identifying assumption is that, in the absence of virtual charter schools, districts that had a high proportion of students enrolling in virtual charter schools would have had similar trends in segregation outcomes as districts that did not. As the analyses later reveal, districts with high and low enrollment in virtual charter schools had similar trends in the years leading up to the introduction of virtual charter schools. Similarly, districts with high and low enrollment in ECOT had similar trends in segregation outcomes in the years leading up to 2016, the year students began to disenroll from ECOT. Thus, the calculated estimates on district segregation are plausibly causal.

The results reveal that the introduction of virtual charter schools reduced racial imbalance or the difference in the likelihood of minority and non-minority students encountering minority

[1] U.S. Department of Education (revised March 2015). Guidance: The community eligibility provision and selected requirements under Title I, Part A of the Elementary and Secondary Education Act of 1965, As Amended. Retrieved from https://oese.ed.gov/files/2020/07/15-0011.doc

peers in districts with high enrollment in virtual charter schools compared to those that did not. In districts where at baseline, on average, minority students had a 2.0% likelihood of encountering minority peers, this likelihood decreased by 0.9–1.5 percentage points (45–75%), driven by a 1.9–3.0 percentage point (48–76%) decrease within urban districts. Regarding poverty segregation, the introduction of virtual charter schools increased the average concentration of high-poverty students in districts that had high enrollment in virtual charter schools than those that did not. Specifically, I find that in a district where a high-poverty student typically attends a school with about 30% of peers from similar backgrounds, virtual charter schools led to a 2.9–7 percentage point increase in the concentration of high-poverty students, representing about 10–24% increase. This increase is primarily driven by 3-13.5 percentage points (about 11-47%) increase in the concentration of high-poverty students across schools in urban districts. Although the difference in expected exposure to high-poverty students between high-poverty and low-poverty students is only statistically significant at the 10% level, I cannot rule out substantively significant impacts in urban districts. In urban districts where at baseline, high-poverty students on average attend a school with a 6.4% likelihood of encountering high-poverty peers, the introduction of virtual charter schools increased this likelihood by 5.1–9.7 percentage points, effectively doubling relative exposure to high-poverty students. I do not find statistically significant effects on poverty segregation in rural districts.

On the other hand, I find that the closure of ECOT decreased racial imbalance and unevenness in urban districts while increasing racial unevenness in rural districts. Specifically, in an urban district where on average, a minority student attends a school with about 1.9% relative likelihood of encountering minority peers, closing ECOT reduced racial imbalance by 0.5 percentage points, or approximately 27%. Similarly, closing ECOT led to a 0.5 percentage point decrease (about 32%) in racial unevenness between minority and non-minority students in urban districts, implying that fewer students would need to change schools to achieve an even distribution of minority students across schools within urban districts. In rural districts, however, closing ECOT increased racial unevenness by 0.5 percentage points (about 38%), indicating that more students would need to change schools so that minority students are evenly distributed across schools within rural districts.

Overall, these findings suggest that the opening and closing of virtual charter schools reshape student racial and poverty composition through patterns of selective exit and selective re-entry, rather than fundamentally restructuring the distribution of students across schools. For the remainder of this paper, I organize the sections as follows: First, I provide relevant background on virtual charter schools in Ohio. Second, I describe the methods, including data, analytic sample, segregation measures, descriptive statistics, and the general statistical model. Third, I present the results and review potential mechanisms. Finally, I conclude with a brief discussion on policy implications.

2. Ohio Context

In this section, I provide an overview of Ohio virtual charter schools and their enrollment patterns, followed by a discussion of key legislative reforms. Then, I provide some context surrounding the closure of the state's largest e-school at the time, Electronic Classroom of Tomorrow, and conclude with key details about Ohio's charter school funding.

2.1 Ohio Virtual Charter Schools and Legislative Reforms

Virtual charter schools, or "e-schools" as they are referred to in Ohio, are publicly funded schools of choice that operate without physical buildings, delivering education to students through technology (Gill et al., 2015). Generally, there are two types of e-schools: fully online and hybrid. Fully online e-schools do not rely on in-person classroom instruction and require students to work via the internet or other computer-based instructional method (Ohio Department of Education, 2021a), while hybrid e-schools operate partially online and partially in-person. These schools provide access to teachers by email, telephone, web and/ or teleconference (Gill et al., 2015). According to the Ohio Department of Education (ODE), a licensed teacher is required to provide the appropriate grade-level instruction, and every student receives a computer at home and online access to the school.[2] Studies suggest that self-paced, independent instruction is the norm in e-schools and that student-teacher interaction is limited (see Gill et al., 2015; Nowicki, 2022). Gill

[2]Department of Education and Workforce (n.d.). E-schools. Retrieved from https://education.ohio.gov/Topics/Community-Schools/eSchools

et al. (2015) also showed that larger online charter schools tend to have somewhat more synchronous instructional time, spending about five hours of synchronous instruction per week in fourth and seventh grades and six hours in high school. In Ohio, as of 2021, the average student-to-teacher ratio in online charter schools is about 30 students per full-time teacher (Ohio Department of Education, 2021b).

Since their introduction in the 2001–02 school year, student enrollment in Ohio e-schools steadily increased, later surpassing the enrollment growth of brick-and-mortar charter schools (Churchill, 2014; Innovation Ohio, 2011). Between 2002 and 2015, virtual charter school enrollment expanded rapidly, reaching its peak around the 2014-15 school year when it accounted for approximately 31 percent of the total charter school share (see Lavertu, 2020). This growth occurred despite a statewide moratorium imposed in 2003, which prohibited the creation of new e-schools until 2013. The state legislature implemented the moratorium to allow the Department of Education to establish accountability standards for charter schools. It was not until 2015 that the Ohio Statehouse passed a bipartisan charter school reform bill that introduced a stricter accountability framework for charter school sponsors—non-profit and government organizations that authorize and oversee Ohio charter schools. The reform bill included several regulations that sought to improve the services provided by e-schools, as well as the financial management of all charter schools (Lavertu, 2020).

In 2013, there were 23 e-schools serving a total of about 40,000 students. In the 2015-16 school year, the state's largest e-school at the time (ECOT) enrolled just over 13,000 students (see Table 16 in the Appendix). In 2016, following 2015 legislative reforms, the state Department of Education launched an investigation of the Electronic Classroom of Tomorrow. The investigation was set up to examine ECOT's student attendance claims that went unchallenged for more than a decade (Bush, 2018). Later, it was revealed that ECOT had received full funding for students based on attendance numbers that could not be verified. Subsequently, the school was ordered to repay $60 million to the state for the 2015-16 school year. The state department's review eventually caused ECOT's sponsor, the Educational Service Center of Lake Erie West, to withdraw its sponsorship. Unable to secure a sponsor as required by Ohio law, ECOT was ultimately forced to shut down and was officially closed in January 2018. Public controversies surrounding ECOT and its closure contributed to a decline in e-school enrollment between 2016 to 2019, until the onset of the COVID-19 pandemic. The pandemic induced an increase in charter school enrollment, rising from 103,000 students in 2018-19 to 114,000 students in the 2020-21 school year (Ohio Department of Education, 2021a), with the majority of enrollment increases occurring in virtual charter schools (Ohio Department of Education, 2022).

2.2 From District Deductions to Direct Charter Funding

Prior to the recent changes to Ohio's school funding formula (see Churchill, 2023), Ohio charter schools, including e-schools, received a per-pupil amount that was deducted from the district's state spending budget where the child resides, regardless of whether the child ever attended school in his or her residential district (Innovation Ohio, 2011). Therefore, when a student selects to attend a virtual charter school, per-pupil funds were deducted and transferred from the student's resident district to a virtual charter school. Similarly, if a student returned to a local public school, the virtual charter school would also lose the funds, which would be transferred to the student's resident district. Under the "new" school funding formula, charter schools and other schools of choice now receive direct funding from the state (Churchill, 2023; Ohio Department of Education and Workforce, 2025).

3. Methods

In this section, I first describe the data and data sources. Second, I show the calculation for the share of district students enrolling in virtual charter schools. Third, I explain the selection of my analytic sample. Fourth, I provide details on the segregation measures that I use for analyses. Fifth, I discuss descriptive statistics before describing the statistical model.

3.1 Data

The data used in this study come from two main sources: The Ohio Department of Education (ODE) and the National Center for Education Statistics (NCES) (Common Core of Data). First, I collect publicly available data on the total number of full-time equivalent students who chose to enroll in a virtual charter school between 2001 and 2019 from the Ohio Department of Education.[3] These data come from charter school funding reports that have been compiled by ODE since 2001. Second, I downloaded publicly available grade-level school enrollment data by race and ethnicity between 1999 and 2019 and school-level data on free- or reduced-price lunch (FRPL) from 1999 and 2013. Race and FRPL data was downloaded from the National Center for Education Statistics.

For poverty segregation, I limit the data to 2013 because Ohio implemented the Community Eligibility Provision (CEP) program in the 2012-13 school year, which allowed all schools in high-poverty communities to provide free lunches and breakfasts to all students. This universal provision complicates the reliable differentiation of students from disadvantaged backgrounds to those from advantaged backgrounds.[4] Finally, the race and ethnicity data were then merged with the poverty data to create a comprehensive dataset, which enabled me to analyze demographic changes as well as changes in segregation patterns over time.

3.2 Share of District Enrollment in Virtual Schools

I take advantage of Ohio's "old" feature of charter school funding to track the proportion of students leaving their local district schools for a virtual charter school. Before the recent changes to Ohio's school funding formula (see Churchill, 2023), Ohio charter schools received a per-pupil amount that was deducted from the district's state spending budget where the child resides. If a student resides within a public school district and attends a charter school, funds were deducted from state spending per-pupil from the district's budget. For each district in the state, I was able to determine the proportion of students leaving their resident district schools and the specific virtual charter school they chose to attend. This information was then used to measure the average share of district students enrolling in virtual charter schools between 2001 and 2019 as well as the share of district students enrolling in ECOT between 2009 and 2019.

Specifically, the share of district enrollment in virtual charter schools was calculated using the

[3] I extend my gratitude to Dr. Jason Cook for generously providing access to clean enrollment data from 2001 to 2011.

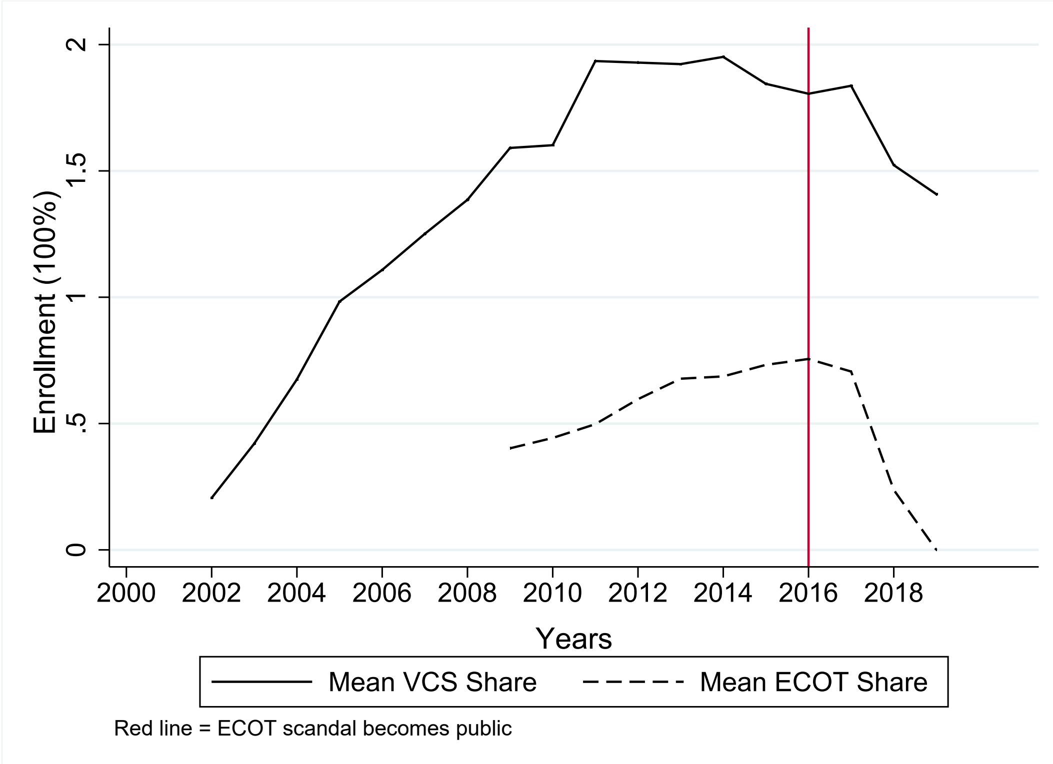
[4] I recognize that the use of FRPL data as a proxy for poverty or socioeconomic status is not perfect, but may still provide a good approximation of students' level of poverty prior to CEP implementation.

fraction of a district's potential membership that instead enrolls in virtual charter schools in a specific year (Equation 1). To calculate the share of district enrollment in ECOT alone, I use the same calculation but replace "virtual charter" with ECOT.

$$\frac{Number\ Enrolled\ in\ Virtual\ Charter)}{Number\ Students\ Enrolled\ in\ LPSD + Number\ Enrolled\ in\ Virtual\ Charter} \tag{1}$$

The number of students who enroll in a virtual charter school is the full-time equivalency count reported in the charter school funding reports for each district. This measure has been used in previous studies to measure charter competition within a district (e.g., see Cook, 2018). However, in this current study, I use it to capture enrollment competition from virtual charter schools as opposed to enrollment competition from brick-and-mortar charter schools. Figure 1 shows enrollment growth in all virtual charter schools and ECOT separately, showing a steady increase in the average share of district students enrolling in virtual charter schools between 2002 and 2013, followed by a sharp decline after the 2015-16 school year. Data indicate that this enrollment decline mostly stems from ECOT's closure. In the 2001-02 school year, the inception year for virtual charter schools in Ohio, the average share of district students enrolling in virtual charter schools was only about 0.2 percent. Peak enrollment reached in 2013 when that share rose to about 2 percent.

Figure 1. Mean share of district students attending virtual charter schools over the years



Note: The data represents the average share of district student enrollment that instead enroll in virtual charter schools and ECOT over the years. *Source*: Author's calculations based on data from Ohio Department of Education.

3.3 Analytic Sample

In this paper, I construct two analytic samples: one to examine the impact of introducing statewide virtual charter schools on district segregation, and another to assess the impact of closing ECOT on district segregation. For the introduction analysis, I restrict the sample to districts in the top and bottom quartiles of virtual charter school enrollment in 2002 (i.e., 2001-02 school year), the baseline year when these schools were first introduced in Ohio. This yields an initial sample of 246 districts (123 treated and 123 control) out of the 606 Ohio districts available in my dataset. To ensure that the control and treated districts are comparable in observable ways at the baseline, I apply coarsened exact matching (CEM) (see Blackwell et al., 2009).[5] The CEM process pruned the sample further and matched 110 treated districts to 96 control districts, for a total of 206 districts in my first analytic sample.[6] I repeat the procedure for the ECOT closure analysis,

[5]For CEM see: https://gking.harvard.edu/software/cem-coarsened-exact-matching-software/

[6]I match districts using pre-treatment averages from 1996 to 2001. These included total enrollment count, total revenue, per-pupil funding, charter share, and Black enrollment count

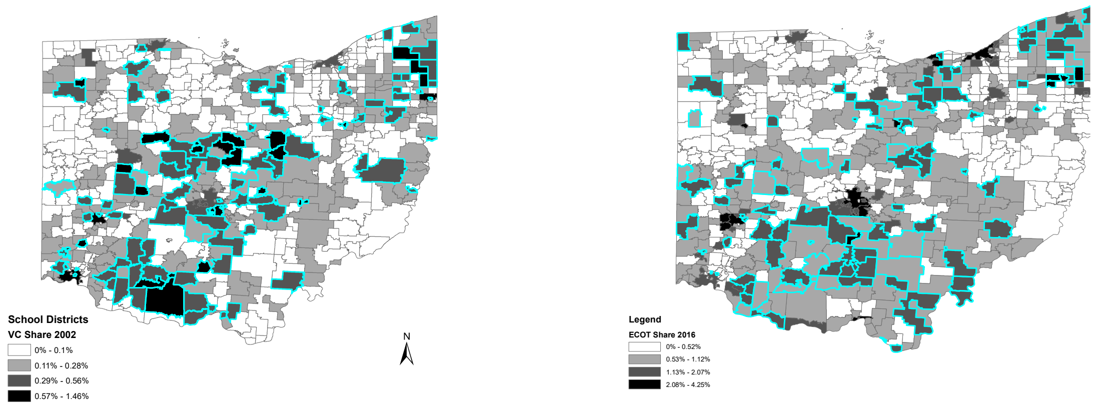
limiting the sample to districts whose 2016 ECOT enrollment share falls in the top and bottom quartiles. This yields a second analytic matched sample of 103 control districts and 96 treated districts, for a total of 199 districts.[7] The choice of which pre-treatment covariates to include in `cem` matching command was mainly based on factors that are likely to affect trends in segregation levels.

To illustrate the geographic distribution of district students enrolled in virtual charter schools in 2001–02 and in ECOT in 2015–16, I present Figure 2 below. Figure 2(a) shows a map of school districts shaded based on their average virtual charter share in 2001-02. Figure 2(b) shows a map of school districts shaded based on their average ECOT share in 2015-16. Dark grey to black shades indicate districts with a higher share of students enrolling in virtual charter schools or ECOT. Figure 2(a) shows that even in their first year of operation, virtual charter schools enrolled students from urban and rural districts throughout the state. Similarly, Figure 2(b) also shows that ECOT drew students from both urban and rural districts across the state. Here I have only highlighted the borders of districts that are included as matched treated districts. Note that not all potential treated districts are included in the final analytic samples (and thus are not highlighted here), as many could not be matched to control districts during the CEM process.

[7]For the ECOT closure analysis, I match districts using pre-treatment averages from 2009 to 2015. These included total enrollment, total revenue, standardized proficiency index (PI) scores, charter school share, share of students enrolled in virtual schools, and minority enrollment (Black and Hispanic students).

Figure 2. The proportion of district students enrolled in virtual charter schools and ECOT

(a) VCS share 2001-02 (b) ECOT share 2015-16



Note: Ohio district boundaries are plotted and each district is shaded based on the fraction of student enrollment that instead choose to enroll in virtual charter schools in the school year 2001-02 and in ECOT in the school year 2015-16. Highlighted districts are treated districts. *Data Source*: Author's calculations based on data from Ohio Department of Education

3.4 Measuring Segregation by Race and Poverty

To estimate the extent to which students are segregated by race and poverty in local districts, I use three measures common in the literature (using race for illustration): i) the difference in expected exposure to minority students between minority and non-minority students (relative exposure index), ii) the expected exposure of minority students to other minority students (isolation index), and iii) the proportion of schools' minority students who would need to change schools in order for minority and non-minority students to be evenly distributed across public schools in a district (dissimilarity index). For racial segregation indices, I use grade-level counts of minority and non-minority students. The calculations for racial segregation are calculated at the school-by-grade level using schools' grade-level enrollments. However, for simplicity, I suppress the grade subscript (g) in the equations below.

$$Relative\ Exposure = \sum_{s=1}^{N}\left(\frac{Min_s}{Min_d} \times \frac{Min_s}{Min_s + nonMin_s}\right) - \sum_{s=1}^{N}\left(\frac{nonMin_s}{nonMin_d} \times \frac{Min_s}{Min_s + nonMin_s}\right) \tag{2}$$

$$Isolation = \sum_{s=1}^{N}\left(\frac{Min_s}{Min_d} \times \frac{Min_s}{Min_s + nonMin_s}\right) \tag{3}$$

$$Dissimilarity\ Index = \frac{1}{2}\sum_{s=1}^{N}\left|\frac{Min_s}{Min_d} - \frac{nonMin_s}{nonMin_d}\right| \tag{4}$$

The subscripts (d) and (s) indicate district and school levels, respectively. I group Black and Hispanic students together as an underrepresented minority rather than estimating the segregation of Black or Hispanic students separately (e.g., see Caetano and Maheshri, 2017; Card et al., 2008). To measure poverty segregation indices, I use the same equations as above, substituting the district and school-level minority and non-minority student counts with district and school-level counts of students eligible for free- or reduced-price lunch (FRPL) and non-FRPL student counts, respectively. NCES's CCD does not provide grade-specific FRPL eligibility data, therefore I calculate poverty segregation indices without grade level enrollment data.

3.5 Baseline Demographics and Segregation

In this section, I present baseline descriptive statistics for the districts and their characteristics in 2001–02 and 2015–16 school years. I examine the descriptive statistics for the 2001–02 and 2015–16 school years because these serve as baseline years for the two studies. To visualize demographic and segregation trends across Ohio over time, I calculate the average proportions of Black, Hispanic, and White students and the average levels of racial and poverty segregation for all school districts in each year. I conclude the section by comparing the demographic characteristics of students enrolled in virtual charter schools, ECOT, brick-and-mortar charter schools, and traditional public schools during the 2015–16 school year. These descriptives offer insight into how changes in demographics across locales and sectors may contribute to patterns of racial and poverty segregation within districts.

3.5.1 District characteristics

Table 1. Baseline values of district characteristics by urbanicity

	2001–02				2015–16			
	Urban		Rural		Urban		Rural	
	M	SD	M	SD	M	SD	M	SD
Demographic (0–100%)								
Percent Black	13.18	21.05	1.56	4.59	16.62	23.75	1.77	5.31
Percent Hispanic	1.43	3.09	1.27	2.77	5.37	6.69	3.22	4.64
Percent White	85.39	21.72	97.17	5.43	78.01	25.48	95.01	7.34
Percent Poverty	26.68	20.86	27.73	16.10	42.41	24.26	41.62	18.29
Racial Segregation								
Relative Exposure (to minority)	0.039	0.080	0.009	0.019	0.019	0.049	0.003	0.010
Isolation (minority)	0.170	0.236	0.043	0.061	0.229	0.261	0.057	0.072
Dissimilarity Index (minority)	0.035	0.040	0.043	0.058	0.015	0.018	0.014	0.032
Poverty Segregation								
Relative Exposure (to high-poverty)	0.064	0.071	0.051	0.073	–	–	–	–
Isolation (high-poverty)	0.287	0.214	0.299	0.170	–	–	–	–
Dissimilarity Index (high-poverty)	0.045	0.040	0.054	0.051	–	–	–	–
No. of Districts	199		384		205		400	

Note: This table presents descriptive statistics for urban and rural districts in 2001–02, the year virtual charter schools were introduced in Ohio, and 2015–16, when students began disenrolling from the Electronic Classroom of Tomorrow. All Ohio urban and rural districts are included. Missing values (–) indicate poverty segregation measures that were not calculated due to Community Eligibility Provision programs.

Table 1 provides the 2001-02 and 2015-16 descriptive statistics for all districts in Ohio disaggregated by urbanicity.[8] Table 1 reveals a higher percentage of Black students in districts located in urban areas compared to those in rural areas. Specifically, during the 2001-02 school year, urban districts had about 13.2 percent Black students while rural districts had only 1.6 percent Black students. By 2015–16, the proportion of Black students in urban districts had risen to almost 17 percent, while in rural districts it increased only slightly, reaching 1.8 percent. In 2001–02, urban and rural districts had nearly identical proportions of Hispanic students (1.4 percent and 1.3 percent, respectively). In 2015–16, these shares increased to 5.4 percent in urban

[8]I use this table to convert urban and rural percentage point estimates into percents. Conversions for the full sample percentages use Table 15 in Appendix.

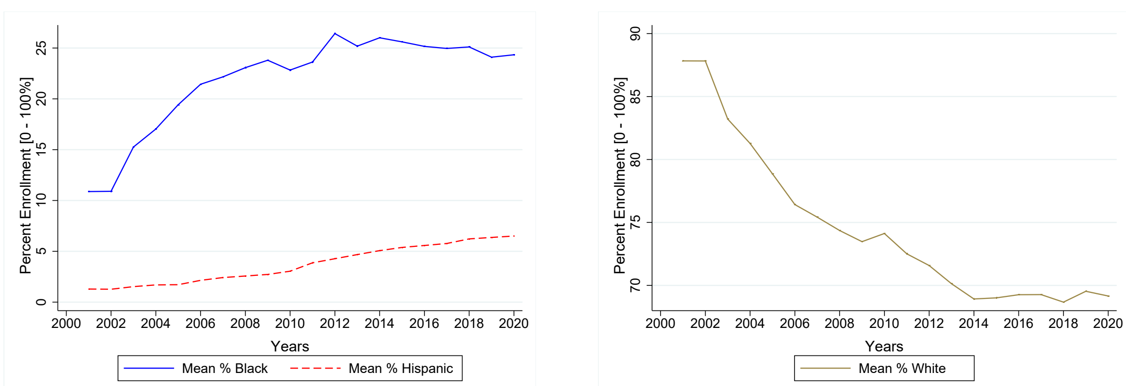
districts and 3.2 percent in rural districts. However, rural districts exhibit a higher percentage of White students compared to urban districts.

Table 1 shows that in 2001–02, urban districts had about 85.4 percent White students, compared to 97.2 percent in rural districts. By 2015-16, the proportion of White students enrolling in both urban and rural districts declined, to 78 and 95 percent, respectively. These shifts indicate that while the proportion of White students enrolling in urban and rural districts declined over the years, the proportion of minority (Black and Hispanic) students increased in both settings. Figure 3 shows a steady decline in the share of White students enrolled in Ohio school districts, accompanied by increases in Black and Hispanic enrollment, though Black enrollment levels off and declines slightly after 2014.

Regarding poverty, Table 1 shows that in the 2001-02 school year, the proportion of students in poverty was similar across urban and rural districts—about 27 percent. By 2015–16 school year, this share increased to roughly 42 percent in both settings, likely reflecting changes in eligibility criteria following the introduction of Community Eligibility Provision (CEP) programs.

Figure 3. Mean district demographic trends over the years

(a) Black & Hispanic (b) White



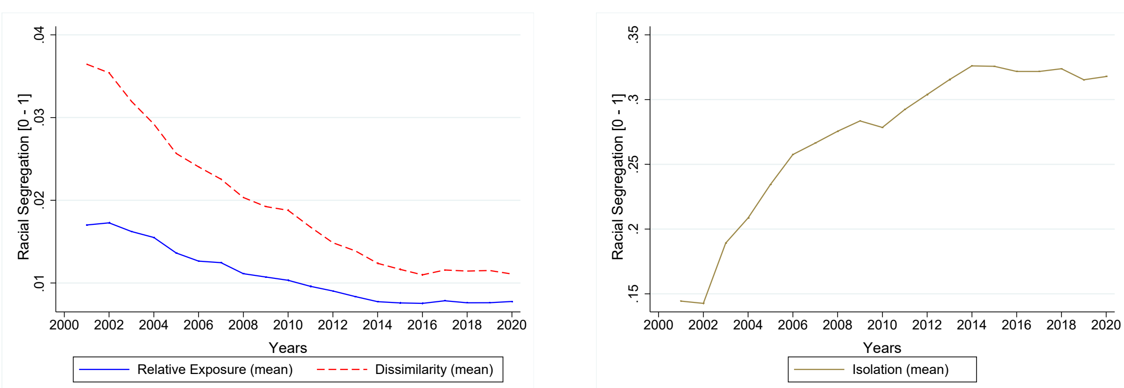
Note: The figures display the average proportions of Black, Hispanic, and White students across school districts for each year. The y-axis scale is percentages ranging from 0 - 100%.

Examining racial segregation during the 2001-02 and 2015-16 school years, Table 1 reveals that urban districts had higher levels of relative exposure to minority students than rural districts. Specifically, in 2001–02, minority students in urban districts had a 3.9 percent likelihood of encountering other minority schoolmates relative to non-minority students, compared to only 0.9

percent in rural districts. By 2015–16, relative exposure to minority students declined to 1.9 percent in urban districts and 0.3 percent in rural districts. Thus, while exposure to minority peers decreased over time, the disparity between urban and rural districts persisted. Table 1 also indicates that urban districts experienced higher levels of minority isolation (expected exposure of minority students to other minority students) than rural districts. During the 2001-02 school year, urban districts had 17 percent minority isolation, compared to 4.3 percent minority isolation in rural districts. In 2015-16, minority isolation increased to almost 23 percent in urban districts and almost 6 percent in rural districts, indicating an increase in the concentration of minority students in both urban and rural districts. In 2001–02, urban districts had a slightly lower dissimilarity index (3.5 percent) than rural districts (4.3 percent), indicating that 3.5 percent and 4.3 percent of minority students would need to move schools to achieve an even distribution in urban and rural districts, respectively. By 2015–16, these percentages declined to 1.5 percent in urban districts and 1.4 percent in rural districts, suggesting more even distribution of minority students over time. Overall, Figure 4 shows steady declines in relative exposure to minority students and dissimilarity between minority and non-minority students, while the concentration or isolation of minority students increased over the years before leveling off around 2014.

Figure 4. Mean district racial segregation trends over the years

(a) Relative Exposure & Dissimilarity (race) (b) Isolation (race)



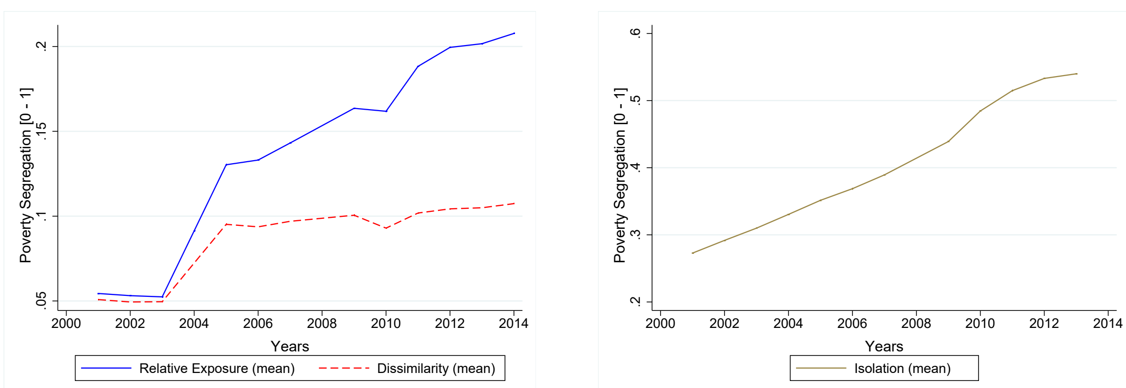
Note: The figures display the average levels of racial segregation across school districts for each year. The y-axis indicates the relative exposure to minority students, dissimilarity between minority and non-minority students, and minority isolation. Each ranging from 0 to 1, where 0 indicates complete racial integration and 1 indicates complete racial segregation.

In terms of poverty segregation during the 2001-02 school year, Table 1 reveals that urban districts had slightly higher levels of relative exposure to high-poverty students than rural districts. Specifically, Table 1 indicates that, on average, high-poverty students in urban districts had a 6.4 percent relative likelihood of encountering high-poverty schoolmates relative to low-poverty students, compared to rural districts with a 5.1 percent relative likelihood of high-poverty students encountering high-poverty schoolmates. On the other hand, urban and rural districts had similar isolation of high-poverty students (about 29-30 percent expected exposure of high-poverty students to other high-poverty students). Table 1 also illustrates that in 2001-02, urban districts had a slightly lower average dissimilarity index of 4.5 percent compared to rural districts with 5.4 percent. This indicates that about 4.5 and 5.4 percent of high-poverty students would need to transfer to even the distribution of high-poverty students in urban and rural districts, respectively. In Figure 5, I present poverty segregation trends between the 2001-02 and the 2013-14 school years, showing an increase over time. Again, the data here are restricted to 2013-14 school year due to the introduction of CEP programs.

Figure 5. Mean district poverty segregation trends over the years

(a) Relative Exposure & Dissimilarity (poverty)

(b) Isolation (poverty)



Note: The figures display the average levels of poverty segregation across school districts for each year. The y-axis indicates the relative exposure to high-poverty students, dissimilarity between high-poverty and low-poverty students, and high-poverty isolation. Each ranging from 0 to 1, where 0 indicates complete poverty integration and 1 indicates complete poverty segregation.

3.5.2 Racial demographics and enrollment by sector (2015–16)

Further descriptive analysis shows that during the 2015-16 school year, virtual charter (VC) schools enrolled a higher percentage of White students and a smaller percentage of minority students compared to brick-and-mortar charters. Table 2 indicates that about 84 percent of White students attended virtual charter schools in the 2015-16 school year, compared to only 27 percent of White students in Brick-and-mortar charter schools. On the other hand, there were about 11 percent Black and about 4 percent Hispanic students enrolled in virtual charter schools, compared to about 64 percent Black and about 9 percent Hispanic students in brick-and-mortar charter schools. Table 2 also shows that the demographic composition of students attending ECOT in the 2015–16 school year was almost identical to that of students in traditional public schools. Specifically, approximately 75 and 77 percent of students enrolled in ECOT and TPS, respectively, were White, while about 19 and 15 percent were Black. Only about 6 and 5 percent of students enrolled in ECOT and TPS, respectively, were Hispanic. Overall, Table 2 illustrates that virtual charter schools enrolled a racial mix of students similar to that of traditional public schools but markedly different from that of brick-and-mortar charter schools. This distinction is important and may help explain why the opening or closing of virtual charter schools may lead to different segregation patterns within school districts than the opening or closing of brick-and-mortar charter schools.

Table 2. Baseline values of racial demographics by sector (2015-16)

	VC		B&M Charter		ECOT		TPS	
	M	SD	M	SD	M	SD	M	SD
Demographic (0-100%)								
Percent White	83.96	5.22	26.54	30.08	76.29	2.29	77.50	26.92
Percent Black	10.59	4.02	63.64	34.43	17.38	2.27	14.84	24.61
Percent Hispanic	3.90	2.16	8.61	13.01	5.75	0.71	5.19	7.62
Observations	113		1661		12		13547	

Note: This table provides school-level baseline racial demographic averages in 2015-16. (Weighted by total school enrollment at grade level, which is why ECOT has 12 observations for each grade). *Source*: Author calculations using common core of data.

3.6 Statistical Model

I use an event study difference-in-differences design to compare changes in segregation outcomes between observationally similar districts with high and low baseline enrollment in virtual charter schools (or ECOT, in the closure analysis). I estimate the impacts using the following Ordinary Least Squares (OLS) regression:

$$Y_{it} = \delta_i + \lambda_{ct} + \sum_{t \neq 0}^{n} \gamma_t (Treat_i \times Period_t) + \epsilon_{it} \tag{5}$$

where the outcome Y captures the segregation of district i in year t, δ_i is district fixed effects accounting for all unobserved time-invariant district-specific characteristics, and λ_{ct} is commuting zone-by-year fixed effects. This ensures that I only compare districts within the same local economy in a given year. $Treat_i$ is a dummy indicator set to 1 if a district had high enrollment in virtual charter schools (or ECOT, in the closure analysis) and 0 if it did not. $Period_t$ is a series of dummy variables relative to the baseline year ($t = 0$). $Treat_i \times Period_t$ is the difference-in-differences estimator, and its parameter γ_t captures how levels of segregation vary between treated and control districts over time. ϵ_{it} is an idiosyncratic error term that varies at the district-year level. I cluster standard errors by districts to address correlation within districts. This specification enables one to observe differences in trends prior to the event year (i.e., baseline year) and, thus, helps one assess the plausibility that the estimates produced are causal.

4. Results

This section presents the estimated impacts using three measures of segregation, namely relative exposure, isolation, and dissimilarity index. First, I present the estimates on the impact of introducing virtual charter schools on racial and poverty segregation, followed by the estimates of ECOT's closure on racial segregation. To examine heterogeneous effects, I disaggregate the analyses by urbanicity—considering all districts in the analytic sample (full sample), as well as urban and rural districts separately. I display the results using both tables and event study graphs to visually illustrate the impacts.

4.1 Impacts of Introduction on Racial and Poverty Segregation

Table 3 and Figures 6 and 7 show the results on the impact of introducing virtual charter schools on racial and poverty segregation within the full analytic sample. The results indicate that schools located in districts that had high enrollment in virtual charter schools experienced a decline in relative exposure to minority students compared to those that did not, implying that there was a reduction in the likelihood that minority students have minority schoolmates. Specifically, Table 3 indicates that the introduction of virtual charter schools led to a 0.9–1.5 percentage points decrease in relative exposure (about 45–75% decline from the baseline). I do not find statistically significant effects on the concentration (isolation) of minority students or the dissimilarity between minority and non-minority students within the full analytic sample.

Regarding poverty segregation, the introduction of virtual charter schools increased the average concentration of high-poverty students in districts that had high enrollment in virtual charter schools than those that did not.[9] Specifically, Table 3 and Figure 7 indicate that the introduction of virtual charter schools led to a 2.9–7 percentage point increase in the concentration of high-poverty students, representing about 10–24% increase. This indicates that high-poverty students are increasingly exposed to one another within schools. I do not find statistically significant effects on relative exposure to high-poverty students and dissimilarity between high-poverty and low-poverty students.

Potential mechanism results suggest that the introduction of virtual charter schools reduces racial imbalance while increasing the concentration of high-poverty students within districts primarily through compositional changes rather than increased integration. Specifically, Table 4 indicates that virtual charter schools may be drawing disproportionately from minority and high-poverty student populations, leading to a gradual decline in the share of these students in traditional public schools. As a result, the remaining district schools become more similar in their racial composition, reducing differences in expected minority exposure across schools and lowering relative exposure indices. This pattern is likely driven by minority students disproportionately exiting high-minority schools.

[9] Poverty data are missing for year 6 (calendar year 2008) and were imputed by taking the average of the 2007 and 2009 poverty values.

Furthermore, while overall poverty enrollment experiences statistically significant declines of approximately 15-18 percent following the introduction of virtual charter schools, this decline is likely not uniform across schools. Instead, some schools experience larger reductions in high-poverty enrollment than others, leading to a concentration of the remaining high-poverty students in a subset of schools. However, because these changes reflect selective exit rather than redistribution across schools, the effects on unevenness are more limited. These patterns suggest a sorting mechanism in which virtual charter schools alter the composition of students through selective exits rather than fundamentally restructuring the distribution of students across schools.

The patterns illustrated here are consistent with sorting models discussed in the school choice literature (e.g., see Cohodes and Parham, 2021; Epple et al., 2016; Epple and Romano, 2003; Ritter et al., 2016), in which the expansion of schooling options induces selective exit rather than within-system reallocation. Virtual charter schools alter the composition of students remaining in district schools, particularly along racial and socioeconomic dimensions, without substantially changing how students are distributed across schools within districts. This suggests that virtual charter schools reshape segregation through cross-sector sorting rather than within-district integration.

Table 3. Estimated Impact of Introducing Virtual Charter Schools on District Segregation

Panel A: Racial Segregation (full sample)

	Year -3	Year -2	Year -1	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16	Year 17
Relative Exposure (to minority)	0.002	0.002	0.001	-0.001	-0.001	-0.003	-0.004	-0.003	-0.004	-0.006*	-0.009**	-0.009**	-0.011**	-0.014***	-0.014***	-0.014***	-0.013***	-0.013**	-0.016***	-0.015***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Isolation (minority)	-0.000	0.001	0.001	0.001	0.001	-0.002	-0.002	-0.005	-0.003	-0.007	-0.009	-0.008	-0.010	-0.009	-0.008	-0.007	-0.007	-0.008	-0.009	-0.010
	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.010)	(0.009)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)
Dissimilarity Index (minority)	0.001	0.002	-0.003	-0.002	-0.002	-0.002	-0.002	-0.003	-0.002	-0.007	-0.003	-0.003	-0.005	-0.004	-0.003	-0.005	-0.005	-0.005	-0.006	-0.006
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Observations											4365									

Panel B: Poverty Segregation (full sample)

	Year -3	Year -2	Year -1	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11
Relative Exposure (to high-poverty)	0.019	0.011*	-0.000	0.012*	-0.004	0.003	0.018	0.021	0.021	0.022	0.005	0.032	0.032	0.031
	(0.014)	(0.006)	(0.007)	(0.007)	(0.010)	(0.022)	(0.025)	(0.027)	(0.028)	(0.031)	(0.032)	(0.035)	(0.035)	(0.037)
Isolation (high-poverty)	0.003	0.005	-0.006	0.011	0.010	0.018	0.029**	0.038**	0.041***	0.045**	0.053***	0.065***	0.065***	0.070***
	(0.010)	(0.006)	(0.007)	(0.007)	(0.011)	(0.011)	(0.014)	(0.015)	(0.015)	(0.017)	(0.019)	(0.020)	(0.020)	(0.022)
Dissimilarity Index (high-poverty)	0.004	0.003	0.001	0.008	-0.001	0.002	0.008	0.013	0.011	0.008	0.003	0.011	0.013	0.012
	(0.011)	(0.004)	(0.004)	(0.006)	(0.008)	(0.013)	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.016)	(0.015)	(0.016)
Observations											3123			

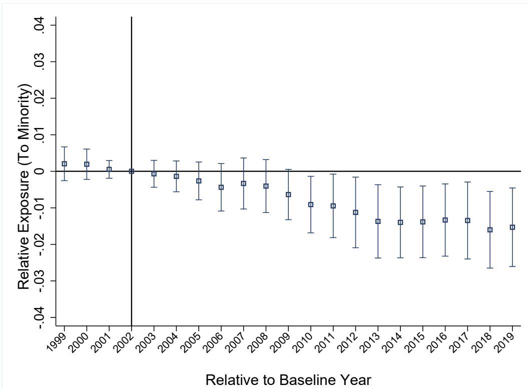
Robust standard errors in parentheses

All models include district and commuting zone-by-year fixed effects

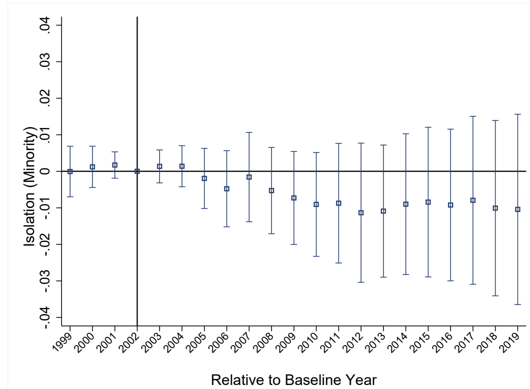
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 6. Estimated impact of introducing virtual charter schools on district racial segregation

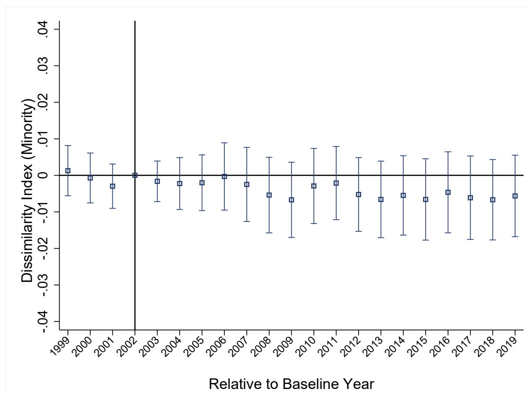
(a) Relative Exposure



(b) Isolation

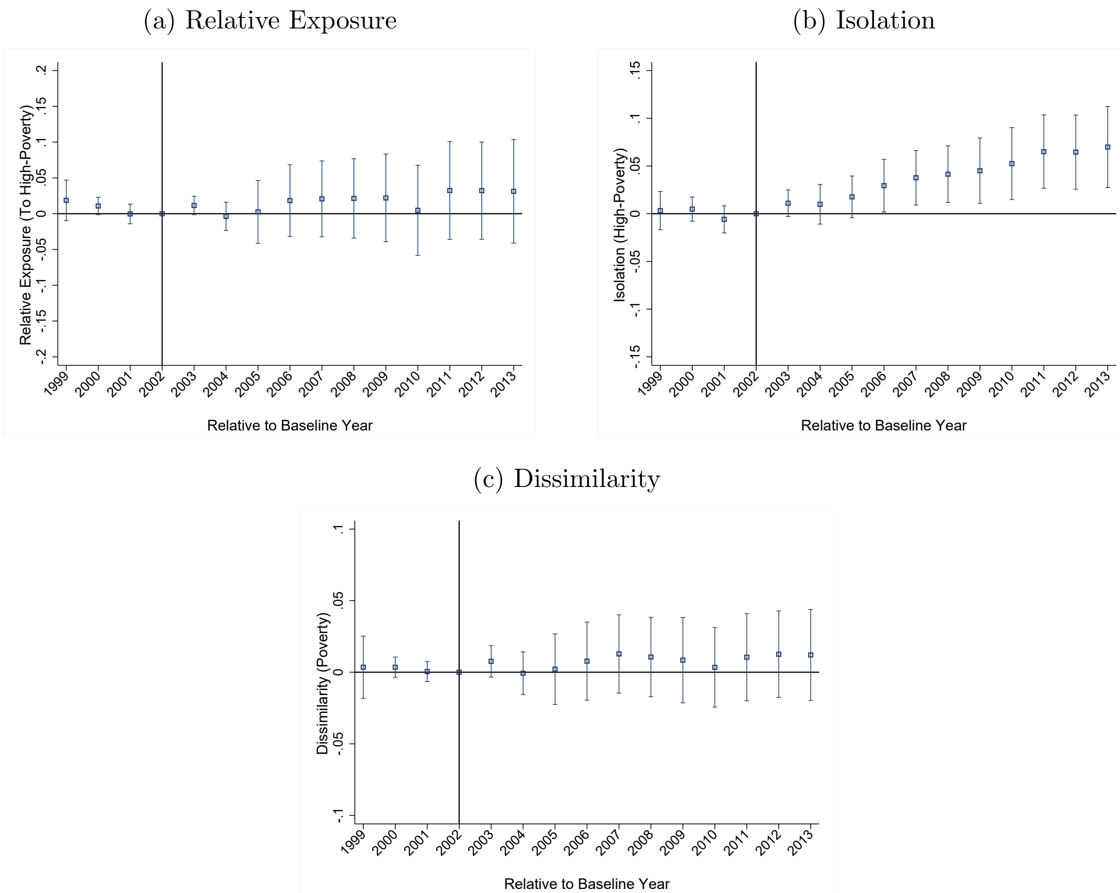


(c) Dissimilarity



Note: The figures illustrate the estimated impact of introducing virtual charter schools on racial segregation within districts in the analytic sample. The x axis captures the year relative to the baseline ($x = 0$). The estimates on the y-axis compare treated and control schools using the outcome in year 0 as a baseline. The boxes are the point estimates and the bars indicate 95 percent confidence intervals.

Figure 7. Estimated impact of introducing virtual charter schools on district poverty segregation



Note: The figures illustrate the estimated impact of introducing virtual charter schools on poverty segregation in districts in the analytic sample. The x axis captures the year relative to the baseline ($x = 0$). The estimates on the y-axis compare treated and control districts using the outcome in year 0 as a baseline. The boxes are the point estimates and the bars indicate 95 percent confidence intervals.

Table 4. Estimated Impact of Introducing Virtual Charter Schools on District Enrollment

	Log Minority	Log White	Log Poverty	Log School Enrollment
Year -3 Effect	0.056	0.020	0.024	0.017
	(0.044)	(0.019)	(0.079)	(0.017)
Year -2 Effect	0.029	0.010	0.070*	0.002
	(0.035)	(0.015)	(0.037)	(0.013)
Year -1 Effect	0.029	-0.006	0.035	-0.007
	(0.023)	(0.009)	(0.028)	(0.009)
Year 1 Effect	-0.048*	-0.005	-0.004	-0.012
	(0.026)	(0.014)	(0.032)	(0.010)
Year 2 Effect	-0.013	-0.003	-0.038	0.011
	(0.036)	(0.022)	(0.030)	(0.022)
Year 3 Effect	-0.020	-0.002	0.029	0.003
	(0.043)	(0.030)	(0.089)	(0.025)
Year 4 Effect	-0.025	-0.002	-0.048	-0.000
	(0.048)	(0.033)	(0.049)	(0.026)
Year 5 Effect	-0.040	0.018	0.022	0.013
	(0.053)	(0.033)	(0.093)	(0.025)
Year 6 Effect	-0.044	0.021	0.001	0.021
	(0.050)	(0.037)	(0.094)	(0.028)
Year 7 Effect	-0.054	0.023	-0.012	0.023
	(0.054)	(0.040)	(0.096)	(0.031)
Year 8 Effect	-0.053	0.030	-0.070	0.009
	(0.053)	(0.044)	(0.101)	(0.028)
Year 9 Effect	-0.002	0.031	-0.180***	0.003
	(0.059)	(0.045)	(0.067)	(0.029)
Year 10 Effect	0.003	0.035	-0.168**	0.021
	(0.062)	(0.048)	(0.069)	(0.030)
Year 11 Effect	-0.017	0.022	-0.155**	0.010
	(0.065)	(0.049)	(0.072)	(0.032)
Year 12 Effect	-0.024	0.014	-0.141*	0.009
	(0.069)	(0.051)	(0.075)	(0.032)
Year 13 Effect	0.002	0.026	-0.107	0.016
	(0.071)	(0.053)	(0.077)	(0.035)
Year 14 Effect	-0.007	0.024	-0.087	0.003
	(0.071)	(0.052)	(0.078)	(0.032)
Year 15 Effect	-0.049	0.009	-0.084	-0.000
	(0.074)	(0.055)	(0.076)	(0.033)
Year 16 Effect	-0.013	0.012	-0.113	-0.003
	(0.073)	(0.056)	(0.080)	(0.037)
Year 17 Effect	-0.050	0.023	–	0.005
	(0.074)	(0.057)	–	(0.037)
Observations	4405	4405	4137	4405

Robust standard errors in parentheses

All models include district and commuting zone-by-year fixed effects

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5 and Figures 8 and 9 show results on the impact of introducing virtual charter schools on racial and poverty segregation within urban school districts. These results indicate that urban districts that had high enrollment in virtual charter schools experienced a decline in relative exposure to minority students compared to districts that did not. In urban districts, I find that the introduction of virtual charter schools led to a 1.9–3.0 percentage point (about 48–76% decline from the baseline) decrease in relative exposure to minority students. Again, I do not find statistically significant effects on the concentration of minority students or the dissimilarity between minority and non-minority students within urban districts.

Regarding poverty segregation in urban districts, I find that urban districts that had high enrollment in virtual charter schools experienced a 3-13.5 percentage point increase in the concentration of high-poverty students following the introduction of virtual charter schools, compared to urban districts that did not. This translates to about 11-47 percent increase from the baseline. For the model estimating the impact of introducing virtual charter schools on the concentration (isolation) of high-poverty students, I do see some differences in trends prior to the introduction of virtual charter schools, although these differences are not statistically significant at the 95% confidence interval.

Additionally, in urban districts, it appears that the introduction of virtual charter schools led to an increase in relative exposure to high-poverty students, implying that there was an increase in the likelihood that high-poverty students have high-poverty schoolmates compared to low-poverty peers. Although only statistically significant at the 10% level, Table 5 shows that the introduction of virtual charter schools led to an increase of 5.1-9.7 percentage points in relative exposure to high-poverty students in urban districts that had high enrollment in virtual charter schools than those that did not. I do not find statistically significant effects on the dissimilarity between high-poverty and low-poverty students in urban districts.

Although the mechanism estimates in Table 6 show pre-treatment differences, following the introduction of virtual charter schools, minority enrollment initially declines before stabilizing, while White enrollment gradually decreases over time, albeit at different rates. These patterns, combined with a pronounced and statistically significant decline between 18 and 47 percent in high-poverty enrollment, suggest differential sorting across student subgroups rather than large-scale demographic shifts. In particular, selective exit among high-poverty students alters the composition of students remaining in district schools without redistributing them across schools. Given the strong correlation between race and poverty, selective exit among high-poverty students alters not only the poverty composition of students remaining in district schools, but also their racial composition, thereby altering both racial and poverty segregation patterns.

Table 5. Estimated Impact of Introducing Virtual Charter Schools on Urban District Segregation

Panel A: Racial Segregation (urban districts)

	Year -3	Year -2	Year -1	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16	Year 17
Relative Exposure (to minority)	0.007	0.006	0.002	-0.003	-0.001	-0.004	-0.007	-0.006	-0.008	-0.014	-0.019**	-0.017	-0.020*	-0.026**	-0.028**	-0.028**	-0.028**	-0.028**	-0.030**	-0.030**
	(0.005)	(0.005)	(0.002)	(0.003)	(0.004)	(0.006)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.011)
Isolation (minority)	-0.006	-0.005	-0.001	0.001	0.009*	0.005	0.002	0.005	0.005	0.001	0.000	0.005	-0.009	0.004	0.007	0.011	0.012	0.015	0.017	0.017
	(0.006)	(0.005)	(0.003)	(0.004)	(0.005)	(0.008)	(0.010)	(0.012)	(0.012)	(0.013)	(0.014)	(0.016)	(0.016)	(0.017)	(0.017)	(0.019)	(0.019)	(0.020)	(0.021)	(0.022)
Dissimilarity Index (minority)	-0.000	0.003	-0.002	-0.000	0.002	0.001	-0.000	-0.001	-0.001	-0.002	-0.003	0.001	-0.003	-0.003	-0.003	-0.001	-0.001	-0.001	-0.000	-0.000
	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.007)
Observations	1528																			

Panel B: Poverty Segregation (urban districts)

	Year -3	Year -2	Year -1	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11
Relative Exposure (to high-poverty)	0.007	-0.011	-0.003	0.019	0.009	0.051*	0.052*	0.067*	0.069*	0.070	0.040	0.096*	0.094*	0.097*
	(0.016)	(0.012)	(0.006)	(0.020)	(0.017)	(0.030)	(0.031)	(0.039)	(0.039)	(0.043)	(0.042)	(0.050)	(0.047)	(0.053)
Isolation (high-poverty)	-0.033*	-0.018	-0.007	0.021*	0.030***	0.041***	0.038***	0.060***	0.071***	0.082***	0.090***	0.110***	0.112***	0.135***
	(0.017)	(0.012)	(0.006)	(0.013)	(0.011)	(0.012)	(0.014)	(0.016)	(0.015)	(0.018)	(0.020)	(0.022)	(0.021)	(0.025)
Dissimilarity Index (high-poverty)	-0.016	-0.010	-0.004	0.011	0.012	-0.003	0.002	0.011	0.010	0.008	0.002	0.011	0.013	0.020
	(0.013)	(0.008)	(0.005)	(0.017)	(0.014)	(0.013)	(0.014)	(0.016)	(0.016)	(0.016)	(0.015)	(0.016)	(0.015)	(0.017)
Observations	1076													

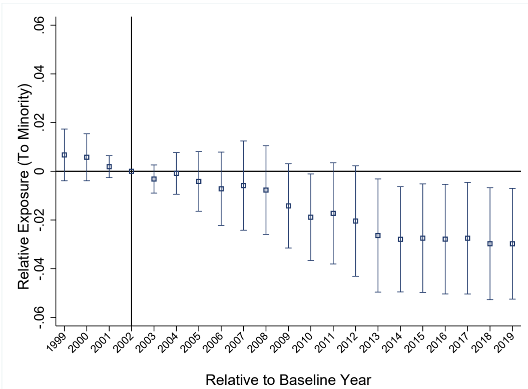
Robust standard errors in parentheses

All models include district and commuting zone-by-year fixed effects

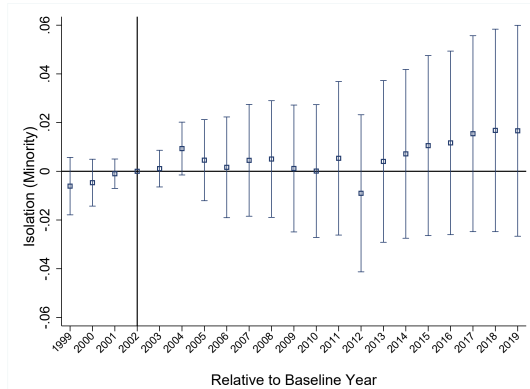
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 8. Estimated impact of introducing virtual charter schools on urban racial segregation

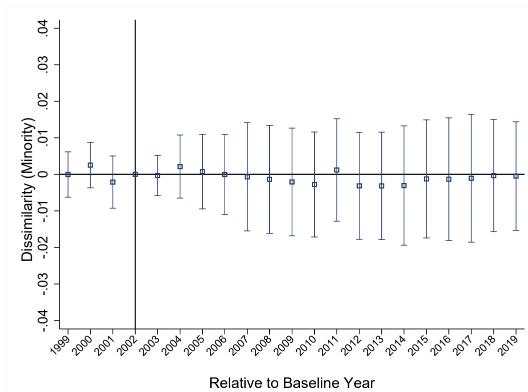
(a) Relative Exposure



(b) Isolation

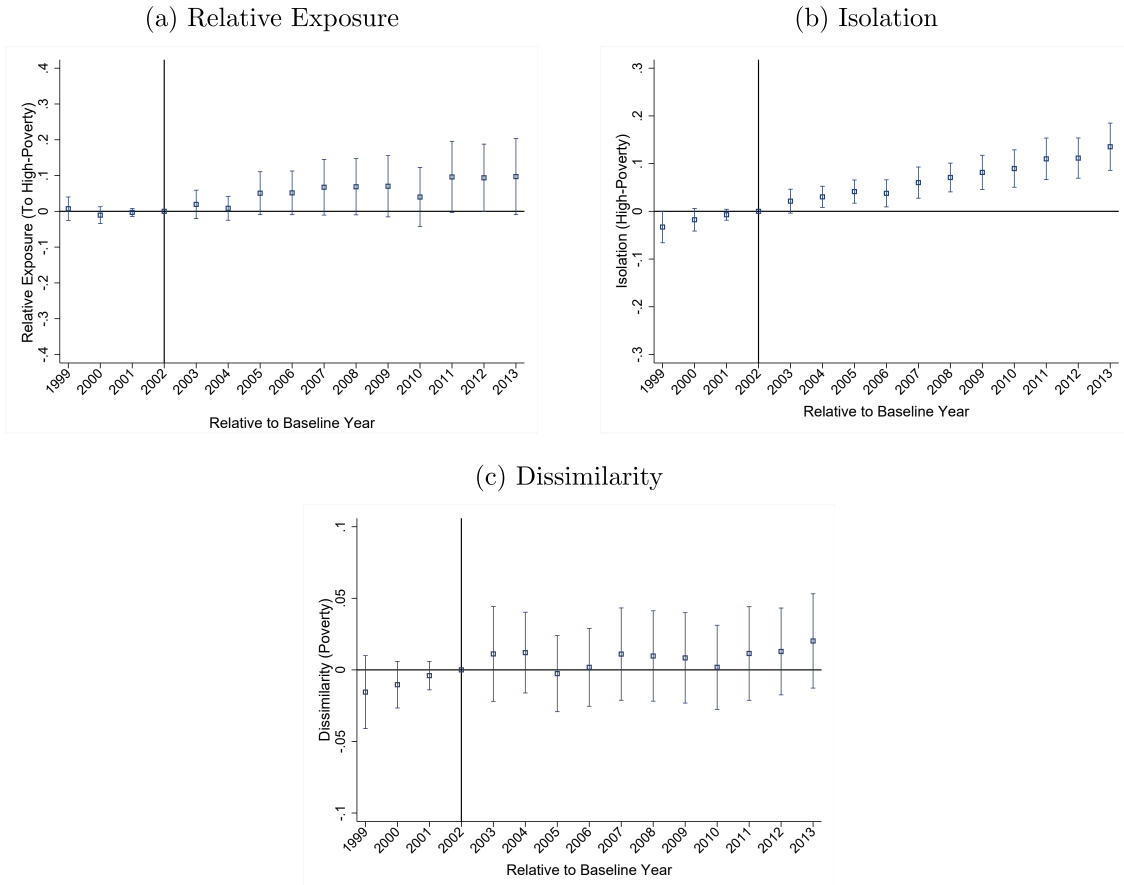


(c) Dissimilarity



Note: The figures illustrate the estimated impact of introducing virtual charter schools on racial segregation within urban districts in the analytic sample. The x axis captures the year relative to the baseline ($x = 0$). The estimates on the y-axis compare treated and control schools using the outcome in year 0 as a baseline. The boxes are the point estimates and the bars indicate 95 percent confidence intervals.

Figure 9. Estimated impact of introducing virtual charter schools on urban poverty segregation



Note: The figures illustrate the estimated impact of introducing virtual charter schools on poverty segregation in urban districts in the analytic sample. The x axis captures the year relative to the baseline ($x = 0$). The estimates on the y-axis compare treated and control districts using the outcome in year 0 as a baseline. The boxes are the point estimates and the bars indicate 95 percent confidence intervals.

Table 6. Estimated Impact of Introducing Virtual Charter Schools on Urban Enrollment

	Log Minority	Log White	Log Poverty	Log School Enrollment
Year -3 Effect	0.142**	0.073*	-0.017	0.056*
	(0.064)	(0.038)	(0.156)	(0.030)
Year -2 Effect	0.054	0.057**	0.093	0.033
	(0.043)	(0.027)	(0.058)	(0.022)
Year -1 Effect	0.067**	0.011	0.082**	0.009
	(0.026)	(0.016)	(0.038)	(0.015)
Year 1 Effect	-0.014	-0.004	-0.012	-0.016
	(0.028)	(0.021)	(0.050)	(0.020)
Year 2 Effect	0.019	-0.021	-0.054*	0.031
	(0.039)	(0.034)	(0.028)	(0.035)
Year 3 Effect	0.015	-0.034	-0.180***	0.003
	(0.059)	(0.055)	(0.066)	(0.047)
Year 4 Effect	-0.004	-0.035	-0.210***	-0.012
	(0.075)	(0.061)	(0.074)	(0.049)
Year 5 Effect	-0.031	-0.018	-0.248***	0.020
	(0.080)	(0.056)	(0.079)	(0.048)
Year 6 Effect	-0.014	-0.045	-0.274***	0.021
	(0.080)	(0.067)	(0.079)	(0.053)
Year 7 Effect	-0.005	-0.037	-0.284***	0.037
	(0.083)	(0.075)	(0.083)	(0.062)
Year 8 Effect	0.024	-0.008	-0.387***	0.036
	(0.081)	(0.076)	(0.094)	(0.049)
Year 9 Effect	0.065	-0.006	-0.469***	0.020
	(0.090)	(0.077)	(0.097)	(0.054)
Year 10 Effect	0.003	-0.006	-0.430***	0.065
	(0.108)	(0.081)	(0.099)	(0.053)
Year 11 Effect	0.061	0.010	-0.407***	0.063
	(0.103)	(0.084)	(0.102)	(0.054)
Year 12 Effect	0.091	-0.002	-0.408***	0.054
	(0.107)	(0.090)	(0.107)	(0.055)
Year 13 Effect	0.072	-0.008	-0.320***	0.057
	(0.108)	(0.096)	(0.109)	(0.059)
Year 14 Effect	0.064	-0.006	-0.262**	0.041
	(0.108)	(0.094)	(0.116)	(0.054)
Year 15 Effect	0.043	-0.042	-0.148	0.034
	(0.116)	(0.100)	(0.113)	(0.056)
Year 16 Effect	0.054	-0.045	-0.174	0.019
	(0.121)	(0.100)	(0.119)	(0.064)
Year 17 Effect	0.044	-0.038	–	0.034
	(0.121)	(0.100)	–	(0.065)
Observations	1531	1531	1427	1531

Robust standard errors in parentheses

All models include district and commuting zone-by-year fixed effects

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7 and Figures 10 and 11 show results on the impact of introducing virtual charter schools on racial and poverty segregation within rural school districts. In rural districts, the results indicate that the introduction of virtual charter schools did not lead to statistically significant impacts on racial segregation between districts that had high enrollment in virtual charter schools and those that did not across all three measures of segregation—relative exposure to minority students, minority student isolation, or dissimilarity between minority and non-minority students. Similarly, I do not find any statistically significant effects on relative exposure to high-poverty students, the concentration of high-poverty students, or the dissimilarity between high-poverty and low-poverty students in rural districts. For models estimating the impact of virtual charter schools on poverty segregation in rural districts, I also notice some differences in trends prior to treatment.

Mechanism analyses in Table 8 suggest that these null results are driven by limited compositional change in rural districts. Table 8 shows that although there is a statistically significant short-run decline in minority enrollment of about 9.7 percent following the introduction of virtual charter schools, this effect is not sustained. Importantly, unlike in urban districts, there is no evidence of pronounced poverty sorting, which appears to be a key channel through which compositional changes affect racial and poverty segregation outcomes. The limited exit of minority students and lack of meaningful exit among high-poverty students in rural districts may reflect constraints such as limited broadband access, which is often necessary to enroll in virtual charter schools. Given the absence of substantial exits across student subgroups, the introduction of virtual charter schools does not meaningfully alter the composition of students within rural schools.

Table 7. Estimated Impact of Introducing Virtual Charter Schools on Rural District Segregation

Panel A: Racial Segregation (rural districts)

	Year -3	Year -2	Year -1	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11	Year 12	Year 13	Year 14	Year 15	Year 16	Year 17
Relative Exposure (to minority)	-0.001	-0.000	0.000	0.003	0.000	0.000	0.000	0.001	0.001	0.000	0.001	-0.000	0.000	0.000	0.000	-0.000	0.001	0.001	-0.004	-0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Isolation (minority)	0.000	0.001	0.002*	0.003	0.000	0.000	-0.001	0.004	-0.001	-0.002	-0.002	-0.004	0.003	-0.003	-0.002	-0.002	-0.003	-0.002	-0.008	-0.005
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)	(0.004)	(0.010)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)
Dissimilarity Index (minority)	0.003	-0.004	-0.001	-0.001	-0.004	-0.001	0.004	0.000	-0.006	-0.009	0.001	0.000	-0.000	-0.003	-0.003	-0.005	-0.002	-0.005	-0.007	-0.004
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Observations											2837									

Panel B: Poverty Segregation (rural districts)

	Year -3	Year -2	Year -1	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8	Year 9	Year 10	Year 11
Relative Exposure (to high-poverty)	0.019	0.022**	-0.003	0.011*	-0.013	-0.035	-0.012	-0.012	-0.015	-0.019	-0.017	-0.003	-0.001	-0.012
	(0.028)	(0.009)	(0.013)	(0.006)	(0.017)	(0.041)	(0.046)	(0.046)	(0.049)	(0.054)	(0.057)	(0.056)	(0.057)	(0.061)
Isolation (high-poverty)	0.022	0.019**	-0.010	0.009	-0.001	0.006	0.026	0.026	0.022	0.018	0.033	0.038	0.038	0.025
	(0.015)	(0.009)	(0.014)	(0.011)	(0.019)	(0.019)	(0.025)	(0.025)	(0.027)	(0.032)	(0.034)	(0.034)	(0.035)	(0.039)
Dissimilarity Index (high-poverty)	0.017	0.010**	0.001	0.007	-0.010	-0.000	0.004	0.008	0.003	-0.002	0.001	0.006	0.009	-0.002
	(0.020)	(0.005)	(0.006)	(0.005)	(0.012)	(0.023)	(0.026)	(0.025)	(0.026)	(0.028)	(0.027)	(0.028)	(0.028)	(0.030)
Observations											2047			

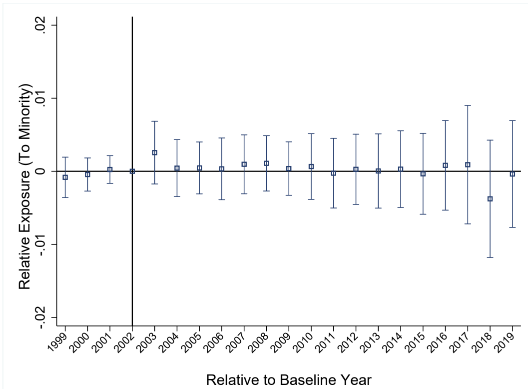
Robust standard errors in parentheses

All models include district and commuting zone-by-year fixed effects

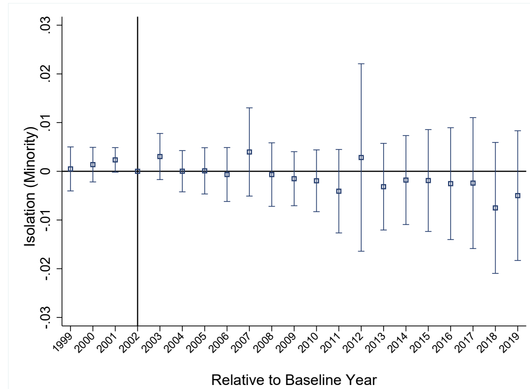
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 10. Estimated impact of introducing virtual charter schools on rural racial segregation

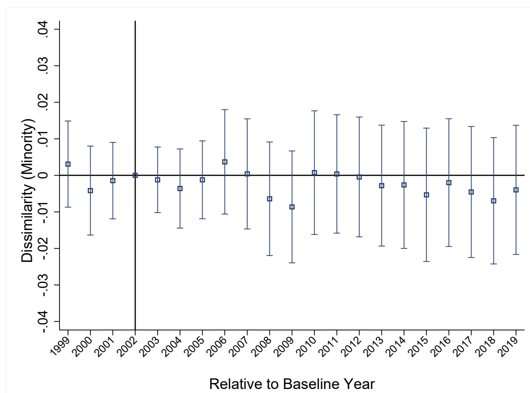
(a) Relative Exposure



(b) Isolation



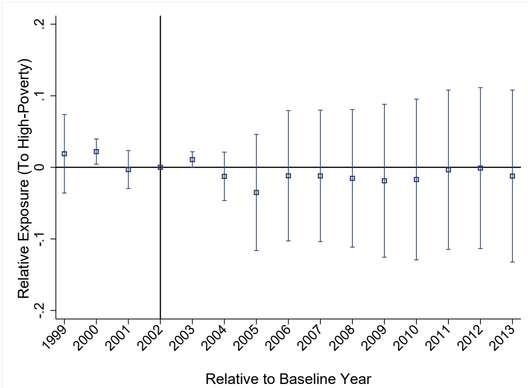
(c) Dissimilarity



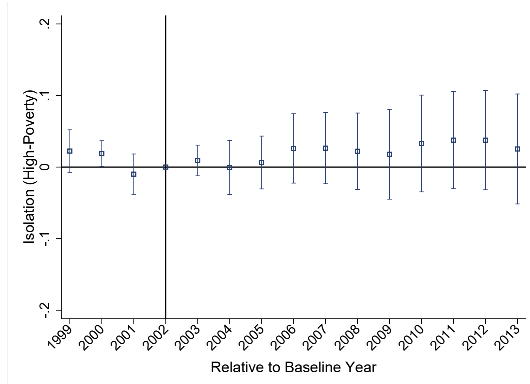
Note: The figures illustrate the estimated impact of introducing virtual charter schools on racial segregation within rural districts in the analytic sample. The x axis captures the year relative to the baseline ($x = 0$). The estimates on the y-axis compare treated and control schools using the outcome in year 0 as a baseline. The boxes are the point estimates and the bars indicate 95 percent confidence intervals.

Figure 11. Estimated impact of introducing virtual charter schools on rural poverty segregation

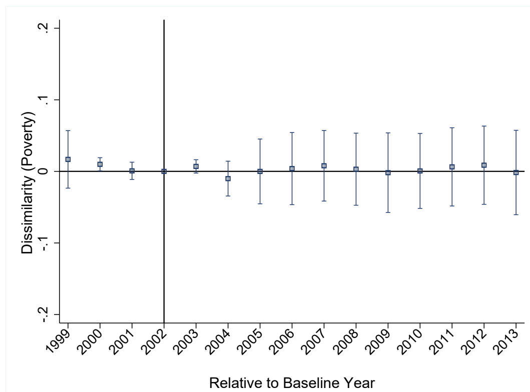
(a) Relative Exposure



(b) Isolation



(c) Dissimilarity



Note: The figures illustrate the estimated impact of introducing virtual charter schools on poverty segregation in rural districts in the analytic sample. The x axis captures the year relative to the baseline ($x = 0$). The estimates on the y-axis compare treated and control districts using the outcome in year 0 as a baseline. The boxes are the point estimates and the bars indicate 95 percent confidence intervals.

Table 8. Estimated Impact of Introducing Virtual Charter Schools on Rural Enrollment

	Log Minority	Log White	Log Poverty	Log School Enrollment
Year -3 Effect	-0.022	-0.011	-0.019	-0.015
	(0.053)	(0.018)	(0.075)	(0.017)
Year -2 Effect	-0.004	-0.017	0.024	-0.014
	(0.052)	(0.015)	(0.035)	(0.014)
Year -1 Effect	-0.011	-0.020*	-0.029	-0.019*
	(0.036)	(0.011)	(0.037)	(0.010)
Year 1 Effect	-0.097**	-0.022	0.006	-0.020*
	(0.042)	(0.018)	(0.039)	(0.011)
Year 2 Effect	-0.013	-0.003	-0.006	-0.013
	(0.061)	(0.027)	(0.052)	(0.018)
Year 3 Effect	-0.032	-0.006	0.220	-0.015
	(0.065)	(0.030)	(0.163)	(0.021)
Year 4 Effect	-0.059	-0.032	0.075	-0.022
	(0.070)	(0.035)	(0.073)	(0.022)
Year 5 Effect	-0.023	0.019	0.253	0.002
	(0.073)	(0.043)	(0.165)	(0.023)
Year 6 Effect	-0.032	0.039	0.243	0.014
	(0.061)	(0.041)	(0.167)	(0.023)
Year 7 Effect	-0.036	0.024	0.235	0.001
	(0.069)	(0.043)	(0.170)	(0.022)
Year 8 Effect	-0.043	-0.002	0.214	-0.022
	(0.069)	(0.058)	(0.180)	(0.030)
Year 9 Effect	-0.033	-0.003	0.064	-0.023
	(0.082)	(0.055)	(0.095)	(0.029)
Year 10 Effect	0.038	-0.010	0.060	-0.027
	(0.084)	(0.057)	(0.101)	(0.031)
Year 11 Effect	-0.028	-0.034	0.078	-0.037
	(0.094)	(0.056)	(0.100)	(0.035)
Year 12 Effect	-0.054	-0.031	0.103	-0.039
	(0.097)	(0.058)	(0.099)	(0.037)
Year 13 Effect	0.010	-0.013	0.123	-0.030
	(0.102)	(0.059)	(0.102)	(0.038)
Year 14 Effect	0.020	-0.016	0.123	-0.038
	(0.101)	(0.059)	(0.104)	(0.039)
Year 15 Effect	-0.051	-0.012	0.049	-0.038
	(0.102)	(0.060)	(0.121)	(0.040)
Year 16 Effect	0.024	-0.003	0.032	-0.031
	(0.096)	(0.060)	(0.122)	(0.041)
Year 17 Effect	-0.047	0.002	–	-0.037
	(0.098)	(0.062)	–	(0.045)
Observations	2874	2874	2710	2874

Robust standard errors in parentheses

All models include district and commuting zone-by-year fixed effects

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

4.2 Impacts of Closing ECOT on Racial Segregation

Finally, I present results on the impact of closing ECOT on racial segregation within school districts in the full analytic sample. Table 9 and Figure 12 show that the closing of ECOT did not have a statistically significant impact on racial segregation in districts that had high enrollment in ECOT as opposed to those that did not. Across all three measures of segregation, the impacts are virtually zero after closure.

In contrast to the introduction of virtual charter schools, the closure of ECOT does not produce meaningful changes in racial segregation across the full sample of districts. Mechanism analyses in Table 10 indicate that, immediately after the closure and though the estimates are not statistically significant, minority enrollment increased by about 4 percent and White enrollment by about 1 percent across district schools. These enrollment changes do not translate into meaningful changes in racial composition in the full analytic sample, largely due to the diffuse nature of student re-entry following ECOT's closure. Additionally, although students are forced to exit ECOT, they do not systematically return to district schools in ways that would alter enrollment composition. Instead, re-enrollment most likely occurs across multiple schooling options, including other virtual charter schools, homeschooling, brick-and-mortar charters, and traditional public schools, resulting in no concentrated compositional shock within districts. As a result, the distribution of students across district schools in the full sample remains largely unchanged, limiting any impact on segregation.

Table 9. Estimated Impact of ECOT Closure on District Racial Segregation

	Racial Segregation (full sample)					
	Year -3	Year -2	Year -1	Year 1	Year 2	Year 3
Relative Exposure (to minority)	0.000	-0.000	-0.000	-0.001	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Isolation (minority)	-0.003	-0.003*	-0.001	-0.002	-0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Dissimilarity Index (minority)	0.004	-0.002	-0.004	-0.001	0.002	0.001
	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Observations	1388					

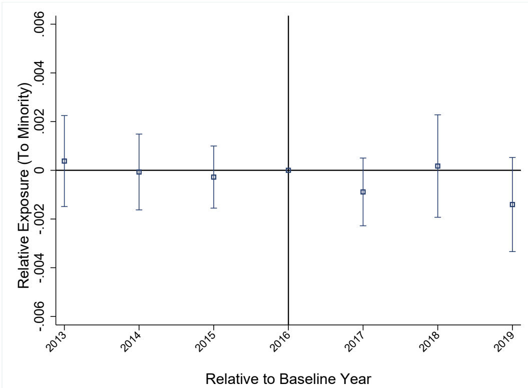
Robust standard errors in parentheses

All models include district and commuting zone-by-year fixed effects

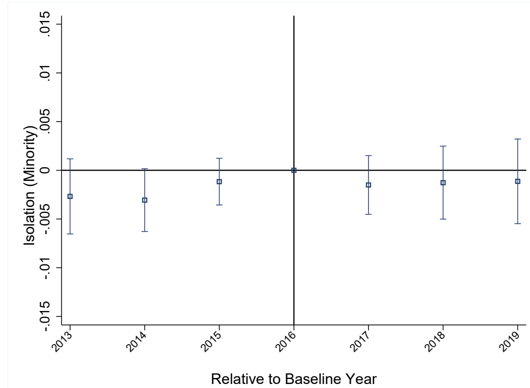
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 12. Estimated impact of ECOT closure racial segregation within districts

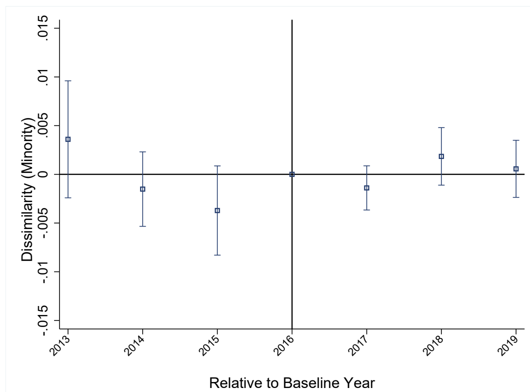
(a) Relative Exposure



(b) Isolation



(c) Dissimilarity



Note: The figures illustrate the estimated impact of closing the Electronic Classroom of Tomorrow (ECOT) on racial segregation within districts in the analytic sample. The x axis captures the year relative to the baseline ($x = 0$). The estimates on the y-axis compare treated and control districts using the outcome in year 0 as a baseline. The boxes are the point estimates and the bars indicate 95 percent confidence intervals.

Table 10. Estimated Impact of ECOT Closure on District Enrollment

	Log Minority	Log White	Log School Enrollment
Year -3 Effect	-0.022	0.006	0.003
	(0.034)	(0.016)	(0.016)
Year -2 Effect	-0.009	0.003	0.001
	(0.027)	(0.013)	(0.013)
Year -1 Effect	0.002	0.008	0.008
	(0.023)	(0.010)	(0.010)
Year 1 Effect	0.037	0.011	0.011
	(0.023)	(0.012)	(0.012)
Year 2 Effect	-0.008	-0.009	-0.009
	(0.029)	(0.011)	(0.011)
Year 3 Effect	0.026	-0.005	-0.003
	(0.035)	(0.017)	(0.017)
Observations	1393	1393	1393

Robust standard errors in parentheses
All models include district and commuting zone-by-year fixed effects
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

However, when analyzing the urban sample, I find that closing ECOT led to a reduction in racial imbalance in urban districts that had high enrollment in ECOT compared to those that did not. Specifically, Table 11 and Figure 13 show that closing ECOT led to a 0.5 percentage point reduction in relative exposure to minority students or about 27% decline from the baseline. This implies that in districts that had a high enrollment in ECOT compared to those that did not, the closing of ECOT reduced the relative likelihood of minority students encountering minority peers by 27 percent. Similarly, closing ECOT led to a 0.5 percentage point or about 32% decrease in the dissimilarity between minority and non-minority students in urban districts, implying that fewer students would need to change schools to achieve an even distribution of minority students across schools within urban districts. Although, I do see some differences in trends prior to closure with the model estimating the impact on the isolation of minority students in urban districts, the post-closure effects are null.

Mechanism analyses on urban enrollment estimates are noisy and not statistically significant, but I cannot rule out substantively significant changes on racial composition in urban districts after closure. This is primarily because racial imbalance and unevenness are relatively low at baseline (see Table 1) such that even small changes in student racial composition could have an effect, in addition to the type of schools that absorb the returning students. Table 12 indicate that immediately after closure, minority and White enrollment in urban districts increased by 1.3 and 1.1 percent, respectively. For these changes to impact racial imbalance, some of the returning minority students are likely re-entering schools with high minority concentrations. For example, if minority students return to a high-minority district school, say 70 percent minority and 30 percent White, an influx of minority students in such a school wouldn't meaningfully affect existing exposure of minority to other minority students but would have a larger exposure effect on White peers, hence reducing the difference in expected exposure between the two subgroups. In other words, minority-minority exposure will increase less than minority-White exposure. Therefore, results on racial imbalance are consistent with minority students returning to district schools with a higher share of minority peers after closure. Perhaps these students are simply returning to the schools they originally left following the introduction of virtual charter schools.

Racial unevenness also declined in urban districts following the closure. This may occur due to the spread of returning minority and White students across schools in urban districts. Therefore, even if minority students are disproportionately returning to high-minority schools, diffuse re-entry of both minority and White students across a heterogeneous set of urban schools reduce overall racial unevenness across schools. It is important to emphasize that although both the introduction of virtual charter schools and the closure of ECOT reduce racial imbalance in urban districts, the underlying mechanisms at play are very different. While the introduction of virtual charters reduces racial imbalance through selective exit, particularly of high-poverty students, the closure of ECOT does so through the selective re-entry of minority and White students into certain urban schools across the districts.

Table 11. Estimated Impact of ECOT Closure on Urban District Racial Segregation

	Racial Segregation (urban districts)					
	Year -3	Year -2	Year -1	Year 1	Year 2	Year 3
Relative Exposure (to minority)	0.001	-0.001	-0.001	-0.004	-0.005**	-0.006*
	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)	(0.003)
Isolation (minority)	-0.006	-0.009***	-0.003	-0.005	-0.006	-0.003
	(0.005)	(0.003)	(0.002)	(0.004)	(0.005)	(0.006)
Dissimilarity Index (minority)	-0.000	-0.002	-0.002	-0.005**	-0.004	-0.003
	(0.006)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)
Observations	280					

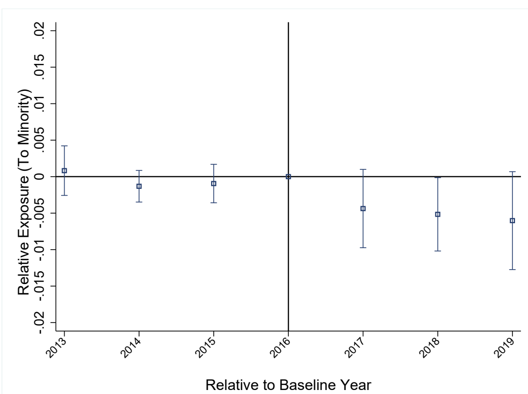
Robust standard errors in parentheses

All models include district and commuting zone-by-year fixed effects

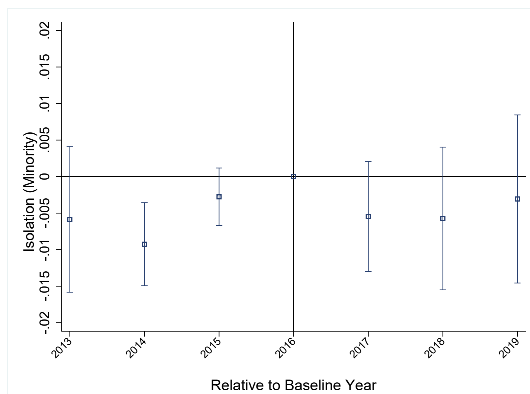
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 13. Estimated impact of ECOT closure on racial segregation within urban districts

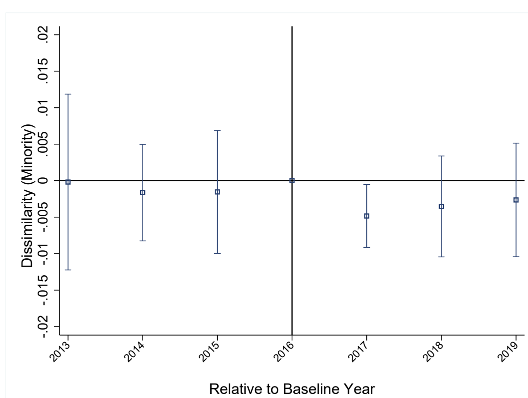
(a) Relative Exposure



(b) Isolation



(c) Dissimilarity



Note: The figures illustrate the estimated impact of closing the Electronic Classroom of Tomorrow (ECOT) on racial segregation within urban districts in the analytic sample. The x axis captures the year relative to the baseline ($x = 0$). The estimates on the y-axis compare treated and control districts using the outcome in year 0 as a baseline. The boxes are the point estimates and the bars indicate 95 percent confidence intervals.

Table 12. Estimated Impact of ECOT Closure on Urban District Enrollment

	Log Minority	Log White	Log School Enrollment
Year -3 Effect	-0.048	-0.009	-0.017
	(0.086)	(0.023)	(0.024)
Year -2 Effect	-0.061	-0.001	-0.009
	(0.086)	(0.027)	(0.029)
Year -1 Effect	-0.021	-0.014	-0.015
	(0.056)	(0.027)	(0.028)
Year 1 Effect	0.013	0.011	0.011
	(0.059)	(0.048)	(0.047)
Year 2 Effect	-0.041	-0.040	-0.039
	(0.064)	(0.040)	(0.040)
Year 3 Effect	0.005	-0.033	-0.027
	(0.080)	(0.058)	(0.058)
Observations	280	280	280

Robust standard errors in parentheses

All models include district and commuting zone-by-year fixed effects

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Results for rural districts show that the closing of ECOT increased racial unevenness in districts that had high enrollment in ECOT compared to those that did not. Specifically, Table 13 and Figure 14 indicate that closing ECOT increased the dissimilarity between minority and non-minority students by 0.5 percentage points, corresponding to about 38% increase in racial unevenness across schools in rural districts. This implies that more students would need to change schools so that minority students are evenly distributed across schools within rural districts. In rural districts, I do not find statistically significant impacts on racial imbalance and on the concentration of minority students, indicating that both the likelihood of minority students encountering one another and the degree of minority clustering remained stable following ECOT closure.

Again, although the rural enrollment estimates are noisy and not statistically significant, I still cannot rule out substantively significant changes on racial composition within rural districts following ECOT closure. Mechanism analyses in Table 14 suggest that minority enrollment in rural districts increased by about 4.5 percent while White enrollment slightly decreased or stayed about the same. Therefore, the increase in racial unevenness in rural districts is consistent with the uneven re-entry of minority students across a small number of schools, most likely schools with a relatively high concentration of minority students compared to other rural schools. Because rural districts have relatively low baseline minority enrollment (see Table 1), even modest increases in minority enrollment will generate noticeable racial unevenness when returning minority students concentrate in high-minority schools. At the same time, White enrollment remained relatively flat or declines slightly, further amplifying unevenness in the distribution of students across rural schools.

Table 13. Estimated Impact of ECOT Closure on Rural District Racial Segregation

	Racial Segregation (rural districts)					
	Year -3	Year -2	Year -1	Year 1	Year 2	Year 3
Relative Exposure (to minority)	0.001	0.001	0.000	0.000	0.002	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Isolation (minority)	-0.002	-0.001	-0.001	0.000	0.002	0.002
	(0.003)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Dissimilarity Index (minority)	0.006	-0.002	-0.005	0.001	0.005***	0.003*
	(0.004)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Observations	1108					

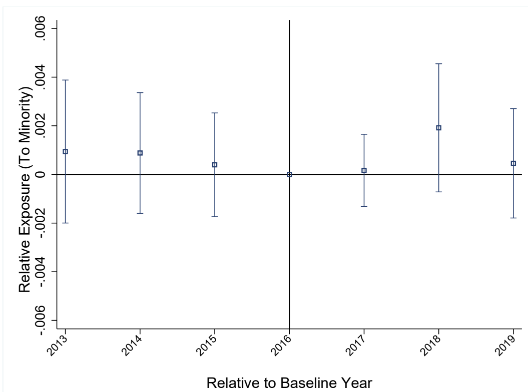
Robust standard errors in parentheses

All models include district and commuting zone-by-year fixed effects

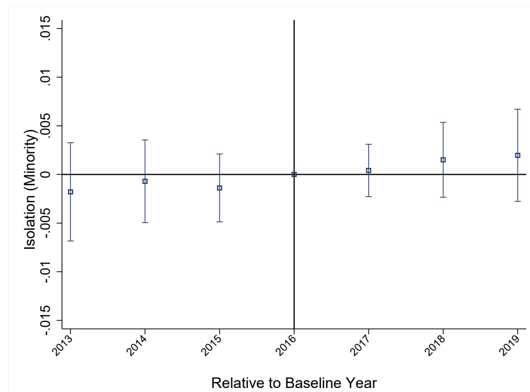
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 14. Estimated impact of ECOT closure on racial segregation within rural districts

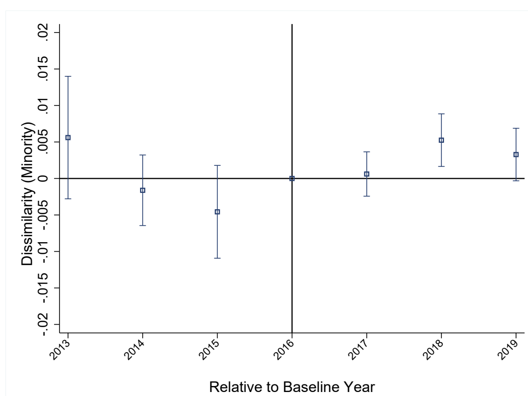
(a) Relative Exposure



(b) Isolation



(c) Dissimilarity



Note: The figures illustrate the estimated impact of closing the Electronic Classroom of Tomorrow (ECOT) on racial segregation within rural districts in the analytic sample. The x axis captures the year relative to the baseline ($x = 0$). The estimates on the y-axis compare treated and control districts using the outcome in year 0 as a baseline. The boxes are the point estimates and the bars indicate 95 percent confidence intervals.

Table 14. Estimated Impact of ECOT Closure on Rural District Enrollment

	Log Minority	Log White	Log School Enrollment
Year -3 Effect	-0.024	0.003	0.002
	(0.038)	(0.023)	(0.023)
Year -2 Effect	0.004	0.006	0.005
	(0.029)	(0.017)	(0.017)
Year -1 Effect	-0.014	0.022	0.020
	(0.029)	(0.013)	(0.013)
Year 1 Effect	0.045	-0.001	-0.000
	(0.030)	(0.011)	(0.011)
Year 2 Effect	0.017	-0.004	-0.002
	(0.037)	(0.011)	(0.011)
Year 3 Effect	0.042	-0.010	-0.007
	(0.045)	(0.016)	(0.016)
Observations	1113	1113	1113

Robust standard errors in parentheses
All models include district and commuting zone-by-year fixed effects
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5. Conclusion

This paper sheds light on the impacts of both the introduction of virtual charter schools and the closure of a large statewide virtual charter school on segregation outcomes within school districts. Findings reveal that the introduction of virtual charter schools reduced racial imbalance in districts with high enrollment in virtual charter schools compared to those that did not. When analyzing the full sample, I show that the introduction of virtual charter schools reduced the likelihood of minority students encountering minority peers by 45–75 percent, mostly driven by 48–76 percent decrease within urban districts. Regarding poverty segregation, I find that the introduction of virtual charter schools led to about 10–24 percent increase in the concentration of high-poverty students, again, primarily driven by 11-47 percent increase in the concentration of high-poverty students across schools in urban districts. I find no statistically significant evidence that the introduction of virtual charter schools impacts racial or poverty segregation in rural districts.

Furthermore, I find that the closure of a large statewide virtual charter school (ECOT) does not produce meaningful changes in racial segregation across the full analytic sample of districts. However, it does reduce racial imbalance in urban districts while increasing racial unevenness in rural districts. Specifically, I find that in urban districts that had high enrollment in ECOT relative to those that did not, closing the virtual charter school reduced the likelihood that minority students encounter minority peers by approximately 27 percent. Additionally, closing ECOT led to about 32 percent reduction in unevenness between minority and non-minority students in urban districts, implying that fewer students would need to change schools to achieve an even distribution of minority students across schools within urban districts. In rural districts, however, closing ECOT increased racial unevenness by about 38 percent, indicating that more students would need to change schools so that minority students are evenly distributed across schools within rural districts.

Potential mechanism analyses indicate that selective exit of high-poverty students after the introduction of virtual charter schools, and selective re-entry of minority students following ECOT's closure, are the primary channels shaping racial and poverty segregation in traditional district schools. For instance, in the full sample, the introduction of virtual charter schools led to statistically significant declines of approximately 15–18 percent in the enrollment of high-poverty students in districts that had high enrollment in virtual charter schools as opposed to those that did not. These declines are even more amplified in urban districts where the introduction of virtual charter schools led to between 18 and 47 percent statistically significant declines in high-poverty enrollment. Given the strong correlation between race and poverty, selective exit among high-poverty students alters not only the poverty composition of students remaining in district schools, but also their racial composition, thereby altering both racial and poverty segregation patterns.

Although mechanism analyses for the closing of ECOT are noisy and not statistically significant, I cannot rule out substantively significant changes on racial composition in urban and rural districts after closure. Immediately after ECOT closure, minority enrollment in urban districts increased by 1.3 percent, while White enrollment increased by 1.1 percent. In contrast, rural districts experienced a 4.5 percent increase in minority enrollment, whereas White enrollment slightly decreased or remained flat. These analyses suggest that for racial imbalance to decline following ECOT's closure, minority students likely returned to urban schools with already high minority exposure, thereby narrowing the gap in expected exposure between minority and non-minority students. Put differently, when minority students leaving ECOT re-entered urban district schools, exposure to minority peers increased less for minority students than for White students. Additionally, the spread of returning minority and White students across schools in urban districts contributed to the overall decline in racial unevenness. Therefore, even if minority students are disproportionately returning to high-minority schools, many others are still spread out across a heterogeneous set of urban schools. Finally, mechanism analyses suggest that for racial unevenness to increase in rural districts, minority students returned to schools with a relatively high concentration of minority peers compared to other rural schools. Given that rural districts are predominantly White, the concentrated re-entry of minority students would lead to an increase in racial unevenness between minority and White students.

The observed results demonstrate that the opening and closing of virtual charter schools reshape student racial and poverty composition through patterns of selective exit and selective or concentrated re-entry, rather than fundamentally restructuring the distribution of students across schools. These patterns suggest differential sorting across student subgroups rather than large-scale demographic changes. Therefore, these findings do not indicate meaningful student integration following either the introduction or closure of virtual charter schools. The concentration of minority and high-poverty students in certain schools following both the introduction and closure of virtual charter schools may exacerbate socioeconomic inequality within traditional public schools, particularly in urban districts. Given the well-documented long-term effects of segregation on students' educational and future economic outcomes (e.g., see Billings et al., 2014; Blanden et al., 2022; Chetty et al., 2022; Cook, 2021; Johnson, 2011), it is critical that all students—whether in brick-and-mortar schools or virtual charter schools—are exposed to peers from different racial and socioeconomic backgrounds.

Overall, these findings indicate that the opening and closing of statewide virtual charter schools do not simply expand or regulate educational choice; they also reshape who exits, returns to, and remains in traditional public schools, as well as how students are distributed across public schools within districts. Therefore, as virtual schooling options continue to expand, state legislatures and policymakers should recognize that online school choice policies may produce important unintended consequences for segregation and educational inequality. Efforts to regulate virtual charter schools should therefore consider not only academic performance and enrollment growth, but also their broader impacts on student composition, equity, and the distribution of educational opportunity across traditional public schools.

Further research is needed to investigate how virtual schooling options shape segregation across different contexts and jurisdictions. To the best of my knowledge, this is the first study to examine the impacts of both the introduction and closure of virtual charter schools on racial and poverty segregation within traditional district schools. Moreover, this study does not examine segregation within virtual charter schools themselves, which may be either more or less severe than the segregation patterns observed among students remaining in traditional public schools. Future research in this area would deepen our understanding of the broader implications of virtual schooling for racial and socioeconomic equity.

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6. APPENDIX

Table 15. Summary Statistics for Ohio Districts

	2001–02		2015–16	
	Mean	SD	Mean	SD
Demographic (0–100%)				
Total Enrollment	101.07	48.73	120.70	69.65
Percent Black	5.38	13.79	6.77	16.05
Percent Hispanic	1.29	2.85	3.93	5.50
Percent White	93.33	14.37	89.30	17.85
Percent Poverty	27.3	17.9	41.8	20.5
Racial Segregation				
Relative Exposure (to minority)	0.019	0.051	0.008	0.030
Isolation (minority)	0.086	0.158	0.115	0.182
Dissimilarity Index (minority)	0.040	0.053	0.014	0.028
Poverty Segregation				
Relative Exposure (to high-poverty)	0.055	0.072	0.198	0.295
Isolation (poverty)	0.294	0.186	0.539	0.257
Dissimilarity Index (poverty)	0.051	0.047	0.105	0.145
Observations	600		608	

Note: This table presents descriptive statistics for Ohio districts in 2001–02, the year virtual charter schools were introduced in Ohio, and 2015–16, when students began disenrolling from the Electronic Classroom of Tomorrow (ECOT).

Table 16. Baseline values for treated and control districts (2001-02)

	Treated		Control	
	M	SD	M	SD
Demographic				
Percent Black	6.22	15.78	6.49	14.35
Percent White	92.31	16.43	92.30	15.04
Percent Hispanic	1.47	3.29	1.21	2.77
Percent Poverty	24.93	18.27	31.94	15.92
Racial Segregation				
Relative Exposure (to minority)	0.017	0.033	0.022	0.052
Isolation (minority)	0.093	0.171	0.097	0.164
Dissimilarity Index (minority)	0.041	0.045	0.048	0.054
Poverty Segregation				
Relative Exposure (to high-poverty)	0.052	0.062	0.064	0.067
Isolation (high-poverty)	0.267	0.189	0.343	0.161
Dissimilarity Index (poverty)	0.051	0.050	0.052	0.044
No. of Districts	110		96	

Note: This table provides descriptive statistics for treated and control districts in the 2001-02 school year, the baseline year.

Table 17. Number of Students Enrolled in ECOT by Grade (2015-16)

	Obs	Total
Grade 1	1	181
Grade 2	1	237
Grade 3	1	296
Grade 4	1	273
Grade 5	1	333
Grade 6	1	530
Grade 7	1	731
Grade 8	1	1003
Grade 9	1	1855
Grade 10	1	1133
Grade 11	1	3727
Grade 12	1	2748
Total Enrollment	12	13047

Note: The table provides ECOT enrollment counts by grade in the 2015-16 school year, the baseline year.
Source: Author's calculations based on NCES's Common Core of Data.