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Abstract

The prevalence of school-based healthcare has increased markedly over the past decade. We study a modern mode of school-based healthcare, telemedicine, that offers the potential to reach places and populations with historically low access to such care. School-based telemedicine clinics (SBTCs) provide students with access to healthcare during the regular school day through private videoconferencing with a healthcare provider. We exploit variation over time in SBTC openings across schools in three rural districts in North Carolina. We find that school-level SBTC access reduces the likelihood that a student is chronically absent by 2.5 percentage points (29 percent) and reduces the number of days absent by about 0.8 days (10 percent). Relatedly, access to an SBTC increases the likelihood of math and reading test-taking by between 1.8-2.0 percentage points (about 2 percent). Heterogeneity analyses suggest that these effects are driven by male students. Finally, we see suggestive evidence that SBTC access reduces violent or weapons-related disciplinary infractions among students but has little influence on other forms of misbehavior.

1 Introduction

Healthcare delivered in a school-based setting plays an increasingly important role in the lives of public school students across the United States (U.S.). The most recent nationwide census of school-based healthcare in 2016/17 found that more than 6.3 million public school students—around 13 percent—had access to healthcare in a school-based setting (Love et al., 2018, 2019b).[1] Survey data from the School Health Policies and Practices Study (SHPPS) of the U.S. Centers for Disease Control and Prevention (CDC) demonstrate that this figure represents more than a doubling in prevalence compared to a decade earlier—when, in 2006, roughly 6.3 percent of public school students had access to school-based healthcare.[2]

School-based healthcare offers the potential to address long-standing and entrenched gaps in access to healthcare by race and family income. Despite the narrowing of race- and income-based gaps in healthcare access in the early 2000s, children from low-income families and children of color in the U.S. remain less likely to have a steady source of care and more likely to have unmet healthcare needs, compared to their white and higher-income peers (Larson et al., 2016). Recent evidence indicates that school-based healthcare in the U.S. is disproportionately offered in schools serving above average percentages of students from low-income families (i.e., Title I schools) and Hispanic and Black students (Love et al., 2018, 2019b). Thus, this mode of delivery may be particularly important for reaching populations with historically low levels of healthcare access and thereby reducing unequal access between groups within communities (Knopf et al., 2016; Thomas et al., 2020).

Despite the recent growth in school-based healthcare, rigorous causal evidence on the effects of this form of healthcare on student outcomes remains scarce. Existing causal work in this area mostly examines the effects of school-based healthcare on older students and a

[1] In this census, school-based healthcare includes traditional brick-and-mortar health clinics located within schools, school-linked health clinics, mobile health clinics, and telehealth services accessed through schools (Love et al., 2018, 2019b).

[2] Authors' calculations using school-level data from the CDC School Health Policies and Practices Study (SHPPS). For more information on the data underlying various waves of this national survey, please see https://www.cdc.gov/healthyyouth/data/shpps/index.htm.

limited number of outcomes (e.g., teen fertility among high school students) or focuses on interventions designed exclusively to address students' mental health (e.g., providing schools with additional guidance counselors). Lovenheim et al. (2016) find that access to school-based health centers (SBHCs) in high school reduces teen birth rates but has no effect on high school dropout rates. Carrell and Carrell (2006) and Carrell and Hoekstra (2014) find that additional guidance counselors per school reduce student disciplinary infractions and Reback (2010a) concludes that state-funded counselor subsidies and mandated minimum student-counselor ratios reduce teacher-reported incidents of student misbehavior, physical fighting, truancy, theft, and drug use. Reback (2010b) also finds that increased funding for counselors reduces disciplinary infractions, particularly the most severe ones.

The bulk of the literature in economics that focuses on isolating causal links between health and education explores the causal direction that flows from education to health, rather than health to education (Eide and Showalter, 2011).[3] The relatively limited research that has examined the relationship between health and educational outcomes has typically focused on associations between childhood health status and longer-run measures of labor market success and educational attainment (e.g., Case et al., 2005) or the effects of early, neonatal health (proxied by birth weight) on cognitive development during childhood (e.g., Figlio et al., 2014). A small literature on the effects of access to health insurance on long-run educational outcomes illuminates the potential role that access to healthcare plays in shaping student success more broadly. Levine and Schanzenbach (2009) find that access to public health insurance at birth leads to small increases in later reading test scores. Brown et al. (2015), Cohodes et al. (2016), and Goodman-Bacon (2016) examine longer-run outcomes and find that access to health insurance during childhood increases the likelihood of high school graduation, college completion, and employment.

In this paper, we address existing gaps in the emerging literature on this topic by investi-

[3] Although the mechanisms are not entirely understood, there is empirical support for education influencing health outcomes through health behaviors (e.g., reduced smoking, higher likelihood of seatbelt use), occupational choice, exercise, income, and increased use of preventive medical care (Cutler and Lleras-Muney, 2006).

gating the effects of access to school-based healthcare on student outcomes among elementary and middle school students. We do so in the unique context of school-based telemedicine, which provides students with access to healthcare during the regular school day through private videoconferencing with a healthcare provider. Although relatively uncommon prior to the COVID-19 pandemic—Love et al. (2019a) estimated that around 2 percent of public school students in the U.S. had access to school-based telemedicine in 2016/17—school-based telemedicine has grown in recent years. Qualitative evidence gathered during the beginning of the COVID-19 pandemic suggests that telemedicine services in schools have expanded and that such shifts will likely become permanent (Goddard et al., 2021).[4]

The expansion of telemedicine within and across public schools follows the fast-paced, pandemic-driven expansion of telemedicine in other parts of the healthcare system in the U.S. (Mehrotra et al., 2020). Prior to the COVID-19 pandemic, telemedicine filled gaps in rural and underserved communities by providing access to specialty and subspecialty pediatric care, even when such care was obtained at local hospitals or managed by other healthcare providers (Burke et al., 2015; Utidjian and Abramson, 2016). Home-based telemedicine visits increase healthcare access by reducing transportation needs, parental time off of work, and childcare, but they also potentially exacerbate health inequalities since such visits require reliable internet access, an internet-connected and platform-compatible device, and fluency in the language spoken by the healthcare provider (Katzow et al., 2020).

In contrast to home-based or hospital-based telemedicine, school-based telemedicine allows a single healthcare provider (e.g., physician, nurse practitioner) to offer private appointments to students across multiple schools from an off-site location via real-time videoconferencing, specialized cameras, and data-transmitting medical equipment. The school-based telemedicine program we study in this paper leverages the capacity of existing school health staff (i.e., school nurses) who manage the queue of student appointments and serve as "pre-

[4] Randi and Girmash (2021) summarize state-level expansions to Medicaid reimbursement for school-based telemedicine services, although they note that it is unclear whether these expansions will be made permanent.

senters" for students during their private telemedicine visits. The presenter does not evaluate nor diagnose but instead assists with the management of video cameras and medical equipment (e.g., stethoscope) during the appointment. The healthcare provider can evaluate, diagnose, and—when appropriate—prescribe medication or designate a course of treatment through telemedicine, which significantly expands the suite of available healthcare services in school-based settings beyond those traditionally offered by school nurses (Graves et al., 2019). This system of centrally managed telemedicine appointments allows a single healthcare provider ("hub") to see students across multiple schools ("spokes") on any given day and thereby eliminates the need for one-to-one staffing (i.e., one healthcare provider per school). This system also eliminates the need for healthcare providers to spend time traveling between schools or for healthcare providers to rotate between schools across days (which leaves some days of the week unstaffed at particular schools).

We exploit variation over time in the openings of 22 school-based telemedicine clinics (SBTCs) across three rural school districts in North Carolina. Over the seven-year period spanning the 2011/12 to 2017/18 academic years, we study SBTCs that were opened in elementary and middle schools in McDowell County Schools, Mitchell County Schools, and Yancey County Schools. A local non-profit organization, the Center for Rural Health Innovation, oversaw the implementation of SBTCs across these three districts under an initiative termed "Health-e-Schools" (described in more detail in the next section).[5] The mission of the Center for Rural Health Innovation is "to apply innovative technologies to improve access to healthcare in rural communities." The Health-e-Schools program is one of several initiatives spearheaded by the organization that focus on improving healthcare in rural parts of western North Carolina.

Using difference-in-differences and event-study methods, we find that school-level SBTC access reduces the likelihood that a student is chronically absent by 2.5 percentage points (29 percent). We find slightly weaker evidence that school-level SBTC access reduces the average

[5] For more information about Health-e-Schools, see https://health-e-schools.com. For more information about the Center for Rural Health Innovation, see http://www.crhi.org.

number of days absent by around 0.8 days per year (10 percent). Related to these absenteeism findings, we examine whether SBTC access affects the likelihood of state-required test-taking in math and reading. We argue that these binary measures of test-taking capture a "point-in-time" reflection of student presence on test administration days and thus serve as additional measures of absenteeism. We find that SBTC access increases the likelihood of math and reading test-taking by between 1.8-2.0 percentage points (around 2 percent).

In addition to our core findings related to absenteeism, we also investigate whether access to SBTCs influences student disciplinary outcomes and whether our absenteeism-related findings vary across policy-relevant subgroups of students. We find some evidence—albeit more sensitive to our choice of comparison group—that SBTC access reduces the likelihood that a student is reported for a violent or weapons-related disciplinary infraction in a given year, which is consistent with the notion that SBTCs can serve as sources of referrals for students with unmet mental healthcare needs (Bains and Diallo, 2016). We do not find any statistical evidence of effects on other types of misbehavior. Our investigation into heterogeneous treatment effects documents patterns of findings that suggest our average results are driven by relatively larger effects of SBTC access among male students.

Our work contributes to a large literature in medicine, public health, and youth services documenting positive associations between access to school-based healthcare and a range of outcomes, including health and academic outcomes (Thomas et al., 2020). Although not necessarily causal (Bersamin et al., 2016), these studies suggest that school-based healthcare is associated with increased access to medical care, increased use of family planning services, and increased use of mental health counseling and social work services (Santelli et al., 1996; Soleimanpour et al., 2010). Self-reported survey data also indicate that access to school-based healthcare is associated with less missed (or forgone) care, lower incidence of hospitalization, and lower emergency department use (Santelli et al., 1996; Britto et al., 2001). Some research also indicates that school-based healthcare may generate positive spillovers onto other health domains, such as physical activity and nutrition (McNall et al., 2010).

In low-income populations, school-based healthcare also correlates with use of preventive care, increased vaccination, and less emergency room use (Allison et al., 2007). Although correlational studies overwhelmingly report that school-based healthcare is associated with increased healthcare access and better health outcomes, the evidence on academic outcomes is more mixed (Geierstanger et al., 2004; Knopf et al., 2016; Arenson et al., 2019). While some studies fail to detect evidence of improvement in students' academic outcomes, others report improved academic performance among sub-populations of children with chronic health conditions, such those with asthma (Murray et al., 2007).

Beyond contributing to the literature on school-based healthcare and its effects on student outcomes, we also contribute to the emerging public policy conversation about the cost of providing healthcare in school-based settings. Several studies suggest that school-based healthcare offers potential cost-savings for public health insurance programs like Medicaid (Guo et al., 2010; Wade and Guo, 2010; Ran et al., 2016). These cost savings are typically realized through averted use of expensive healthcare resources and include examples such as fewer asthma-related hospitalizations, less emergency department use, and less prescription drug use (Guo et al., 2010; Ran et al., 2016). We add to this conversation by presenting brief, descriptive evidence on how the cost of telemedicine equipment for school-based settings has declined over the past decade. We discuss several ways that school-based telemedicine in particular may allow school districts, non-profit organizations, and hospitals to overcome cost- and resource-related barriers to addressing students' unmet healthcare needs.

2 Background

2.1 Children's Health and Absences

Although microdata linking children's health information with detailed records of school absences are scarce, existing evidence indicates that the health status of children—both physical and mental—is strongly associated with attendance and engagement in school. Among young children in the U.S., children with lower levels of overall health were much more likely to be chronically absent from school, relative to their peers with higher levels of health, net of a range of controls that capture socio-demographic characteristics of students and their families as well as measures of educational activities and parent-child interactions at home (Gottfried and Gee, 2017). Survey evidence from Australia on older children (14-15 years old) paints a similar picture: the most common reason reported by students for excused absence was illness/health (55 percent); the smattering of other reasons were much less common, all in the 4 to 9 percent range (Hancock et al., 2018). Finally, Kearney (2008) notes that mental health issues that underlie school absenteeism often intensify during out-of-school time, leading to even more absence from school.

Figure 1 plots differences in the average number of health-related school absences (days) and the likelihood of chronic absenteeism (0/1)[6] due to health-related reasons between children with and without several health conditions, separately for elementary-aged students (7-10 years old) and middle school-aged students (11-14 years old), using nationally representative data from the U.S.[7] The figure depicts these differences for the four health conditions identified as the most common among public school students in North Carolina by annual surveys of public school nurses: asthma, severe allergies, emotional/behavior/concentration difficulties, and Attention Deficit Disorder (ADD)/Attention Deficit Hyperactivity Disorder (ADHD). The figure illustrates that common—and often chronic—physical and mental health challenges represent key barriers to learning for children and families. Across all conditions—jointly reflective of physical and mental health challenges—students with each condition missed more days of school for health-related reasons on average and were more likely to be chronically absent for health-related reasons than those without each condition. For example, 7-10 year-old children whose parents reported that they had ever been diagnosed with asthma missed an average of 1.8 more days of school during the preceding 12

[6] There is no uniform definition of "chronic absenteeism" in the academic literature; however, the majority of states define it as a student missing at least 10 percent of the school year (Schanzenbach et al., 2016). We follow this convention and define it as missing 18 or more attendance days during the academic year. We consider an alternative definition of chronic absenteeism later in the paper and demonstrate that our results are robust to such definitional adjustments.

[7] For more about the data and methods used to create this figure, please see Appendix B.

months than children without asthma, an increase of roughly 64 percent. Moreover, the differences in the average number of missed school days for health-related reasons are at least partially driven by students in the right tail of the distribution. By generating a measure of chronic absenteeism (i.e., missing 18 or more days of school in a year for health-related reasons), we again find statistically and practically significant differences between groups of students with and without these health conditions. The rate of chronic absenteeism for 7-10 year-old children ever diagnosed with asthma is 2.6 percentage points higher than the rate for those without a diagnosis (i.e., 3.7 percent versus 1.1 percent, respectively). Gaps between children with and without severe allergies, emotional/behavior/concentration challenges, and ADD/ADHD are similar in magnitude at 2.3, 2.5, and 1.7 percentage points, respectively.

2.2 The Health-e-Schools Program in North Carolina

The Center for Rural Health Innovation is a 501(c)(3) non-profit organization[8] located in Spruce Pine, North Carolina. The organization's mission is "to apply innovative technologies to improve access to health care in rural communities."[9] The Health-e-Schools program—which we study here—is one of the center's initiatives operating in rural areas of western North Carolina. We study the Health-e-Schools program's gradual introduction of SBTCs at the school level across schools in three districts: McDowell County Schools, Mitchell County Schools, and Yancey County Schools.[10] Appendix Figure A1a depicts the geographic location of these school districts in the state of North Carolina. Appendix Figure A1b plots

[8] A 501(c)(3) organization is a non-profit entity that qualifies for tax-exempt status under Internal Revenue Service (IRS) guidelines. For more information, please see `https://www.irs.gov/charities-non-profits/charitable-organizations/exemption-requirements-501c3-organizations`.

[9] See `http://www.crhi.org`.

[10] SBTCs were also introduced in a fourth school district, Burke County Schools. We exclude Burke County Schools from this analysis because the timing of the introduction was later and therefore limits our ability to conduct event-study analyses. Burke County (where Burke County Schools operates) is also different in terms of its observable characteristics when compared to the other three counties (school districts) in our analysis. Burke County is considerably more populous (with more people than the other three treatment counties combined) and has substantially more healthcare providers per capita. Burke County is not classified as rural nor as partially rural by the NC Office of Rural Health.

the rollout of telemedicine services across schools in treatment districts. There was variation both within and across districts in the timing of school-level telemedicine receipt. That is, in Mitchell and Yancey counties, school-specific adoption dates spanned 2012 to 2014, whereas in McDowell adoption occurred in 2015 or 2017.

The school districts in our are study are located in rural areas of North Carolina where the supply of healthcare providers is low. Figure 2 depicts time series plots for the number of physicians and psychologists per 10,000 residents, respectively, across five groups of counties in North Carolina. Four of the groups—labeled as City, Suburban, Town, and Rural—collectively contain the 97 counties in North Carolina that are not included in our study of SBTCs, grouped based on their rurality.[11] The fifth group—labeled as Treatment—includes the three counties (McDowell, Mitchell, and Yancey) that contain the schools that received SBTCs. Two striking patterns emerge from this figure: First, rural counties have—on average—substantially lower population-adjusted levels of healthcare providers. Second, the trend for rural counties is flatter than the trends for the other three groups—City, Suburban, and Town. The levels and trends for treatment counties typically mirror those for rural counties (McDowell, Mitchell, and Yancey counties are themselves classified as rural). Taken together, these patterns illustrate growing divergence in the supply of healthcare providers between rural counties and other counties in the state—and spotlight the opportunity for healthcare provided in school-based settings to help address such gaps.

SBTCs from the Health-e-Schools program layer the services, expertise, and capacity of a physician or advanced practice provider (e.g., nurse practitioner, physician assistant) onto the services, expertise, and capacity of existing school nurses working within schools. School nurses serve as "presenters" who facilitate a virtual exam during the student's private telemedicine appointment with the off-site healthcare provider. During the telemedicine appointment, the healthcare provider can evaluate, diagnose, and—when appropriate—prescribe medication or design a course of treatment for the student. This hub-and-spoke

[11] These classifications are based on the Common Core of Data (CCD) Locale Index.

model (the healthcare provider is "hub" who is connected to and serving many "spokes") brings substantial benefits to a rural setting—like our treatment schools—where the existing supply of healthcare providers is low and where schools are located far from one another (thus making it costly for healthcare providers to travel between schools for in-person visits). Comparison schools have similar levels of healthcare staffing; hence, the default school-based health provision in the counterfactual situation would likely include a nurse.[12]

The SBTCs of the Health-e-Schools program provide services to all students—regardless of health insurance status—and to school employees and staff.[13] Parents/guardians must consent for their children to receive medical services and are provided with basic information about the clinics each school year. Using aggregated data on student visits for the 2016/17-2018/19 school years paired with enrollment information for schools with SBTCs, we estimate that the share of students who received healthcare services through the Health-e-Schools SBTCs was between 1.3 and 9.5 percent across districts, or around 3.6 percent of students overall.[14] We display the uptake rates visually, separately by district and year, in Appendix Figure A3.

The centralized oversight and management of the SBTCs by the Health-e-Schools program provides benefits to the schools where the clinics are located. First, the common management and oversight across schools standardizes the set of healthcare services provided to students, which creates predictability for parents/caregivers (and students) as children move across schools from year-to-year (or possibly across schools due to local moves). Second, the oversight and management of a nonprofit organization eliminates the need for school staff to take on additional administrative tasks to support clinic operations.

[12] Appendix Figure A2 depicts average levels of health staff (full time equivalents) per 100 students at the district level, separately for treatment, comparison, and other school districts in North Carolina. We note that these measures only reflect healthcare personnel on school district payrolls and thus exclude health staff working on a contract basis. For more detail about these data, please see Appendix B.

[13] For more information on "Health-e-Schools," please see `http://www.crhi.org/MY-Health-e-Schools/index.html.`

[14] Data collected by the non-profit are at the aggregate (district) level and are not separated by school level (i.e., elementary, middle, high school). These estimates include elementary, middle, and high school students who had at least one visit to an SBTC.

2.3 Candidate Mechanisms

SBTCs offer the potential to reduce student absenteeism through a number of channels. First, school-based healthcare may aid in the diagnosis of previously undetected—and therefore untreated—chronic physical and mental health conditions that cause students to miss school regularly. For students who lack access to a regular source of healthcare, undiagnosed physical or mental health conditions may contribute to increased absences from school. Healthcare in a school-based setting—where access barriers such as insurance status, immigration status, and financial burden are potentially reduced—may aid in diagnosing these previously undetected conditions and facilitating referrals to appropriate treatment. This could potentially happen in one-off visits (e.g., due to the acute onset of symptoms) or long-term, repeated contact with the school-based telemedicine center. Detection and diagnosis of previously unidentified conditions may happen during a student's telemedicine appointment or through a referral to another provider.

Second, school-based healthcare may assist students with medical management of previously diagnosed, chronic physical and mental health conditions that—when insufficiently managed—may result in missed days of school. Chronic conditions associated with student absences are asthma, type 1 diabetes, chronic pain (e.g., headaches), chronic fatigue, mental health conditions, and conditions that cause seizures, such as epilepsy (Allison et al., 2019; Mir et al., 2012). Moreover, seasonal pollen levels have been linked to lower levels of academic achievement (Marcotte, 2015) and may exacerbate some of these chronic health conditions (Mir et al., 2012). Access to healthcare in a school-based setting may help students (and parents/caregivers) determine when it is medically necessary to leave school and seek care, make primary care or specialist referrals for students whose conditions are insufficiently managed or who are experiencing flare-ups, and assist with medication management for students requiring prescription medication.

Third, access to healthcare in school may provide students with timely diagnoses of common conditions, such as ear infections, rashes, and colds, that cause students to leave school early or miss school when left untreated or when treatment is delayed. Access to school-based healthcare may reduce the time necessary to determine whether a child needs to leave school due to illness, since a healthcare provider may be able to make the determination during the telemedicine appointment. In the extreme, this could eliminate the need for a child to wait until a parent/caregiver can pick up the child from school, take the child to a healthcare provider, or keep the child at home until the symptoms have resolved. This could minimize lost instructional time (e.g., while waiting for the appointment to begin) and entirely eliminate the need to leave school. If the healthcare provider determines that a child should leave school during a telemedicine appointment, school-based healthcare can substantially speed up the child's recovery (and eventual return to school) by providing immediate treatment at school or calling/faxing a prescription into a local pharmacy. This pathway may generate positive spillovers onto other students in the school if early identification of contagious diseases reduces the spread of such diseases to other children in the school.

Finally, school-based healthcare may increase detection of serious non-medical issues that cause students to miss school such as housing instability, food insecurity, and child maltreatment. Previous work by Fitzpatrick et al. (2020) highlights the role that teachers and school staff play in identifying cases of child maltreatment, which suggests that school-based healthcare providers could play a similar role.

3 Data

3.1 Data Sources

We employ data from two sources: (1) a database of SBTC openings (month and year) in the three treatment districts and (2) student-level microdata from a statewide longitudinal data system that tracks all students enrolled in North Carolina public and charter schools. We constructed the database of school-level SBTC openings based on a combination of sources including local newspaper articles, school webpages, and publicly available school and district Facebook pages. Each school-level record documents the month and year in which the the school opened its SBTC.[15] We then validated these records using historical information made available to us by the Health-e-Schools program at the Center for Rural Health Innovation. In our coding of treatment timing, we chose to code school years in which SBTCs opened—even after the start of the school year—as treated. This conservative approach suggests that our treatment effect estimates should be interpreted as lower bounds, since some untreated school-months are included in our treatment variable by construction.

We obtained student-level, administrative education data from the North Carolina Education Research Data Center (NCERDC) at Duke University. These student-level data cover the universe of public and charter students in North Carolina during the 2007/08-2018/19 school years. These data contain annual information on student demographics, enrollment, absences, test scores, and reported disciplinary infractions. We matched these student-level data to the information from our database on the rollout of SBTCs using annual information on student enrollment, which included each student's school.

3.2 Analytic Samples

We constructed two separate analytic samples to carry out our analyses. We restricted our attention to third through eighth grade students with non-missing enrollment and absence data who were enrolled in schools in the three treatment districts (McDowell County Schools, Mitchell County Schools, and Yancey County Schools) or in schools located in one of two comparison groups between the 2007/08-2018/19 school years.[16]

We constructed the first comparison group based on an index of rurality and the local healthcare environment. We included all school districts located within counties in western North Carolina that were designated as (1) rural or partially rural and (2) Health Professional Shortage Areas (HPSAs) for primary care providers for low-income or "medically indigent"

[15] We had two undergraduate research assistants assemble the initial school-level records in parallel and independently from one another. We then checked these two sets of records against each other to construct our initial database.

[16] We chose third through eighth grade students because these are the grades in which End-of-Grade (EOG) tests are required in North Carolina and for whom absence and enrollment data are known to be complete.

populations.[17] Hence, this comparison group includes students enrolled in schools in the following nine school districts: Cherokee County Schools, Cleveland County Schools, Gaston County Schools, Haywood County Schools, Jackson County Schools, Lincoln County Schools, Macon County Schools, Rutherford County Schools, and Wilkes County Schools.[18] We constructed the second comparison group based on geographic proximity to the treatment school districts—it includes county school districts that bordered the treatment districts: Avery County Schools, Buncombe County Schools, Madison County Schools, and Rutherford County Schools. Both comparison groups have intuitive and empirical appeal: the first captures commonalities based the local healthcare environment, while the second captures unobserved but common geographic and labor market conditions.

3.3 Descriptive Statistics

Table 1 presents descriptive statistics for our two analytic samples at baseline. Columns (1), (2), and (5) report means and standard deviations for selected characteristics and outcomes at baseline for the treatment group, rural HPSA comparison group, and border comparison group, respectively. Columns (3) and (6) present the differences in means (and accompanying p-values) between students in the treatment group and the two comparison groups. All descriptive statistics reflect the baseline school year, 2007/08, and all p-values come from two-tailed t-tests of the differences in means.

We see evidence of some baseline differences between students in the treatment group and rural HPSA comparison group. Specifically, students in the treatment group were more likely to be white (10.3 percentage points) and Hispanic (1.4 percentage points) and less likely to be Black (11.1 percentage points). Students in the treatment group were also more

[17] HPSAs are flagged by the U.S. federal government based on several socioeconomic and health indicators. The Centers for Medicare and Medicaid (CMS) provides a 10 percent bonus payment for Medicare-covered services provided within the bounds of a geographic HPSA; for more information see https://www.cms.gov/Outreach-and-Education/Medicare-Learning-Network-MLN/MLNProducts/downloads/HPSAfctsht.pdf.

[18] We restricted to HPSAs designated as "rural" or "partially rural" by the Health Resources and Services Administration (HRSA). For more information on HRSA's rural designation, see https://www.hrsa.gov/rural-health/about-us/definition/index.html.

likely to be economically disadvantaged (3.3 percentage points), eligible for special education services (2.4 percentage points), and identified as having Limited English Proficiency (2.5 percentage points). Similar baseline differences appear between students in the treatment group and the border comparison group. Compared to students in the border comparison group, students in the treatment group were more likely to be white (5.3 percentage points) and less likely to be Black (4.3 percentages) or identifying as part of another racial/ethnic group (1.6 percentage points). Students in the treatment group were once again more likely to be economically disadvantaged (5.7 percentage points), less likely to identified as gifted (2.1 percentage points), and more likely to be identified has having Limited English Proficiency (0.8 percentage points).

Beyond these differences in student characteristics, students in treatment districts had worse outcomes at baseline when compared to students in both of our comparison groups. Students in the treatment group were more likely to be chronically absent (1.9 percentage points and 3.8 percentage points), were absent for more days on average (0.98 days and 1.18 days), were less likely to have taken an EOG math test (1.7 percentage points less likely than students in both comparison groups) and were less likely to have taken an EOG reading test (1.8 percentage points less likely than students in both comparison groups).

Although we observe a number of differences in student characteristics across our treatment and comparison groups in the baseline year, our identification strategy does not depend on baseline equivalency (i.e., "balance"). Instead, our difference-in-differences and event-study approaches depend on the equivalency of trends in observables and unobservables between treatment and comparison groups prior to introduction of SBTC access. We discuss this identification assumption more fully in the next section.

4 Empirical Strategy

To combat growing concerns about the use of two-way fixed effects (TWFE) estimators in staggered-adoption difference-in-differences (DiD) research designs, we follow the approach of Gardner (2022) and implement the "two-stage difference-in-differences" (TSDiD) estimator.[19] Using TSDiD, we produce difference-in-differences and event-study estimates from a context with staggered program adoption that are robust to the presence of heterogeneous treatment effects across groups and over time. We implement the TSDiD approach to estimate the effect of SBTC access on student outcomes using the following two equations:

$$Y_{ist} = \delta_s + \theta_t + \phi X_{it} + \varepsilon_{ist} \tag{1}$$

Y_{ist} is an outcome (e.g., the number of days absent, etc.) for student i who was enrolled in school s during year t. δ_s is a vector of school fixed effects and θ_t is a vector of year fixed effects. X_{it} is a vector of student-level covariates including gender, race/ethnicity, economic disadvantage,[20] special education status, gifted designation, Limited English Proficiency (LEP) status, and grade level. ε_{ist} a student-year-specific error term that is assumed to be uncorrelated with other determinants of student outcomes. We estimate the first-stage equation for the subset of observations in our sample that are untreated (i.e., students in treated schools prior to the opening of the SBTC and students in comparison-group schools). From Equation (1) we obtained coefficient estimates on the school indicators (group), year indicators (period), and covariates. We then formed a residualized outcome, $\tilde{Y}_{ist}$, for all students in our sample by subtracting off these estimated relationships from the observed outcome: $\tilde{Y}_{ist} = Y_{ist} - \hat{\delta}_s - \hat{\theta}_t - \hat{\phi} X_{it}$.

In the second stage, we regress these residualized outcomes for all students in the sample on a binary treatment indicator as follows:

$$\tilde{Y}_{ist} = \beta \times SBTC_{st} + \nu_{ist} \tag{2}$$

$\tilde{Y}_{ist}$ is the residualized outcome described above and $SBTC_{st}$ is a binary indicator that

[19]We use the STATA package developed by Butts (2022) to estimate all TSDiD models in this paper. More details about the software can be found in Butts and Gardner (2022).

[20]In the administrative data, a student is deemed "economically disadvantaged" if she qualifies for free or reduced-price meals.

takes on the value of one in year t (and all subsequent years) following the opening of an SBTC at school s. Thus, our key coefficient of interest (β) is identified from differences in the evolution of mean outcomes for students in treatment schools relative to students in comparison schools after removing the influence of year effects, school effects, and student-level covariates on those outcomes.

In addition to Equation (1), we also report results from other econometric specifications to assess the robustness of our results to assumptions about functional form and concerns about omitted time-varying factors that might influence both SBTC openings and student outcomes. We augment the specification outlined in Equation (1) with a more flexible specification of time-trends (grade-by-year fixed effects) and with time-varying, school-district-level controls including total population, the child poverty rate, the unemployment rate, the number of full-time teachers in the district, the number of guidance counselors in the district, and the number of school support staff in the district.[21] In all cases, we report heteroskedasticity-robust standard errors that are clustered by school.

We augment our presentation of difference-in-differences estimates with event-study estimates by modifying Equation (2) as follows:

$$\tilde{Y}_{ist} = \sum_{\substack{k=-4 \\ k \neq -1}}^{2} \left[\gamma_k \cdot SBTC_s \cdot \mathbf{1} \cdot \Big(t - T_s^* = k \Big) \right] + \upsilon_{ist} \tag{3}$$

Equation (3) is the same as Equation (2) except that we interact an eventual-treatment indicator, $SBTC_s$, with event-time indicators to trace out the time path of treatment effects (note: T_s^* is the year the SBTC was introduced at school s and $k = -1$ is omitted). The estimated effects of SBTC access in years prior to the introduction of SBTCs permit an assessment of concerns about pre-trends, and estimated effects in years following the introduction of SBTCs provide insights about treatment dynamics.

Prior to presenting our results, we show unadjusted trends (raw data) for absenteeism,

[21] We detail the data sources for these district-level covariates in Appendix B.

test-taking, and reported disciplinary infraction outcomes, separately for schools that were eventually treated versus comparison schools that were not. These plots appear in Appendix Figures A4-A6. Across all three sets of outcomes, we see that in the school years prior to 2011/12 (the first year of the rollout of SBTCs), outcomes were evolving similarly (i.e., in parallel) between the two groups. This supports our identifying assumption by suggesting that trends in outcomes among both groups of comparison schools can plausibly serve as counterfactual trends for our treatment schools, since the trajectories were nearly identical prior to the introduction of any SBTCs. The visual evidence in these raw plots also previews part of the underlying story captured in our difference-in-differences estimates (presented in the next section): namely, the introduction of SBTCs at the school-level improved outcomes for students in treatment schools so that their outcomes more closely resembled those of students in comparison schools (i.e., convergence of outcomes for students in treatment schools up to the level of outcomes for students in comparison schools).[22]

In addition to presenting difference-in-differences and event-study estimates using the TSDiD approach, we conduct two additional empirical checks (focusing on our outcomes that capture absenteeism). First, we compute the weights attached to the standard TWFE difference-in-differences regressions.[23] Within the most basic difference-in-differences setup (i.e, with no controls), 100 percent of the weights attached to the standard TWFE estimator are positive.[24] Second, we implement an alternate estimator developed by de Chaisemartin

[22]To illustrate this point more clearly, we divided the school years following 2011/12 into three "phases," which roughly demarcate periods with notable upticks in the number of schools where SBTCs were introduced (See Appendix Figure A1b). Across all three sets of outcomes, we see slight convergence (i.e., improvement) in average outcomes among students in treatment schools in Phase 1, which roughly corresponds to the incremental addition of treated schools across the 2011/12, 2012/13, and 2013/14 school years. This is followed by stronger convergence in outcomes during Phase 2, which is also unsurprising given that the number of treated schools nearly doubled in the 2014/15 school year alone. Finally, we see outcomes roughly tracking each other in Phase 3, during which only a modest number of SBTCs were introduced into the remaining eventually treated schools.

[23]To do so, we use the *twowayfeweights* command developed by de Chaisemartin and D'Haultfœuille (2020).

[24]When we add controls to this command, the share of positive weights remains extremely close to 100 percent—ranging between 97 and 100 percent, depending on the comparison group and sets of included controls (i.e., school-level or school- and district-level covariates).

and D'Haultfœuille (2020).[25] This estimator traces out the evolution in outcomes for units that become treated relative to units that remain untreated over the full period. Thus, it estimates the the "average treatment effect at the time when a group starts receiving treatment, across all groups that become treated at some point" de Chaisemartin and D'Haultfœuille (2020, p. 2976). de Chaisemartin and D'Haultfœuille (2020) demonstrate that their approach is robust to heterogeneous treatment effects over time or across groups.

5 The Effects of SBTC Access on Student Absenteeism

5.1 Chronic Absenteeism and Days Absent

Table 2 presents TSDiD estimates for two outcomes related to student absenteeism: an indicator for whether the student was chronically absent (Panel A), and the number of days the student was absent during the school year (Panel B).[26] The point estimate in Column (1) of Panel A indicates that SBTC access decreased the likelihood that a student was chronically absent by about 2.5 percentage points—or 29 percent relative to the baseline mean. To more flexibly specify time trends we replace year fixed effects with grade-by-year fixed effects and report the results in Column (2). The point estimate and standard errors are identical. To increase precision and address the possibility of omitted, district-level factors correlated with treatment timing, we add time-varying, district-level covariates in Column (3). This specification yields a point estimate that is unchanged (i.e., 2.5 percentage points) and a standard error that is slightly smaller. We consider this specification to be our preferred specification because it allows time trends to vary flexibly across grade levels—thereby controlling for any statewide policy changes that affected a particular grade—and accounts for time-varying factors the level of the school district. Finally, to probe the sensitivity of our results to our choice of comparison schools, we produce estimates for the same three

[25] Specifically, we use their *did_multiplegt* command in STATA.

[26] Due to slight anomalies in the 2016 absence data from North Carolina, we produce a version of our absenteeism results excluding this year of data. These results are qualitatively similar to our main findings and are reported in Appendix Table A1.

econometric specifications using untreated schools from counties that share a border with our three treatment counties (school districts). These results, which we report in Columns (4)-(6), are also slightly larger in magnitude and suggest that SBTC access could reduce the likelihood that a student is chronically absent by as much as 3.3 percentage points—a 38 percent decline relative to the baseline mean—although we note that the ninety-five percent confidence intervals associated with these estimates contain the estimate from our preferred specification in Column (3).

Figures 3a and 3b present coefficient estimates and associated ninety-five percent confidence intervals for event-study estimates related to the binary outcome of chronic absenteeism. The plots depict sequences of γ_k coefficients from $k = -4, ..., 2$ with $k = -1$ omitted and $k = 0$ representing the year in which SBTC access was introduced at the school level. The sequences of γ_k coefficients with negative event-time indices permit us to assess the extent of differential pre-trends between the treatment and comparison group. The coefficients on those negative event-time indicators hover near zero and, as a whole, support the core identifying assumption of our empirical approach—namely, that the treatment and comparison schools were not on systematically different trends prior to the adoption of SBTCs. In the years coinciding with ($k = 0$) and immediately following the introduction of SBTC access (i.e., the nonnegative event-time indices), we see an immediate, permanent, and constant decrease in chronic absenteeism in treated schools that is similar in magnitude to our TSDiD estimates.

In Panel B of Table 2 we repeat the same analyses using two comparison groups for the outcome of number of days absent. Results from our preferred specification in Columns (3) and (6) suggest that school-level SBTC access led to around 0.8 fewer absences per student per year on average—a 10 percent decline relative to baseline—although these results are only marginally statistically significant in the border comparison group. Combined with our results for chronic absenteeism, we interpret this as evidence that SBTC access led to larger declines in absenteeism for students in the upper tail of the absences distribution. We present accompanying event-study results in Figures 3c and 3d. The patterns are broadly similar to those for chronic absenteeism: although not entirely flat, we do not see concerning evidence of a strong upward or downward pre-trend, and the reduction in days absent due to SBTC access appears to be immediate and constant.

To support our main findings related to student absenteeism, we present robustness checks, falsification tests, and an alternate approach to statistical inference. We first report estimates from several robustness checks in which we use the same econometric specifications but substitute alternative—yet related—absenteeism outcomes: the first is an alternative measure of chronic absenteeism that follows the definition used by the State Board of Education in North Carolina[27] and the second is a student-level annual absence rate, which explicitly accounts for the number of days each student was enrolled in school. Results using these alternative dependent variables are entirely consistent with our main findings and appear in Appendix Table A2.

Through the inclusion of time-varying district-level controls and the use of multiple comparison groups, we aimed to limit concerns about omitted social, economic, or policy factors that might provide alternate explanations for our main results. As an additional assessment of the causal warrant of our findings, we conduct falsification tests at the school level in which we explore the effects of SBTCs on outcomes that ought not to be influenced, such as school-level enrollment, the demographic composition of students in the school, as well as measures of staffing and class size. The results are reported in Appendix Table A3. With the exception of the share of economically disadvantaged students, we do not find any statistical evidence that any enrollment or demographic outcomes were affected by the introduction of SBTC access. The associated ninety-five confidence intervals are small enough to rule out large positive or negative effects on these measures. We note that in Column (1) of Panel D

[27]The State Board of Education in North Carolina defines chronic absenteeism as "a student who is enrolled in a North Carolina public school for at least 10 school days at any time during the school year, and whose total number of absences is equal to or greater than 10 percent of the total number of days that such student has been enrolled at such school during such school year." For more information, please see https://stateboard.ncpublicschools.gov/rules-apa/hb-362/16-ncac-06e-0106-final-atnd-004-definition-of.pdf.

the share of economically disadvantaged students declines by 11.4 percentage points, but this effect disappears with the addition of district-level covariates, as shown in Column (2). The effect is small (-0.024) and statistically insignificant in Column (3) and moderate (-0.06) and marginally statistically significant in Column (4). We take this evidence as weakly suggestive of the possibility that SBTC access attracted economically advantaged students to the school, although we find this somewhat implausible given that no other school-level outcomes (e.g., demographic composition, student-teacher ratios) provide strong evidence to support this possibility.

Finally, we conclude by presenting two alternative approaches to statistical inference: bootstrapped standard errors and permutation p-values. The former approximates the empirical distribution of estimated effects using resampling while the latter characterizes uncertainty in our estimates that arises from the assignment of schools to treatment instead of sampling. Bootstrapped standard errors and associated p-values are reported in Appendix Table A4.[28] We report approximations to permutation p-values in Appendix Table A5. We note that our conclusions regarding the statistical significance of our estimates are very similar, with the lone exception of permutation p-values for math and reading test-taking outcomes in the border sample, which are no longer statistically significant at conventional levels.

In Columns (1) and (2) Appendix Table A6, we present results from the alternative estimator of de Chaisemartin and D'Haultfœuille (2020) for both of our comparison groups for the following outcomes: chronic absenteeism and days absent. Encouragingly, for chronic absenteeism we see point estimates that are extremely similar in magnitude and statistical significance to estimates from our preferred specifications (see Table 2). The results for the number of days absent are weaker—the magnitudes are slightly smaller and the results are statistically insignificant. Despite this, we view this evidence as largely supportive of and

[28] Because the TSDiD estimator is new to the econometric literature as of this writing, we view the bootstrapped standard errors as a complement to those produced by the user-written STATA command for the TSDiD estimator. The standard errors are extremely similar across these two approaches.

consistent with our main findings regarding absence-related outcomes.

5.2 Test-Taking as an Additional Measure of Absenteeism

The reduction in chronic absenteeism that we uncovered above suggests that students exposed to SBTCs were consistently more present in school than they otherwise would have been, in the absence of access to school-based healthcare. Thus, as an alternate measure of persistent presence in school, we investigate whether SBTC access increased the likelihood of student test-taking.

We first assess the face validity of our test-taking measures. To do so, we use data on all students enrolled in public and charter schools in North Carolina between 2008 and 2019 (excluding our three treatment counties), and document robust and strikingly stable correlations between our two preferred measures of absenteeism—chronic absenteeism and the number of days absent—and student-test taking. Averaging our cross-sectional regression results across years, we find that a student who is chronically absent is 14.4 percentage points less likely to take the end-of-grade math test and 14.5 percentage points less likely to take end-of-grade reading test. Similarly, each additional annual student absence is associated with a 0.6 percentage point decrease in the likelihood of taking the end-of-grade math (reading) test. For visual depictions of these cross-sectional regression results, please see Appendix Figures A7a and A7b.

Given the robust and stable correlation between our two measures of student absenteeism and end-of-grade test-taking, we explore the relationship between SBTC access and test-taking in support of our main absenteeism results. Table 3 reports results for math test-taking in Panel A and for reading test-taking in Panel B. Our point estimates are very similar across specifications. For math, our estimates in Columns (1)-(6) of Panel A indicate that SBTC access increased the likelihood of student test-taking by between 1.8 and 3.1 percentage points (1.9 to 3.3 percent in relative terms). For reading, our estimates in Columns (1)-(6) of Panel B indicate that SBTC access increased the likelihood of student test-taking by between 1.4 and 2.8 percentage points (1.5 to 3.0 percent in relative terms). Figures 4a-4d present corresponding event-study estimates. We observe clear, sustained, and slightly increasing effects of SBTC access on the likelihoods of test-taking in reading and math, respectively, which we interpret as strongly corroborative of our core findings regarding the effects of SBTC access on measures of student absenteeism.[29]

5.3 Discussion of Absenteeism Findings

Our core findings underscore the potential that school-based telemedicine—and school-based healthcare more broadly—holds to address inequalities in educational opportunities that are rooted in unequal health status and unequal access to healthcare. Our findings point to school-based healthcare as one way to improve gaps in educational opportunities related to instructional time. Research on absenteeism highlights the importance of students' presence in the classroom—and instructional time—for student achievement (Lavy, 2015; Marcotte and Hemelt, 2008; Pischke, 2007; Fitzpatrick et al., 2011; Goodman, 2014) as well as for longer-run measures of attainment such as high school completion and college enrollment (Gershenson et al., 2016; Liu et al., 2019).

Although we find strong evidence regarding the effects of SBTC access on absenteeism-related outcomes, we fail to detect statistically significant effects of school-level SBTC access on math or reading test scores. This is not entirely unanticipated, as we may not expect sharp nor immediate increases in test scores for two reasons. First, there may be some lag between decreased absenteeism (and hence increased student instructional time) and meaningful effects on student achievement, particularly given the magnitude (0.8 days) of the effect we observe and the modest rates of district-level usage by students exposed to SBTCs. Second, given our findings related to increases in the likelihood of test-taking, we might anticipate decreases in short-run average test scores, as SBTC access induces more

[29]In Columns (3) and (4) Appendix Table A6, we once again present results from the alternative estimator of de Chaisemartin and D'Haultfœuille (2020) for outcomes related to test-taking. The point estimates are very similar in magnitude and our conclusions regarding the statistical significance of our estimates are similar to our main results (see Table 3).

test-taking and thus changes the composition of tested students. As more students are drawn back into the pool of tested students, this could potentially decrease average test scores if those being drawn back into testing were students with previously below-average test scores (likely due to missed school). We do not find any statistically significant evidence of either increases or decreases in short-run reading and math test scores. For completeness, we present these results in Appendix Table A7.

We can use the rough, district-level SBTC usage rates along with our estimates of the effect of exposure to an SBTC on absence outcomes to approximate the effect of using an SBTC on absence from school. For example, if we divide our estimate of the effect of SBTC exposure on days absent (0.80) by the average usage rate across all treatment districts (0.04), we arrive at a figure of 20 days—implying that, on average, using the services provided by an SBTC would reduce a student's total yearly absences by about 20 days. Moreover, if we assume that the students most likely to use SBTC services are those with chronic health conditions—who are much more likely to be chronically absent than their peers without such conditions—and thus embody the greatest capacity for absence reduction, we would expect to see effects on our measures of absenteeism quite similar to what we find. Thus, one way to interpret our analytic story is that telemedicine services reduce absence substantially for a modest share of students who tend to occupy the right tail of the absences distribution. Of course, future shifts in the scope and intensity of SBTC use by students and families may refine this story.

6 Behavioral Outcomes and Subgroup Treatment Effects

6.1 Telemedicine and Student Behavior

One channel through which SBTCs may shape student outcomes is the provision of referrals for mental healthcare. To the extent that untreated mental health challenges manifest in observable ways, we may expect to detect effects of school-level SBTC access on measures of student misbehavior. Thus, in Table 4, we present TSDiD results for two outcomes that partition the universe of reported student disciplinary infractions into two bins: (1) violent or weapons-related and (2) all others.[30] We report results for binary variables indicating that a student had at least one reported violent or weapons-related infraction (0/1) in Panel A and that a student had at least one other reported infraction (0/1) in Panel B.

Our estimates in Columns (1)-(3) of Panel A indicate that SBTC access decreased the likelihood that a student had at least one violent or weapons-related infraction by between 1.7 and 2.0 percentage points (40 to 47 percent decline relative to the baseline mean). Although our estimates in Columns (4)-(6) of Panel A are smaller in magnitude and statistically insignificant, they are similarly signed (i.e., all point estimates are negative). In addition, the ninety-five percent confidence intervals that correspond to those point estimates—although substantially wider—contain the point estimates presented in Columns (1)-(3). Companion event-study estimates appear in Figures 5a and 5b. These estimates are more convincing in our comparison sample of rural HPSAs than in our sample of border counties. Taken as a whole, we view this evidence as suggestive. These findings support the idea that access to healthcare in a school-based setting offers the potential to address not only students' physical health but possibly mental and behavioral health as well.

We repeat the same analyses for all other reported disciplinary infractions in Panel B. Our point estimates in Columns (1)-(6) are small in magnitude and statistically insignificant. We present accompanying event-study results in Figures 5c and 5d. We fail to detect statistically significant effects of school-level SBTC access on reported incidents of other misbehavior (i.e., nonviolent and non-weapons-related infractions).

[30] In the North Carolina data, examples of "violent or weapons-related" infractions include fighting, bullying, and assaults; whereas other infractions include nonviolent misbehaviors such as honor code violations and inappropriate language. We roughly follow the classification scheme presented in (Holbein and Ladd, 2017). A complete list of violent or weapons-related infractions appears in Appendix B.

6.2 Investigation of Treatment Heterogeneity

To gain additional insight into how SBTC access affects student outcomes we investigated treatment heterogeneity on the basis of students' demographic characteristics and level of schooling (i.e., elementary versus middle school). Although our story regarding treatment effect heterogeneity is not entirely clear-cut, we see some evidence of larger effects among male and among economically disadvantaged students. We do not find any statistically significant evidence of differential treatment effects by student race/ethnicity nor by school level.[31]

Table 5 presents results in which we interact SBTC access at the school level with student demographics (i.e., gender and economic disadvantage) and then report the results from the statistical test of whether the effects are different between the two groups. The results in Columns (1)-(6) of Panels A and B consistently demonstrate that reductions in the likelihood of chronic absenteeism and the number of days absent are larger among males. Although the evidence in Columns (1)-(3) from the rural HPSA comparison group is slightly weaker (in the statistical sense) than the evidence in Columns (4)-(6) from the border comparison group, the patterns of effects are similar. Our results in Panels C and D reinforce these findings by showing that increases in test-taking in math and reading were also larger among males. We do not find any evidence that treatment effects were statistically different between males and females for outcomes related to reported disciplinary infractions.

Columns (7)-(12) of Table 5 present results from a similar exercise in which we interact SBTC access at the school level with a binary indicator for economic disadvantage. Patterns of results are a bit more murky. One the one hand, we find that increases in test-taking and reductions in the likelihood of at least one reported violent or weapons-related infraction due to SBTC access are larger for economically disadvantaged students than for their more affluent peers. However, we see relatively larger effects on chronic absenteeism rates and

[31] For completeness, we present our results by student race/ethnicity in Appendix Table A8 and by school level in Appendix Table A9.

days absent for students who are not economically disadvantaged.

7 Conclusion

The prevalence of school-based healthcare has increased markedly over the past decade. In this paper we study a modern mode of school-based healthcare, telemedicine, that offers the potential to reach places and populations with historically low access to such care. We exploit variation over time in the openings of school-based telemedicine clinics (SBTCs) across three rural school districts in North Carolina to estimate the effects of SBTC access on a range of student outcomes.

We find strong evidence that school-level access to an SBTC reduces the likelihood that a student is chronically absent (2.5 percentage points or 29 percent) and slightly weaker evidence that SBTC access decreases the average number absences (0.8 days per year or 10 percent). Relatedly, access to an SBTC increases the likelihood of math and reading test-taking, which we consider to be evidence of decreased student absences at a single point-in-time. The magnitude of the reduction in rates of chronic absence is roughly equivalent to the gap in such rates between kids with and without several common health conditions, based on nationally representative survey data. We find suggestive evidence that SBTC access reduces the likelihood that a student is reported for a violent or weapons-related disciplinary infraction, but has little influence on other forms of misbehavior. Finally, patterns of results across policy-relevant subgroups of students suggest that our core absenteeism findings are driven by relatively larger effects among male students.

Technological advances in computing, the availability of data-transmitting medical equipment and high-resolution video cameras, as well as the diffusion of high-speed internet access have enabled recent growth in school-based telemedicine. This model for healthcare delivery—and access—offers the potential to be especially effective in places where large numbers of students have unmet healthcare needs and where traditional, brick-and-mortar school-based healthcare centers (SBHCs) would be logistically or financially infeasible.

Using public school enrollment data from the National Center for Education Statistics and healthcare provider data from the Health Resources and Services Administration (HRSA), we estimate that about 13.23 million students attend public schools located in counties with Health Professional Shortage Areas (HPSAs)—similar to the counties we study in this paper. If we restrict our attention to students in first through eighth grade, the figure is 7.76 million, of which 72 percent reside in rural areas. School-based telemedicine is one potential policy intervention that could be used to reach these students, improve their healthcare access, and ultimately reduce missed school and learning opportunities in the aggregate.

One alluring feature of school-based telemedicine that distinguishes it from other possible policy interventions designed to reach children with unmet healthcare needs is its cost, which is lower than in-person alternatives and on a steep downward trajectory. Using cost data obtained from two separate telemedicine-in-schools programs, we estimate that over the past 10 years the cost of telemedicine equipment for SBTCs has declined by nearly an order of magnitude. These equipment costs are important because they include the requisite technical infrastructure—such as computers, cameras, and data-transmitting medical equipment (e.g., stethoscope and otoscope)—needed to establish a school-based telemedicine clinic.

Using these cost data, we estimate that school-based telemedicine clinic equipment costs were around \$24,000 per school in the early 2010s but are now closer to \$2,400 per school.[32] This dramatic decline is due in large part to improvements in personal computers (including laptops and tablets), which are now much cheaper, much faster, and can serve as platforms to integrate the cameras and medical equipment needed in a school-based telemedicine clinic.

Other costs associated with school-based telemedicine clinics, such as labor and staffing costs (i.e., healthcare provider time, technical support/maintenance), facilities costs, and broadband access, have not declined as steeply but would be higher (or the same) for in-person alternatives. We have in mind a comparison to a counterfactual world in which the school has an on-site nurse or other healthcare provider. Of course, if the comparison is

[32] Please see Appendix B for more information about school-based telemedicine equipment data and costs.

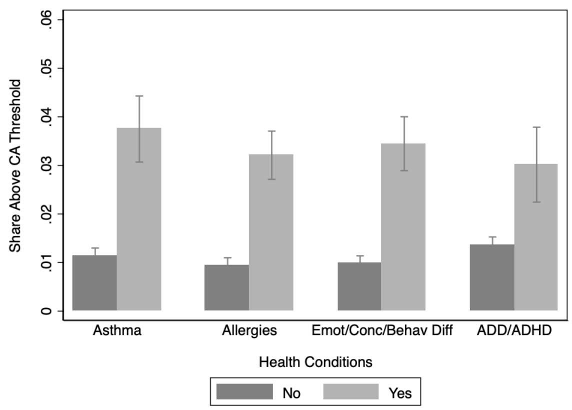
instead a world with no on-site personnel, the marginal costs of school-based telemedicine would need to include staff such as a nurse.

Other informational, non-health-based interventions—such as sending parents electronic information on students' attendance and academic progress—have also shown promise in terms of reducing absence from school (Bergman and Chan, 2019; Rogers and Feller, 2018). However, by their nature, such interventions do not address health-related barriers to school attendance and engagement. Thus, depending on local context, schools and districts may be wise to pursue a mix of strategies—that may very well target different subsets of students—in effort to support overall student success.

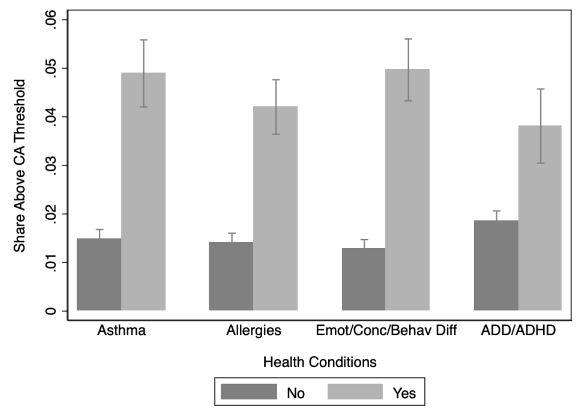
Finally, non-academic, school-based interventions capable of boosting student outcomes can speak to evolving federal policy demands. The passage of the Every Student Succeeds Act (ESSA) solidified the salience of non-test-score measures of student flourishing. The law requires states to adopt a broader set of accountability metrics for assessing the performance and progress of students and schools. Indeed, a recent report by the Hamilton Project encouraged states to adopt a measure of chronic absenteeism as the fifth accountability indicator for benchmarking progress toward states' educational goals under ESSA (Schanzenbach et al., 2016). As of 2018, 26 states and the District of Columbia had done so (Gottfried and Hutt, 2019). As ESSA unfolds, there will be great need for high-quality evidence on initiatives capable of boosting a broad range of student- and school-level outcomes.

School-based telemedicine provides a new approach for schools and communities that face healthcare provider shortages—particularly in difficult-to-staff settings where other models of healthcare delivery may be infeasible or cost prohibitive. School-based healthcare offers the potential to address long-standing gaps in access to healthcare by race and family income, and an opportunity to reduce unequal access to healthcare between groups within communities.

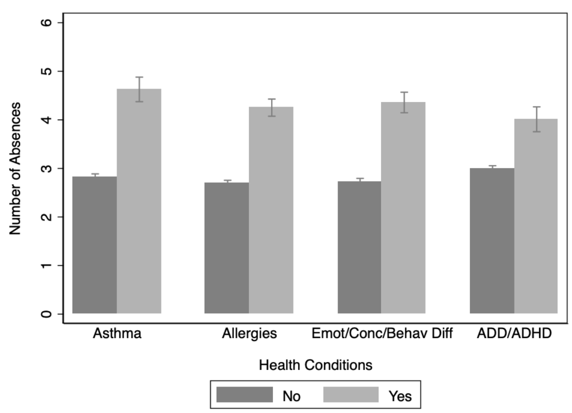
Figures and Tables



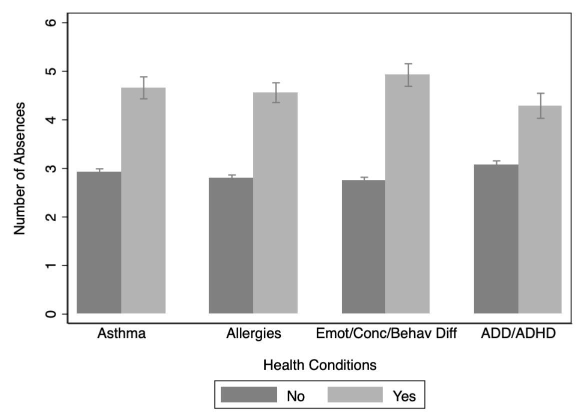
(a) Chronically Absent (0/1) - Ages 7-10



(b) Chronically Absent (0/1) - Ages 11-14



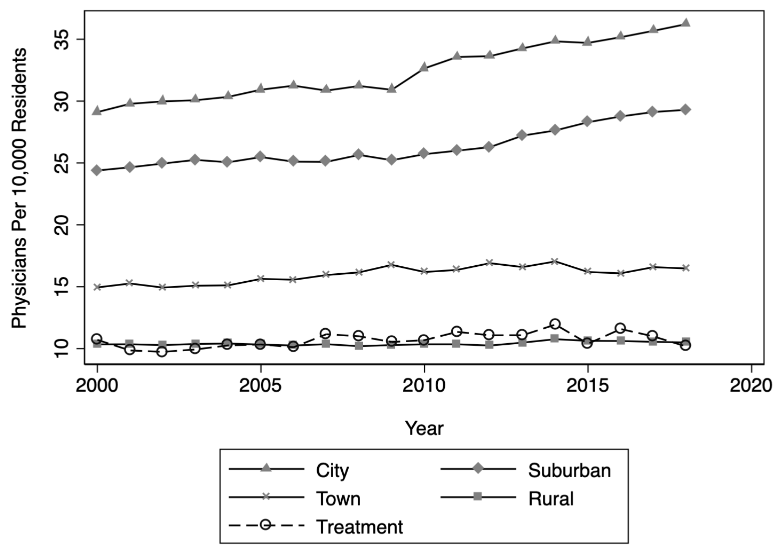
(c) Days Absent - Ages 7-10



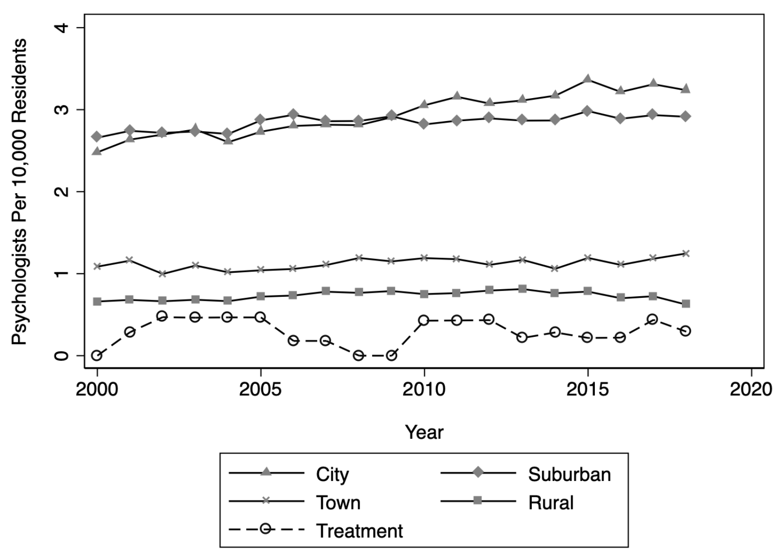
(d) Days Absent - Ages 11-14

Figure 1: Average Number of School Absences and Share of Students Chronically Absent Among Children With and Without Health Conditions

Notes: $N = 39,621$. Microdata for waves of the 2010-2017 National Health Interview Survey (NHIS) were obtained from IPUMS: https://nhis.ipums.org/nhis/. Sample restricted to children ages 7-14 with non-missing data.



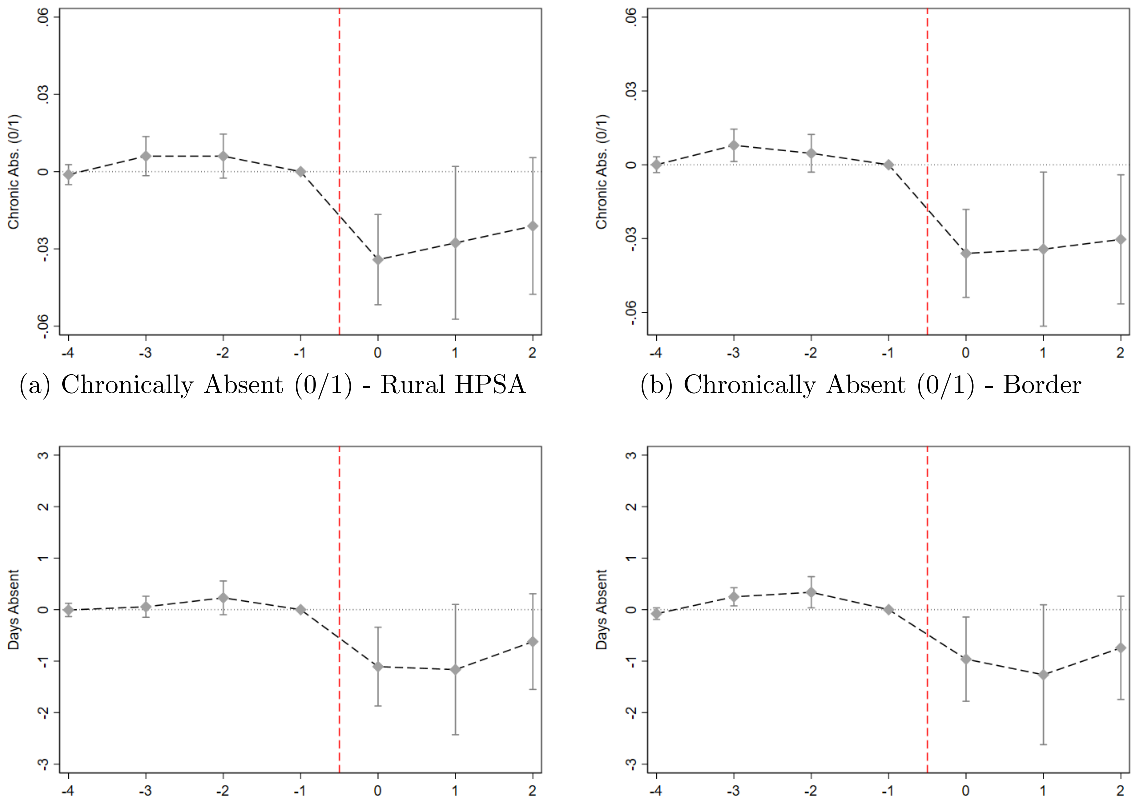
(a) Physicians Per 10,000 Residents



(b) Psychologists Per 10,000 Residents

Figure 2: Healthcare Providers by Rurality in North Carolina, 2000-2018

Notes: Data on healthcare providers come from the North Carolina Health Professions Data System, Program on Health Workforce Research and Policy, Cecil G. Sheps Center for Health Services Research, University of North Carolina at Chapel Hill. Population estimates come from the North Carolina Office of State Budget and Management via NC LINC. City, Suburban, Town, and Rural classifications are based on county-level locale codes obtained from the National Center for Education Statistics (NCES) Common Core of Data. Treatment counties include McDowell, Mitchell, and Yancey counties. Plots depict the average number of healthcare providers per 10,000 residents.



(a) Chronically Absent (0/1) - Rural HPSA

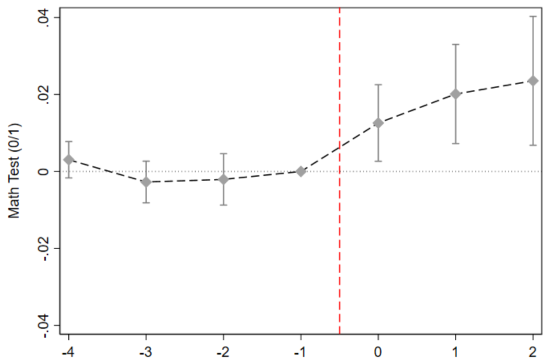
(b) Chronically Absent (0/1) - Border

(c) Days Absent - Rural HPSA

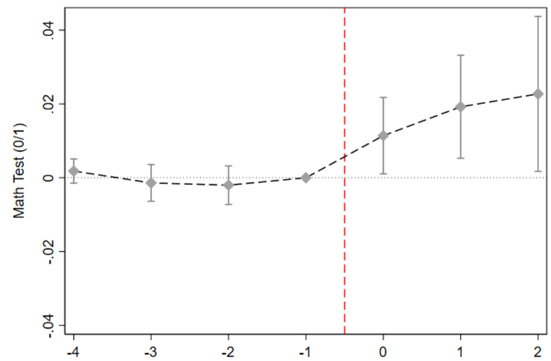
(d) Days Absent - Border

Figure 3: Event-Study Estimates of the Effect of SBTC Access on Outcomes Related to Student Absenteeism

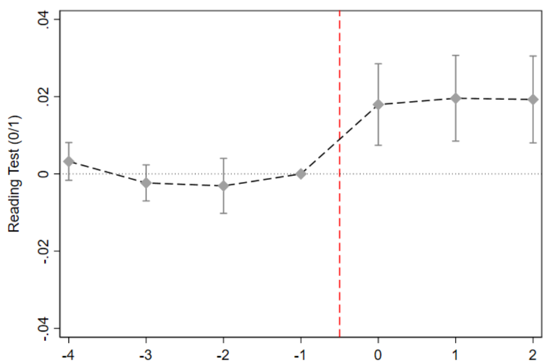
Notes: This figure depicts event-study results for chronic absenteeism (0/1) and absences (number of days). All specifications include school fixed effects, grade-by-year fixed effects, student-level covariates (grade level, gender, race/ethnicity, economically disadvantaged, special education status, gifted status, and Limited English Proficiency (LEP) status), and district-level covariates (population, child poverty rate, the number of full-time teachers, the number of guidance counselors, and the number of school support staff). Heteroskedasticity-robust standard errors are clustered at the school level.



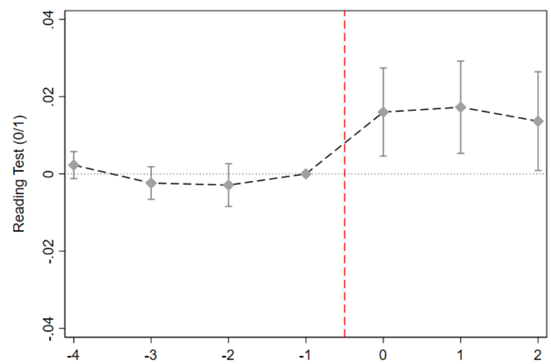
(a) Math Test (0/1) - Rural HPSA



(b) Math Test (0/1) - Border



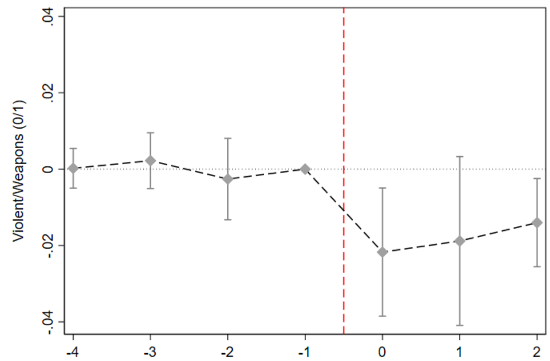
(c) Reading Test (0/1) - Rural HPSA



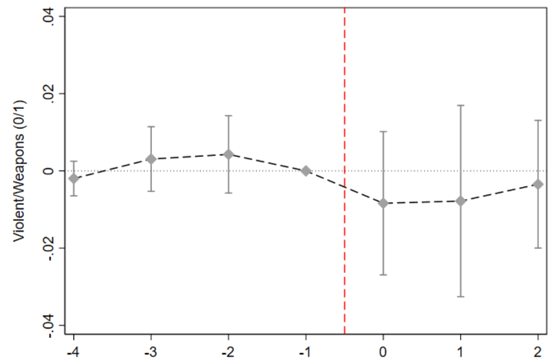
(d) Reading Test (0/1) - Border

Figure 4: Event-Study Estimates of the Effect of SBTC Access on Outcomes Related to Student Test-Taking

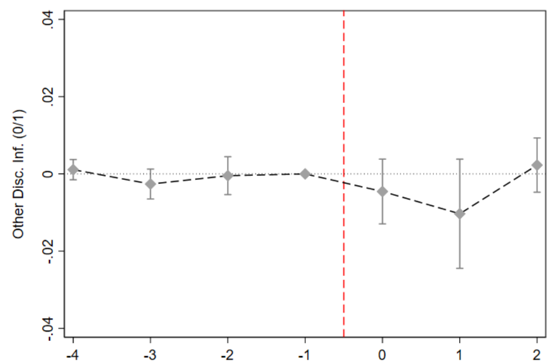
Notes: This figure depicts event-study results for test-taking in math (0/1) and reading (0/1). All specifications include school fixed effects, grade-by-year fixed effects, student-level covariates (grade level, gender, race/ethnicity, economically disadvantaged, special education status, gifted status, and Limited English Proficiency (LEP) status), and district-level covariates (population, child poverty rate, the number of full-time teachers, the number of guidance counselors, and the number of school support staff). Heteroskedasticity-robust standard errors are clustered at the school level.



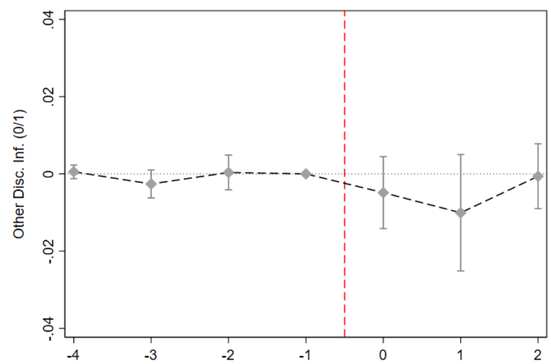
(a) Viol./Weap. Infraction (0/1) - Rural HPSA



(b) Viol./Weap. Infraction (0/1) - Border



(c) Other Disc. Infraction (0/1) - Rural HPSA



(d) Other Disc. Infraction (0/1) - Border

Figure 5: Event-Study Estimates of the Effect of SBTC Access on Outcomes Related to Reported Disciplinary Infractions

Notes: This figure depicts event-study results for reported disciplinary infractions that are violent/weapons-related (0/1) and all others (0/1). All specifications include school fixed effects, grade-by-year fixed effects, student-level covariates (grade level, gender, race/ethnicity, economically disadvantaged, special education status, gifted status, and Limited English Proficiency (LEP) status), and district-level covariates (population, child poverty rate, the number of full-time teachers, the number of guidance counselors, and the number of school support staff). Heteroskedasticity-robust standard errors are clustered at the school level.

Table 1: Descriptive Statistics, Students in Grades 3-8 in Treatment and Comparison Schools, 2007/08

		Comparison: Rural HPSAs			Comparison: Border		
	(1) Treatment	(2) Comp.	(3) Diff.: (1)-(2)	(4) p-value	(5) Comp	(6) Diff.: (1)-(5)	(7) p-value
Panel A. Student Characteristics							
Female	0.479	0.486	-0.006	0.410	0.488	-0.009	0.302
	(0.500)	(0.500)	(0.008)		(0.500)	(0.008)	
White	0.848	0.746	0.103***	0.000	0.795	0.053***	0.000
	(0.359)	(0.435)	(0.006)		(0.404)	(0.006)	
Black	0.025	0.136	-0.111***	0.000	0.068	-0.043***	0.000
	(0.156)	(0.343)	(0.003)		(0.252)	(0.003)	
Hispanic	0.082	0.068	0.014***	0.001	0.076	0.006	0.172
	(0.275)	(0.252)	(0.004)		(0.265)	(0.005)	
Other	0.044	0.049	-0.005	0.123	0.061	-0.016***	0.000
	(0.206)	(0.217)	(0.003)		(0.239)	(0.004)	
Econ. Disadvantaged	0.543	0.511	0.033***	0.000	0.486	0.057***	0.000
	(0.498)	(0.500)	(0.008)		(0.500)	(0.008)	
Gifted	0.146	0.145	0.001	0.836	0.167	-0.021***	0.000
	(0.353)	(0.352)	(0.006)		(0.373)	(0.006)	
Special Education	0.145	0.120	0.024***	0.000	0.137	0.008	0.188
	(0.352)	(0.325)	(0.005)		(0.344)	(0.006)	
Limited English Proficiency	0.061	0.036	0.025***	0.000	0.053	0.008**	0.039
	(0.239)	(0.186)	(0.004)		(0.224)	(0.004)	
Panel B. Baseline Outcomes							
Chron. Abs. (0/1)	0.086	0.067	0.019***	0.000	0.048	0.038***	0.000
	(0.281)	(0.249)	(0.004)		(0.214)	(0.004)	
Days Absent	8.235	7.256	0.978***	0.000	7.060	1.175***	0.000
	(8.282)	(7.303)	(0.129)		(6.843)	(0.134)	
Took Math Test (0/1)	0.946	0.963	-0.017***	0.000	0.963	-0.017***	0.000
	(0.226)	(0.188)	(0.003)		(0.188)	(0.004)	
Took Reading Test (0/1)	0.942	0.960	-0.018***	0.000	0.960	-0.018***	0.000
	(0.234)	(0.197)	(0.004)		(0.196)	(0.004)	
N	4461	45489			18082		

Notes: Column (1) reports means and standard deviations for student characteristics among third through eighth grade students in McDowell County Schools, Mitchell County Schools, and Yancey County Schools. Column (2) reports means and standard deviations for student characteristics among third through eighth grade students attending schools in counties classified as rural health professional shortage areas (HPSAs) in western North Carolina. Column (3) reports the difference in means (Treatment - Comparison Group) and the associated standard error. Column (4) reports the p-value from a two-tailed t-test of the difference in means. Column (5) reports means and standard deviations for student characteristics among third through eighth grade students attending schools in counties sharing a border with our treatment counties (districts). Column (6) reports the difference in means (Treatment - Comparison Group) and the associated standard error. Column (7) reports the p-value from a two-tailed t-test of the difference in means. Asterisks indicate statistical significance: * p <0.10, ** $p < 0.05$, *** $p < 0.01$.

Table 2: The Effect of SBTC Access on Student Absenteeism

	Comparison: Rural HPSAs			Comparison: Border		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Chronic Abs. (0/1)	-0.025**	-0.025**	-0.025**	-0.032***	-0.033***	-0.032***
	(0.012)	(0.012)	(0.011)	(0.012)	(0.012)	(0.011)
N	574,992	574,992	574,992	259,845	259,845	259,845
Baseline Mean	0.086	0.086	0.086	0.086	0.086	0.086
Panel B. Days Absent	-0.876**	-0.902**	-0.836**	-1.019**	-1.032**	-0.880*
	(0.427)	(0.444)	(0.409)	(0.440)	(0.444)	(0.452)
N	574,992	574,992	574,992	259,845	259,845	259,845
Baseline Mean	8.235	8.235	8.235	8.235	8.235	8.235
Grade and Year FE	X			X		
Grade-by-Year FE		X	X		X	X
District Covariates			X			X

Notes: Each coefficient comes from separate two-stage regressions. All specifications include school fixed effects and the following student-level covariates: grade level, gender, race/ethnicity, economically disadvantaged, special education status, gifted status, and Limited English Proficiency (LEP) status. When indicated, specifications include the following time-varying district-level covariates: population, child poverty rate, the number of full-time teachers, the number of guidance counselors, and the number of school support staff. Heteroskedasticity-robust standard errors are clustered at the school level. Asterisks indicate statistical significance: * p <0.10, ** $p < 0.05$, *** $p < 0.01$.

Table 3: The Effect of SBTC Access on Test-Taking in Math and Reading

	Comparison: Rural HPSAs			Comparison: Border		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Math Test (0/1)	0.020***	0.020***	0.020***	0.031***	0.029***	0.018***
	(0.006)	(0.004)	(0.005)	(0.007)	(0.005)	(0.006)
N	574,992	574,992	574,992	259,845	259,845	259,845
Baseline Mean	0.946	0.946	0.946	0.946	0.946	0.946
Panel B. Reading Test (0/1)	0.020***	0.020***	0.019***	0.028***	0.027***	0.014**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
N	574,992	574,992	574,992	259,845	259,845	259,845
Baseline Mean	0.942	0.942	0.942	0.942	0.942	0.942
Grade and Year FE	X			X		
Grade-by-Year FE		X	X		X	X
District Covariates			X			X

Notes: Each coefficient comes from separate two-stage regressions. All specifications include school fixed effects and the following student-level covariates: grade level, gender, race/ethnicity, economically disadvantaged, special education status, gifted status, and Limited English Proficiency (LEP) status. When indicated, specifications include the following time-varying district-level covariates: population, child poverty rate, the number of full-time teachers, the number of guidance counselors, and the number of school support staff. Heteroskedasticity-robust standard errors are clustered at the school level. Asterisks indicate statistical significance: * p <0.10, ** $p < 0.05$, *** $p < 0.01$.

Table 4: The Effect of SBTC Access on Reported Disciplinary Infractions

	Comparison: Rural HPSAs			Comparison: Border		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Violent/Weapons Inf. (0/1)	-0.019***	-0.020***	-0.017***	-0.013*	-0.014*	-0.006
	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.009)
N	574,992	574,992	574,992	259,845	259,845	259,845
Baseline Mean	0.042	0.042	0.042	0.042	0.042	0.042
Panel B. Other Inf. (0/1)	0.002	0.002	-0.001	-0.000	-0.001	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
N	574,992	574,992	574,992	259,845	259,845	259,845
Baseline Mean	0.066	0.066	0.066	0.066	0.066	0.066
Grade and Year FE	X			X		
Grade-by-Year FE		X	X		X	X
District Covariates			X			X

Notes: Each coefficient comes from separate two-stage regressions. All specifications include school fixed effects and the following student-level covariates: grade level, gender, race/ethnicity, economically disadvantaged, special education status, gifted status, and Limited English Proficiency (LEP) status. When indicated, specifications include the following time-varying district-level covariates: population, child poverty rate, the number of full-time teachers, the number of guidance counselors, and the number of school support staff. Heteroskedasticity-robust standard errors are clustered at the school level. Asterisks indicate statistical significance: * p <0.10, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Heterogeneous Effects of SBTC Access by Student Gender and Economic Disadvantage

	Comparison: Rural HPSAs			Comparison: Border			Comparison: Rural HPSAs			Comparison: Border		
	Male	Female	p-value	Male	Female	p-value	ED	Not ED	p-value	ED	Not ED	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. Chronic Abs. (0/1)	-0.028***	-0.022*	0.047	-0.036***	-0.028**	0.027	-0.022*	-0.031***	0.064	-0.028**	-0.039***	0.042
	(0.011)	(0.012)		(0.011)	(0.012)		(0.012)	(0.010)		(0.012)	(0.011)	
N	298,333	277,916		134,350	125,976		320,144	254,848		148,415	111,430	
Baseline Mean	0.073	0.064		0.059	0.052		0.099	0.036		0.082	0.030	
Panel B. Days Absent	-0.930**	-0.729*	0.074	-1.024**	-0.717	0.011	-0.878**	-0.768*	0.368	-0.849*	-0.929**	0.601
	(0.416)	(0.408)		(0.456)	(0.455)		(0.424)	(0.400)		(0.466)	(0.448)	
N	298,333	277,916		134,350	125,976		320,144	254,848		148,415	111,430	
Baseline Mean	7.529	7.147		7.503	7.069		8.488	6.135		8.315	6.279	
Panel C. Took Math Test (0/1)	0.024***	0.016***	0.080	0.023***	0.011*	0.005	0.025***	0.012**	0.000	0.024***	0.007	0.000
	(0.004)	(0.006)		(0.006)	(0.007)		(0.005)	(0.006)		(0.006)	(0.007)	
N	298,333	277,916		134,350	125,976		320,144	254,848		148,415	111,430	
Baseline Mean	0.934	0.958		0.934	0.959		0.925	0.967		0.929	0.963	
Panel D. Took Reading Test (0/1)	0.022***	0.016***	0.121	0.019***	0.008	0.013	0.024***	0.010*	0.000	0.021***	0.002	0.000
	(0.005)	(0.006)		(0.006)	(0.006)		(0.005)	(0.006)		(0.006)	(0.007)	
N	298,333	277,916		134,350	125,976		320,144	254,848		148,415	111,430	
Baseline Mean	0.928	0.957		0.928	0.958		0.920	0.965		0.923	0.962	
Panel E. Viol./Weap. Inf. (0/1)	-0.025***	-0.009	0.141	-0.015	0.004	0.114	-0.025***	-0.004	0.000	-0.014	0.008	0.000
	(0.009)	(0.008)		(0.012)	(0.010)		(0.007)	(0.007)		(0.010)	(0.010)	
N	298,333	277,916		134,350	125,976		320,144	254,848		148,415	111,430	
Baseline Mean	0.097	0.034		0.085	0.027		0.093	0.038		0.075	0.039	
Panel F. Other Inf. (0/1)	-0.000	-0.002	0.730	-0.002	-0.005	0.562	-0.002	0.001	0.490	-0.006	0.000	0.181
	(0.005)	(0.005)		(0.005)	(0.005)		(0.004)	(0.005)		(0.005)	(0.006)	
N	298,333	277,916		134,350	125,976		320,144	254,848		148,415	111,430	
Baseline Mean	0.090	0.044		0.097	0.049		0.087	0.048		0.094	0.054	

Notes: Each pair of coefficients comes from separate two-stage regressions. All specifications include school fixed effects, grade-by-year fixed effects, student-level covariates (grade level, gender, race/ethnicity, economically disadvantaged, special education status, gifted status, and Limited English Proficiency (LEP) status), and district-level covariates (population, child poverty rate, the number of full-time teachers, the number of guidance counselors, and the number of school support staff). Heteroskedasticity-robust standard errors are clustered at the school level. Asterisks indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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Appendix A: Supplemental Results

Table A1: The Effect of SBTC Access on Student Absenteeism (Excluding 2016)

	Comparison: Rural HPSAs			Comparison: Border		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Chronic Abs. (0/1)	-0.026**	-0.026**	-0.026**	-0.033***	-0.034***	-0.034***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)
N	532,663	532,663	532,663	241,098	241,098	241,098
Baseline Mean	0.086	0.086	0.086	0.086	0.086	0.086
Panel B. Days Absent	-0.893**	-0.922**	-0.852**	-1.056**	-1.068**	-0.929**
	(0.448)	(0.465)	(0.433)	(0.460)	(0.465)	(0.474)
N	532,663	532,663	532,663	241,098	241,098	241,098
Baseline Mean	8.235	8.235	8.235	8.235	8.235	8.235
Grade and Year FE	X			X		
Grade-by-Year FE		X	X		X	X
District Covariates			X			X

Notes: Each coefficient comes from separate two-stage regressions. All specifications include school fixed effects and the following student-level covariates: grade level, gender, race/ethnicity, economically disadvantaged, special education status, gifted status, and Limited English Proficiency (LEP) status. When indicated, specifications include the following time-varying district-level covariates: population, child poverty rate, the number of full-time teachers, the number of guidance counselors, and the number of school support staff. Heteroskedasticity-robust standard errors are clustered at the school level. Asterisks indicate statistical significance: * p <0.10, ** $p < 0.05$, *** $p < 0.01$.

Table A2: The Effect of SBTC Access on Student Absenteeism (Alternative Measures)

	Comparison: Rural HPSAs			Comparison: Border		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Chronic Abs. NC (0/1)	-0.030**	-0.031**	-0.034***	-0.039***	-0.039***	-0.040***
	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)
N	574,992	574,992	574,992	259,845	259,845	259,845
Baseline Mean	0.101	0.101	0.101	0.101	0.101	0.101
Panel B. Absence Rate	-0.006**	-0.006**	-0.006**	-0.006**	-0.006**	-0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
N	574,968	574,968	574,968	259,840	259,840	259,840
Baseline Mean	0.051	0.051	0.051	0.051	0.051	0.051
Grade and Year FE	X			X		
Grade-by-Year FE		X	X		X	X
District Covariates			X			X

Notes: Each coefficient comes from separate two-stage regressions. All specifications include school fixed effects and the following student-level covariates: grade level, gender, race/ethnicity, economically disadvantaged, special education status, gifted status, and Limited English Proficiency (LEP) status. When indicated, specifications include the following time-varying district-level covariates: population, child poverty rate, the number of full-time teachers, the number of guidance counselors, and the number of school support staff. Heteroskedasticity-robust standard errors are clustered at the school level. Asterisks indicate statistical significance: * p <0.10, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Falsification Exercise: Influence of SBTCs on School Enrollment, Composition, and Staffing

	Comparison: Rural HPSAs		Comparison: Border	
	(1)	(2)	(3)	(4)
Panel A. Log Enrollment	-0.043	-0.022	0.037	0.008
	(0.043)	(0.044)	(0.042)	(0.043)
N	2,026	2,026	934	934
Baseline Mean	5.712	5.712	5.712	5.712
Panel B. Share Black	-0.001	0.003	0.004	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
N	2,026	2,026	934	934
Baseline Mean	0.016	0.016	0.016	0.016
Panel C. Share Hispanic	-0.001	-0.001	-0.007	0.003
	(0.007)	(0.007)	(0.007)	(0.008)
N	2,026	2,026	934	934
Baseline Mean	0.078	0.078	0.078	0.078
Panel D. Share Economically Disadvantaged	-0.114***	-0.030	-0.024	-0.060**
	(0.028)	(0.021)	(0.030)	(0.025)
N	2,026	2,026	934	934
Baseline Mean	0.581	0.581	0.581	0.581
Panel E. Number of Teachers (FTE)	-0.525	-0.527	0.857	-0.682
	(0.694)	(0.714)	(0.739)	(0.685)
N	2,026	2,026	934	934
Baseline Mean	24.965	24.965	24.965	24.965
Panel F. Student-Teacher Ratio	-0.306	-0.029	0.274	0.218
	(0.425)	(0.427)	(0.417)	(0.425)
N	2,026	2,026	934	934
Baseline Mean	14.370	14.370	14.370	14.370
School and Year FE	X	X	X	X
District Covariates		X		X

Notes: Each coefficient comes from separate two-stage regressions. All specifications include school fixed effects and year fixed effects. Results in Columns (2) and (4) also include the following time-varying district-level covariates: population, child poverty rate, the number of full-time teachers, the number of guidance counselors, and the number of school support staff. Heteroskedasticity-robust standard errors are clustered at the school level. Asterisks indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Alternate Inference, Bootstrapped Standard Errors

	Comparison: Rural HPSAs			Comparison: Border		
	(1) Estimate	(2) SE	(3) p-value	(4) Estimate	(5) SE	(6) p-value
Chron. Ab.	-0.025	0.011	0.027	-0.032	0.012	0.007
Days Abs.	-0.836	0.417	0.048	-0.880	0.464	0.061
Math Test	0.020	0.005	0.000	0.018	0.006	0.007
Read Test	0.019	0.006	0.001	0.014	0.006	0.028
Viol./Weap.	-0.017	0.007	0.014	-0.006	0.010	0.561
Oth. Inf.	-0.001	0.004	0.786	-0.003	0.005	0.474

Notes: Columns (1) and (4) reproduce two-stage difference-in-differences estimates obtained using Equations (1) and (2) augmented with grade-by-year fixed effects and time-varying district covariates. Columns (2) and (5) report bootstrapped standard errors that were obtained by resampling schools (blocks) with replacement 1,000 times. Columns (3) and (6) report the p-value associated with a two-sided hypothesis test of the null hypothesis of no effect.

Table A5: Alternate Inference, Randomization-Based Inference

	Comparison: Rural HPSAs		Comparison: Border	
	(1) Estimate	(2) p-value	(3) Estimate	(4) p-value
Chron. Ab.	-0.025	0.000	-0.032	0.019
Days Abs.	-0.836	0.010	-0.880	0.032
Math Test	0.020	0.000	0.018	0.175
Read Test	0.019	0.000	0.014	0.228
Viol/Weap	-0.017	0.065	-0.006	0.612
Oth. Inf.	-0.001	0.718	-0.003	0.547

Notes: Columns (1) and (3) reproduce two-stage difference-in-differences estimates obtained using Equations (1) and (2) augmented with grade-by-year fixed effects and time-varying district covariates. Columns (2) and (4) report approximations to permutation p-values obtained by randomly assigning treatment and comparison status at the school-level 1,000 times and then calculating the fraction of estimated treatment effects that were larger in magnitude than our treatment effect estimate.

Table A6: The Effect of SBTC Access on Absenteeism (Alternate Estimator)

	(1) Chron. Ab.	(2) Days Abs.	(3) Math Test	(4) Read. Test
Panel A. Comparison = Rural HPSAs	-0.022**	-0.663	0.024***	0.026***
	(0.010)	(0.472)	(0.009)	(0.010)
N	233,646	233,646	233,646	233,646
Panel B. Comparison = Border	-0.024**	-0.714	0.021**	0.025***
	(0.011)	(0.502)	(0.009)	(0.009)
N	101,213	101,213	101,213	101,213

Notes: Estimates come from the alternative estimator introduced by de Chaisemartin and D'Haultfœuille (2020). Asterisks indicate statistical significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: The Effect of SBTC Access on Student Achievement

	Comparison: Rural HPSAs			Comparison: Border		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Math Achievement (SDs)	-0.003	0.000	0.019	0.003	0.004	-0.031
	(0.037)	(0.041)	(0.043)	(0.040)	(0.041)	(0.037)
N	554,319	554,319	554,319	249,282	249,282	249,282
Baseline Mean	-0.056	-0.056	-0.056	-0.056	-0.056	-0.056
Panel B. Reading Achievement (SDs)	-0.009	-0.008	-0.020	0.005	0.005	-0.024
	(0.021)	(0.021)	(0.022)	(0.022)	(0.023)	(0.023)
N	554,937	554,937	554,937	249,832	249,832	249,832
Baseline Mean	0.053	0.053	0.053	0.053	0.053	0.053
Grade and Year FE	X			X		
Grade-by-Year FE		X	X		X	X
District Covariates			X			X

Notes: Each coefficient comes from separate two-stage regressions. All specifications include school fixed effects and the following student-level covariates: grade level, gender, race/ethnicity, economically disadvantaged, special education status, gifted status, and Limited English Proficiency (LEP) status. When indicated, specifications include the following time-varying district-level covariates: population, child poverty rate, the number of full-time teachers, the number of guidance counselors, and the number of school support staff. Heteroskedasticity-robust standard errors are clustered at the school level. Asterisks indicate statistical significance: * p <0.10, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Heterogeneous Effects of SBTC Access by Student Race/Ethnicity

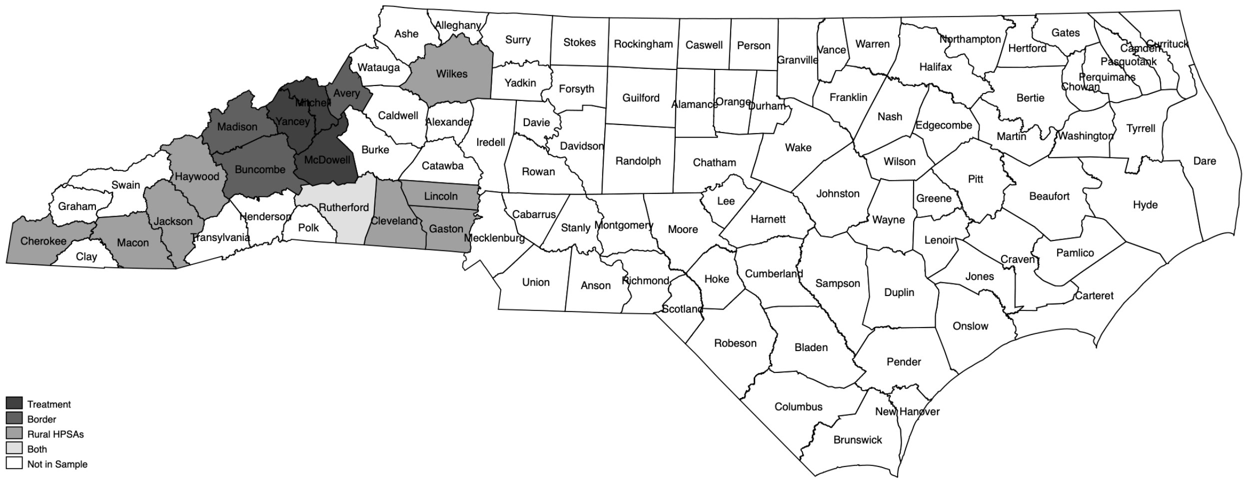
	Comparison: Rural HPSAs			Comparison: Border		
	White (1)	Nonwhite (2)	p-value (3)	White (4)	Nonwhite (5)	p-value (6)
Panel A. Chronic Abs. (0/1)	-0.024**	-0.029***	0.551	-0.031**	-0.039***	0.372
	(0.012)	(0.008)		(0.013)	(0.008)	
N	417,854	158,395		200,211	60,115	
Baseline Mean	0.072	0.059		0.057	0.049	
Panel B. Days Absent	-0.829*	-0.866***	0.873	-0.879*	-0.885**	0.982
	(0.435)	(0.331)		(0.480)	(0.374)	
N	417,854	158,395		200,211	60,115	
Baseline Mean	7.653	6.391		7.572	6.132	
Panel C. Took Math Test (0/1)	0.020***	0.023***	0.591	0.018***	0.018**	0.970
	(0.005)	(0.007)		(0.006)	(0.007)	
N	417,854	158,395		200,211	60,115	
Baseline Mean	0.950	0.930		0.950	0.932	
Panel D. Took Reading Test (0/1)	0.018***	0.024***	0.231	0.013**	0.017**	0.585
	(0.005)	(0.007)		(0.006)	(0.007)	
N	417,854	158,395		200,211	60,115	
Baseline Mean	0.947	0.926		0.947	0.927	
Panel E. Viol./Weap. Inf. (0/1)	-0.016**	-0.022***	0.295	-0.004	-0.013	0.133
	(0.007)	(0.008)		(0.010)	(0.010)	
N	417,854	158,395		200,211	60,115	
Baseline Mean	0.054	0.105		0.053	0.072	
Panel F. Other Inf. (0/1)	-0.001	-0.002	0.839	-0.002	-0.007	0.516
	(0.004)	(0.007)		(0.005)	(0.007)	
N	417,854	158,395		200,211	60,115	
Baseline Mean	0.068	0.066		0.073	0.078	

Notes: Each pair of coefficients comes from separate two-stage regressions. All specifications include school fixed effects, grade-by-year fixed effects, student-level covariates (grade level, gender, race/ethnicity, economically disadvantaged, special education status, gifted status, and Limited English Proficiency (LEP) status), and district-level covariates (population, child poverty rate, the number of full-time teachers, the number of guidance counselors, and the number of school support staff). Heteroskedasticity-robust standard errors are clustered at the school level. Asterisks indicate statistical significance: * p <0.10, ** $p < 0.05$, *** $p < 0.01$.

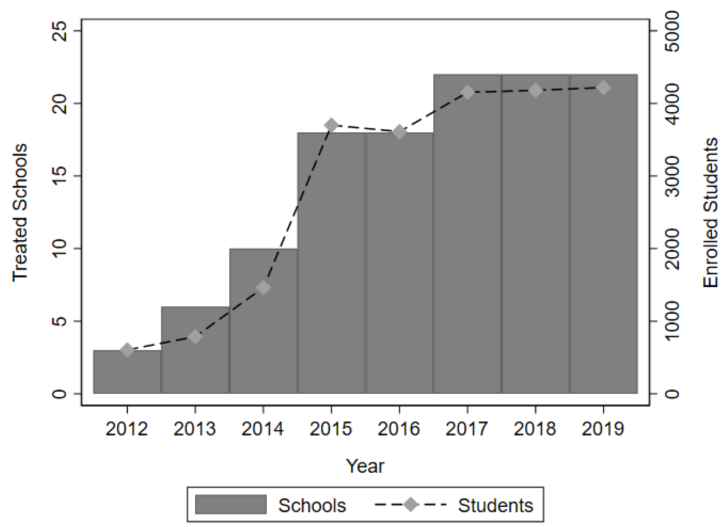
Table A9: Heterogeneous Effects of SBTC Access by School Level

	Comparison: Rural HPSAs			Comparison: Border		
	Elementary (1)	Middle (2)	p-value (3)	Elementary (4)	Middle (5)	p-value (6)
Panel A. Chronic Abs. (0/1)	-0.019*	-0.034	0.526	-0.025**	-0.041*	0.514
	(0.010)	(0.022)		(0.010)	(0.023)	
N	290,819	285,430		133,224	127,102	
Baseline Mean	0.043	0.094		0.040	0.072	
Panel B. Days Absent)	-0.737*	-0.957	0.793	-0.654	-1.157	0.581
	(0.387)	(0.768)		(0.452)	(0.831)	
N	290,819	285,430		133,224	127,102	
Baseline Mean	6.400	8.307		6.667	7.936	
Panel C. Took Math Test (0/1)	0.023***	0.017**	0.542	0.017**	0.018**	0.922
	(0.006)	(0.007)		(0.007)	(0.008)	
N	290,819	285,430		133,224	127,102	
Baseline Mean	0.950	0.941		0.950	0.942	
Panel D. Took Reading Test (0/1)	0.023***	0.014**	0.273	0.018**	0.010	0.378
	(0.007)	(0.006)		(0.008)	(0.007)	
N	290,819	285,430		133,224	127,102	
Baseline Mean	0.944	0.939		0.945	0.940	
Panel E. Viol./Weap. Inf. (0/1)	-0.018***	-0.016	0.868	-0.012	0.002	0.337
	(0.005)	(0.013)		(0.009)	(0.015)	
N	290,819	285,430		133,224	127,102	
Baseline Mean	0.037	0.097		0.028	0.086	
Panel F. Other Inf. (0/1)	0.003	-0.007	0.182	0.001	-0.009	0.182
	(0.005)	(0.006)		(0.006)	(0.006)	
N	290,819	285,430		133,224	127,102	
Baseline Mean	0.077	0.058		0.085	0.063	

Notes: Each pair of coefficients comes from separate two-stage regressions. All specifications include school fixed effects, grade-by-year fixed effects, student-level covariates (grade level, gender, race/ethnicity, economically disadvantaged, special education status, gifted status, and Limited English Proficiency (LEP) status), and district-level covariates (population, child poverty rate, the number of full-time teachers, the number of guidance counselors, and the number of school support staff). Heteroskedasticity-robust standard errors are clustered at the school level. Asterisks indicate statistical significance: * p <0.10, ** $p < 0.05$, *** $p < 0.01$.



(a) Map of Treatment and Comparison Counties (School Districts)



(b) Number of Treated Students and Schools by School Year

Figure A1: School-Based Telemedicine Center (SBTC) Locations and Rollout, 2011/12-2018/19

Notes: Panel (a) depicts the locations of treatment and comparison counties (school districts) in our sample. We note that although Burke County shares a border with McDowell County (treated), we exclude Burke County from the Border comparison group because telemedicine clinics were introduced in schools there during the 2018/19 school year. Panel (b) plots the number of students and schools, respectively, in the treatment group by school year.

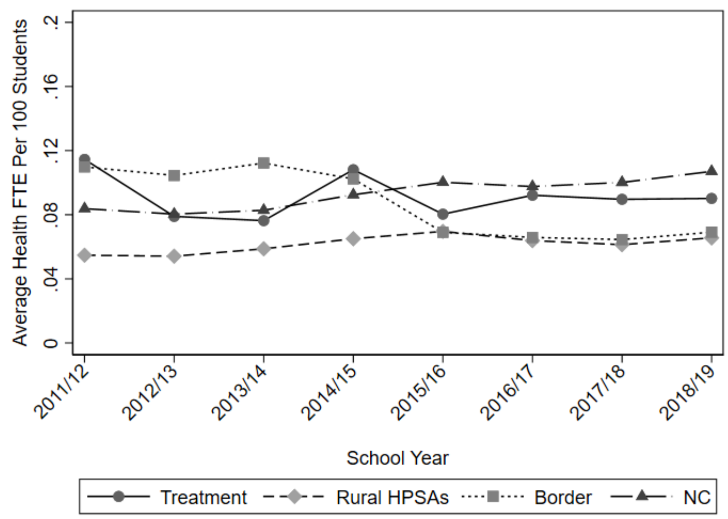


Figure A2: Average Health Staff (FTE) Per 100 Students, Separately for Treatment, Comparison, and Other North Carolina School Districts

Notes: This figure plots the average number of health staff (FTE) per 100 students at the school district level, separately for treatment, comparison, and all other school districts in North Carolina. For more information, see Appendix B.

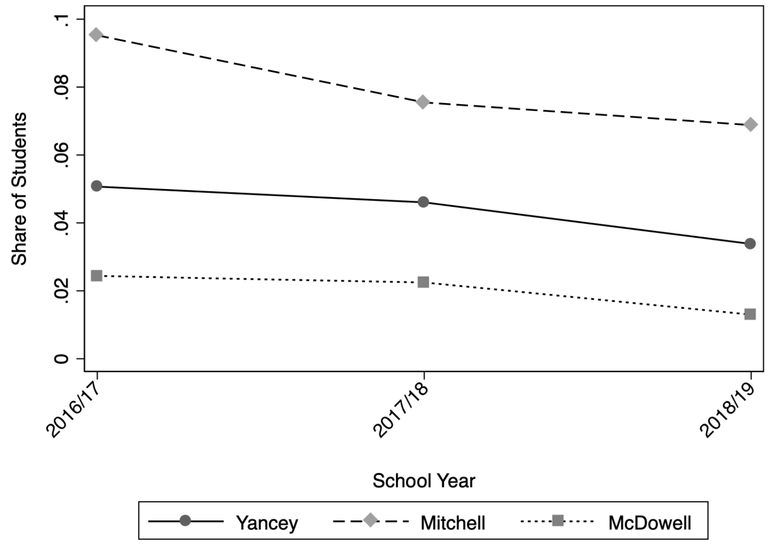
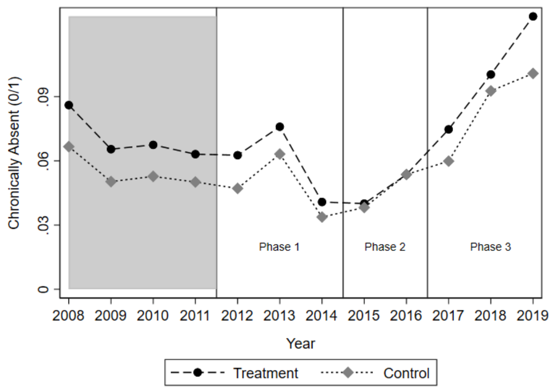
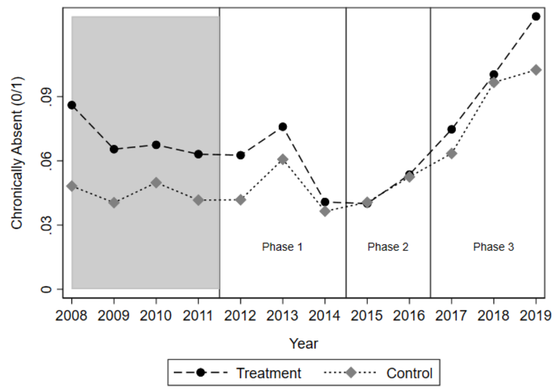


Figure A3: Share of Students Who Accessed SBTCs, Separately by School District and School Year

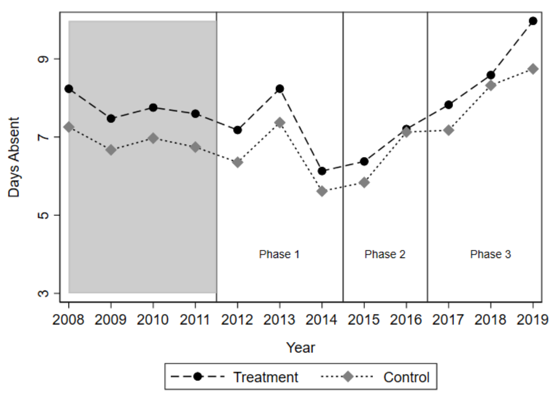
Notes: Data on annual visits were provided by the Health-e-Schools program. Enrollment data by district and school year come from the Common Core of Data, United States Department of Education and were obtained using the Urban Institute Education Data Portal.



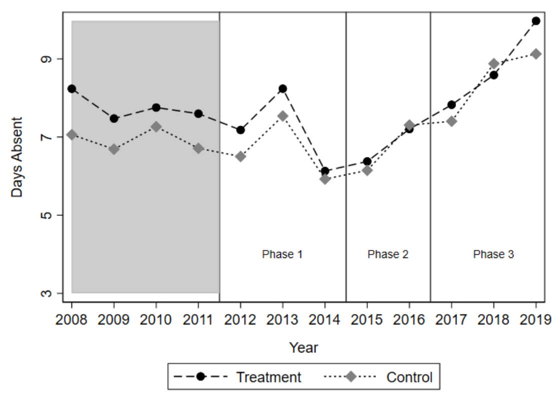
(a) Chronically Absent (0/1) - Rural HPSA



(b) Chronically Absent (0/1) - Border



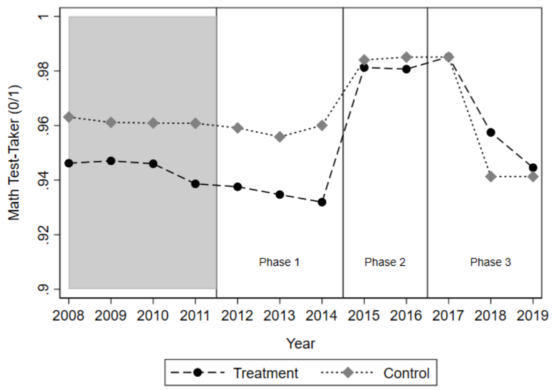
(c) Days Absent - Rural HPSA



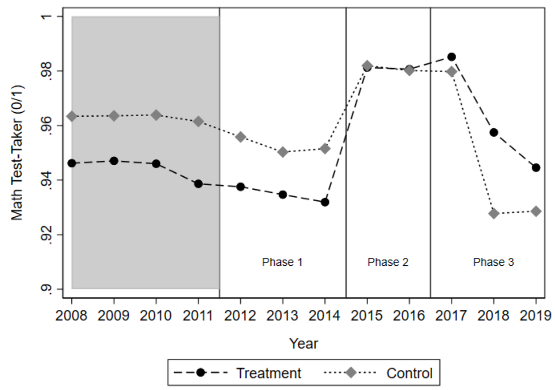
(d) Days Absent - Border

Figure A4: Unadjusted Trends in Absenteeism Outcomes, Treatment versus Comparison Groups, 2007/08-2018/19

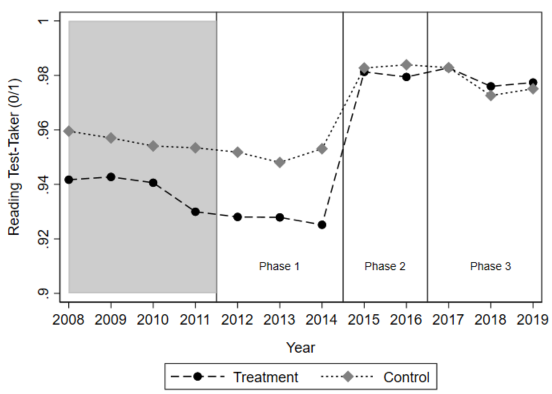
Notes: This figure illustrates unadjusted trends in chronic absenteeism (0/1) and days absent separately for treatment and comparison groups in the 2007/08-2018/19 school years. The gray shading demarcates pre-treatment school years in which no students had SBTC access.



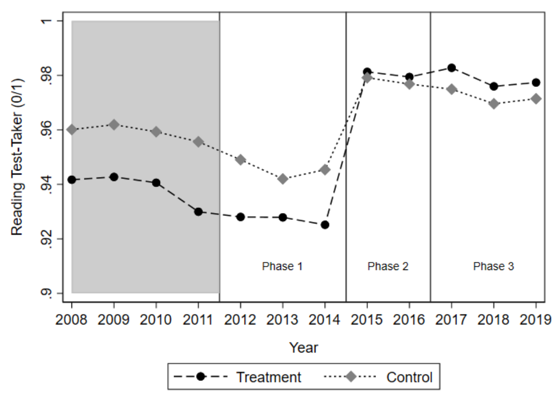
(a) Math Test (0/1) - Rural HPSA



(b) Math Test (0/1) - Border



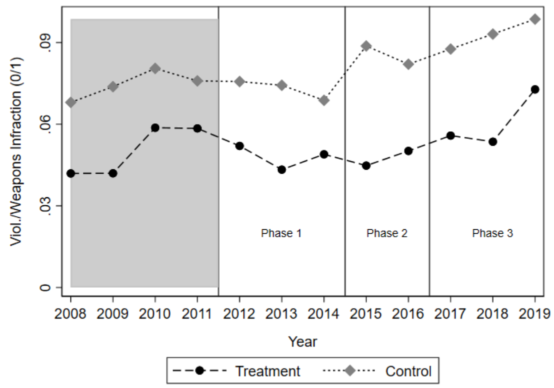
(c) Reading Test (0/1) - Rural HPSA



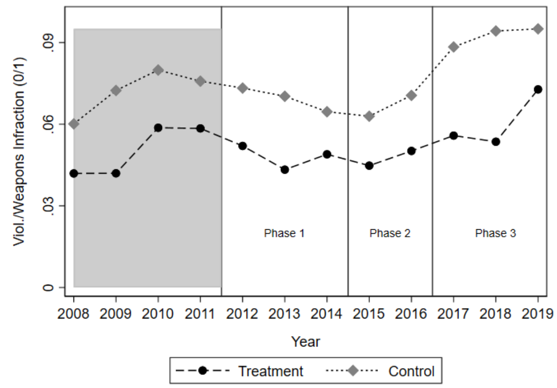
(d) Reading Test (0/1) - Border

Figure A5: Unadjusted Trends in Test-Taking Outcomes, Treatment versus Comparison Groups, 2007/08-2018/19

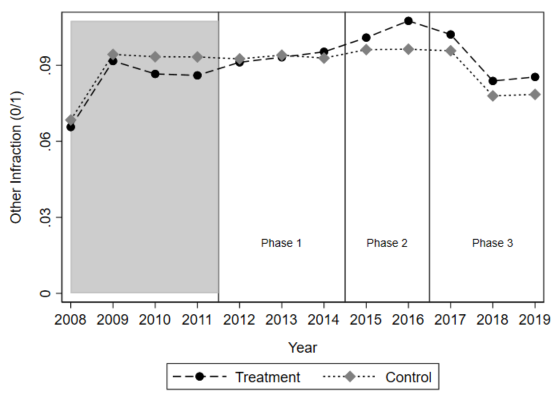
Notes: This figure illustrates unadjusted trends in student test-taking in math (0/1) and reading (0/1) separately for treatment and comparison groups in the 2007/08-2018/19 school years. The gray shading demarcates pre-treatment school years in which no students had SBTC access.



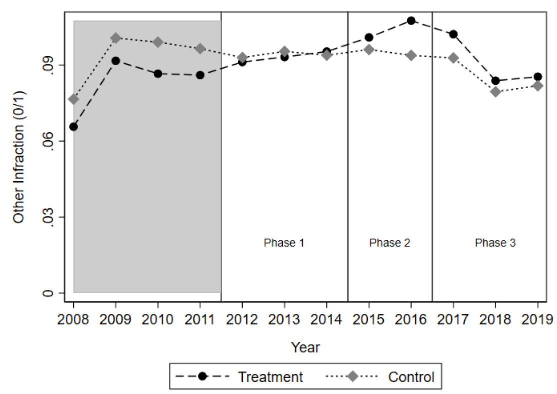
(a) Violent/Weapons Infractions (0/1) - Rural HPSA



(b) Violent/Weapons Infractions (0/1) - Border



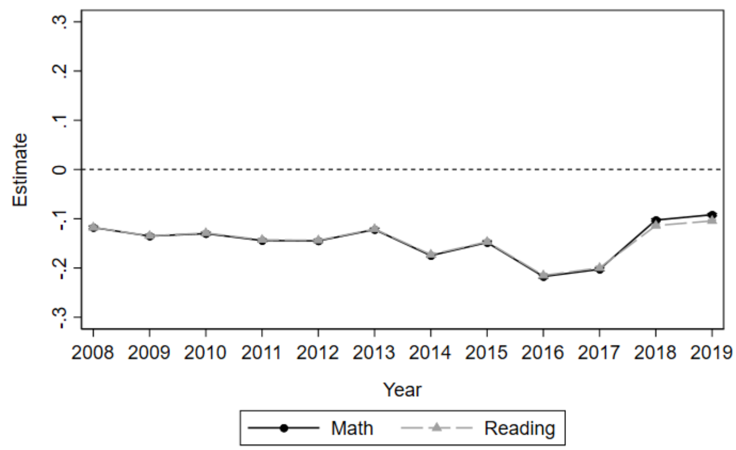
(c) Other Infractions (0/1) - Rural HPSA



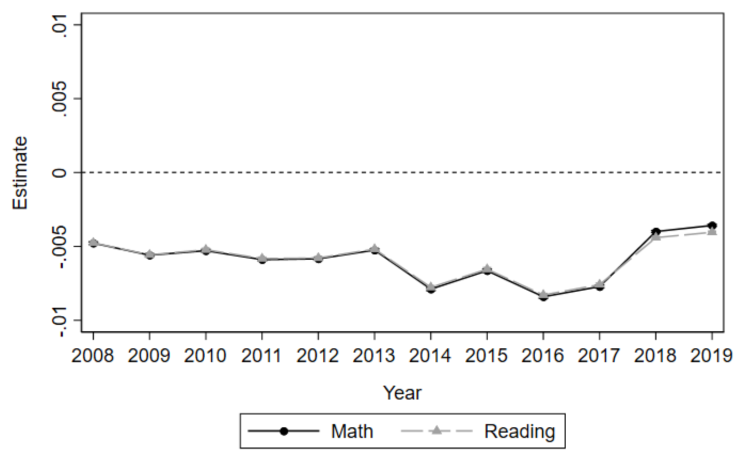
(d) Other Infractions (0/1) - Border

Figure A6: Unadjusted Trends in Reported Disciplinary Infractions, Treatment versus Comparison Groups, 2007/08-2018/19

Notes: This figure illustrates unadjusted trends in the share of students with at least one reported disciplinary infraction that was violent or weapons-related (0/1) and other (0/1) separately for treatment and comparison groups in the 2007/08-2018/19 school years. The gray shading demarcates pre-treatment school years in which no students had SBTC access.



(a) Estimates from Cross-Sectional Regressions of Test-Taking on Chronic Absenteeism (0/1)



(b) Estimates from Cross-Sectional Regressions of Test-Taking on the Number of Days Absent

Figure A7: Cross-Sectional Regression Estimates of the Effect of Chronic Absenteeism and Number of Days Absent on Test-Taking in Math and Reading, 2008-2019

Notes: Each estimate (and associated ninety-five percent confidence interval) was obtained from a separate cross-sectional regression in which a binary indicator for math or reading test-taking was regressed on a binary indicator for chronic absenteeism (0/1) or the number of days absent.

Appendix B: Data Appendix

Methodological Details for Figure 1

To investigate the descriptive relationship between children's health status and school absences, we obtained microdata from the 2010-2017 waves of the National Health Interview Survey (NHIS), a nationally representative survey of the U.S. population (Blewett et al., 2019).[33] We restricted the sample to children between 7-14 years old—mirroring the ages of the students in our study (i.e., third to eighth grade students)—and compared the average number of school absences between those with and without several health conditions, separately for elementary-aged students (7-10 years old) and middle school-aged students (11-14 years old). We focused our analysis on four health conditions identified as the most common among public school students in North Carolina by annual surveys of public school nurses.[34] These conditions included asthma, severe allergies, emotional/behavior/concentration difficulties, and Attention Deficit Disorder (ADD)/Attention Deficit Hyperactivity Disorder (ADHD).

We approximate annual school absences due to health-related reasons and chronic absenteeism due to health-related reasons based on parental responses to the following question: "During the past 12 months about how many days did [$CHILD$] miss school because of illness or injury?" We acknowledge that these measures are imperfect due to the inclusion of school days missed due to injury.

Other Data Sources

Teachers, Guidance Counselors, and School Staff

We obtained school district data from the Elementary and Secondary Information System (ELSI) of the National Center for Education Statistics (NCES) of the United States Department of Education. Annual, district-level counts of full-time teachers (FTE), guidance counselors, and student support services staff were available for the 2007/08-2018/19 school years. These data are public-use and can be accessed here: `https://nces.ed.gov/ccd/elsi/`. Date of download: June 28, 2020.

Child Poverty

We obtained annual child poverty rates by school district from the Small Area Income and Poverty Estimates (SAIPE) Program of the United States Census Bureau. Annual data were available for the years 2007-2018. We use linear extrapolation to obtain data for 2019.

[33] These data are public-use and can be obtained from IPUMS here: `https://nhis.ipums.org/nhis/`.

[34] We used rank-ordered lists of commonly encountered health conditions among students in North Carolina public schools as reported in the 2011/12-2018/19 editions of the Annual School Health Report Survey.

Annual data were averaged to more closely match the school year calendar (e.g., the average child poverty rate in 2015 and 2016 was calculated for the 2015/16 school year). These data are public-use and can be accessed here: https://www.census.gov/programs-surveys/saipe.html. Date of download: January 16, 2020.

Unemployment

We obtained county-level unemployment data from the Local Area Unemployment Statistics (LAUS) program of the Bureau of Labor Statistics (BLS) of the United States Department of Labor. County-level unemployment rates are annual averages (averaged over 12 calendar months) and are unadjusted for seasonality. These data are public-use and can be accessed here: https://www.bls.gov/data/. Date of download: August 12, 2019.

Population

We obtained annual county-level population estimates from the Surveillance, Epidemiology, and End Results (SEER) program of the National Cancer Institute of the United States Department of Health and Human Services. These data are public-use and can be accessed here: https://seer.cancer.gov/popdata/download.html. Date of download: August 12, 2019.

Telemedicine Equipment Cost Data and Calculations

We obtained information on equipment costs for school-based telemedicine from the Center for Rural Health Innovation and from the Ulysses USD 214 (Ulysses, Kansas).

Health Staff in North Carolina

We obtained information on school-level health staff (FTE) from the North Carolina Education Research Data Center (NCERDC). Health staff are inclusive of school staff that provide medical, nursing, and dental services. Our examination of data on the educational credentials (i.e., highest degree obtained) of health staff revealed that fewer than 2 percent of these staff had doctorate degrees (e.g., MD, DDS, PhD) and therefore we believe that most staff in this position are providing school nursing services.

Violent and Weapons-Related Disciplinary Infractions

- Assault resulting in a serious injury
- Assault with a weapon
- Assault on school personnel not resulting in a serious injury
- Homicide

- Kidnapping
- Communicating threats
- Affray
- Fighting
- Hazing
- Aggressive behavior
- Assault on student
- Assault – other
- Bullying
- Assault on non-student w/o weapon, no serious injury
- Assault on student w/o weapon, no serious injury
- Violent assault no serious injury
- Robbery without a weapon
- Cyber-bullying
- Threat of physical attack without a weapon
- Possession of a firearm or powerful explosive
- Possession of a weapon (excluding firearms and explosives)
- Robbery with a dangerous weapon
- Unlawfully setting a fire
- False fire alarm
- Bomb threat
- Burning of a school building
- Robbery with a firearm or explosive device
- Physical attack with a firearm or explosive device
- Threat of physical attack with a firearm
- Threat of physical attack with a weapon