SCHOOL DISTRICT AND COMMUNITY FACTORS AND THE IMPACT OF COVID-19 SCHOOL CLOSURES ON CHRONIC ABSENTEEISM

by

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This study uses school district level variation in COVID closures and census data to quantify the effects that virtual and hybrid instruction had on the increases in post-pandemic chronic absenteeism. We find statistically significant evidence of a positive relationship with our best model estimating that each 1% increase in the proportion of the 2020/2021 school year spent away from fully in-person instruction increased chronic absenteeism by 0.20%, after controlling for race, income, education, school expenditures, and family structure. This thesis includes collaboratively produced work.

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Introduction

The national issue of chronic absenteeism, defined as missing 10% or more of the school year, has been a persistent challenge affecting students' education, which, in turn, significantly affects achievement well into later life. The Department of Education found that over seven million k-12 students missed fifteen or more school days during the 2015-2016 school year. These absences can negatively affect students' academic success and educational attainment. Studies on early education show that chronic absenteeism results in lower math and literacy scores and that these effects are compounded with each coming school year. Moreover, these effects translate into adverse socioeconomic outcomes in adulthood. Chronic absenteeism involves social and personal elements, which include differences in parental involvement, geographical location, race, income grade level, and a plethora of other factors within school environments that contribute to student's absent behavior.

The COVID-19 pandemic brought unprecedented challenges and dilemmas to educational systems across the globe. Policymakers and educators were quickly forced to transition their educational modality from in-person to online, with very little research on just what consequences such a drastic shift would entail to guide them. However, despite heterogeneous degrees of closure across and within states, every state ended up with higher levels of chronic absenteeism post-pandemic. Furthermore, the effects of temporary teaching changes were persistent: more than two years after such measures were relieved, chronic absenteeism is still significantly elevated above pre-pandemic levels.

By examining the factors contributing to pre-pandemic chronic absenteeism and then using the COVID-induced school closures as an instrument for online learning's effect on chronic absenteeism, this research will provide empirical results for the benefit-cost analysis that policymakers were in dire need of four years ago and will serve as one of the few papers to look into absenteeism on a large scale (i.e., across multiple districts and states) thus far, as we were unable to find other papers that focus outside of the district level.

Literature Review

Chronic Absenteeism

Absenteeism is a serious problem that affects the learning of students from kindergarten up to twelfth grade in the United States, and due to its severity, it has been referred to as not only a public health issue but also a hidden educational crisis (Allen et al., 2018). While absenteeism refers to absences from school, the body of literature that discusses it and state legislatures that enact policies to address it needs more consistency in its definition (Eklund et al., 2020). For instance, some schools will mark a student as present if he or she is physically present for a percentage of the day while others will require a student to be present for one hundred percent of the day (Eklund et al., 2020). Moreover, across the literature, terms such as “chronic absenteeism” and “truancy” are often used interchangeably, but they each have different technical definitions. This study will look at chronic absenteeism specifically, which refers to a student who misses ten percent or more of the academic school year due to an unexcused and excused reason, as opposed to “truancy” which only involves absences for unexcused reasons (Gibbons et al., 2018).

The data on chronic absenteeism is inconsistent, due to state variation in definitions and recording However, one source that offers a snapshot of absenteeism in an aggregated format is the U.S. Department of Education, which has tried to showcase this persistent issue. In a 2016 report they show that seven million students were chronically absent during the 2015-2016 school year, which translates to about sixteen percent of the student population or one in every six students. These data also show that different races and ethnicities experience chronic absenteeism differently, with American Indian students having higher rates of chronic absenteeism. Moreover, across education divisions high school shows the highest share of chronically absent students. While this report highlights the problem, these data are too aggregated, other sources of disaggregated data are available involving smaller geographic areas and individual level data, however there is not much of a nationwide picture of absenteeism. What can be said, however, is that across the board, chronic absenteeism has increased because of the pandemic, with estimates that show a ninety-one percent increase since 2019 levels (Dee, 2023).

Effects of Chronic Absenteeism

With so many students missing 10% or more of school days, there are repercussions in academic achievement associated with these absences due to the loss of instruction (Eklund et al., 2020). A longitudinal study was performed in Chicago that analyzed the effects of Pre-K attendance using a sample of about 1,265 students and comparing standardized math and letter recognition scores from the beginning of the year to the end of the year, considering how students' attendance patterns impacted their performance (Ehrlich, 2013). The researchers found that school absences were associated with lower math and letter recognition scores (Ehrlich, 2013). What the authors then considered was potential variability within students who had "incoming" skills before school, and even after accounting for this middle factor, they found that "students who missed 10 percent or more of school—those considered chronically absent—still performed significantly worse on the math and letter recognition portions of the test than students who had the best attendance." (Ehrlich, 2013) Moreover, another longitudinal study that utilized national data taken from the Early Childhood Longitudinal Study found that students who are chronically absent in kindergarten had lower levels of achievement in math and reading in later grades (Eklund et al., 2020). These lower levels of achievement in later grades indicate that the effects of absenteeism are persistent and would not just affect the student in one academic year. The following studies have discussed the negative academic impacts of chronic absence in preschool and middle school, but it appears that chronic absence is highest among high school students. Since ninth-grade attendance is a significant indicator for graduation, with a ninety percent success rate in its predictive capabilities, chronic absenteeism in high school emerges as a critical factor, revealing a dire impact on students' chances of graduating, with less than a ten-percent success rate (Gibbons et al., 2018). Research conducted using Baltimore City Public School data supplements these findings. The research suggests that most students who dropped out of high school had entered ninth grade with a pattern of chronic absenteeism that dates several years back; this points to chronic absenteeism as an early predictor for students at risk of dropping out of school (Mac Iver, 2010). Moreover, the study also points to behavioral patterns like chronic absenteeism as extremely difficult to change, and interventions are required during early middle grades to improve graduation outcomes (Mac Iver, 2010).

Correlates of Chronic Absenteeism

Most studies examining the causes of chronic absenteeism tell a personalized story of these correlates due to smaller geographic locations and individual-level data. Thus, generalizing the causes of chronic absenteeism becomes troublesome, but what the collective literature attempting to understand this phenomenon shares is consistent; therefore, it can be assumed that chronic absenteeism results from a combination of child-, family-, peer-, school-, and community-based factors (Gibbons et al., 2018). For example, disparities in absenteeism rates are most notable in the racial background (Gibbons et al., 2018). National Department of Education figures taken during the 2015-2016 school year showed twenty percent or more of Black, Hispanic, and American Indian students experiencing chronic absenteeism in comparison to only fourteen percent of white students. Moreover, economic disadvantages often drive absences due to income (Allen et al., 2018). An analysis of the Early Childhood Longitudinal Study data shows an inverse relationship between family income and higher absenteeism rates–that is, the lower the family income, the higher the absenteeism rate (Romero et al., 2007). Lack of parental involvement, either because of a single-parent household or a lack of structure and supervision due to parents having to work many hours or multiple jobs, is also shown as another factor contributing to absenteeism due to the lack of consistent support system to ensure regular attendance (Allen et al., 2018). Finally, other quantifiable factors associated with chronic absenteeism are parental education level and school expenditures (Allen et al., 2018).

COVID-19 and Chronic Absenteeism

The COVID-19 pandemic provides a unique opportunity to explore causal effects due to the semi-random variance in school closures. This natural experiment allows for a closer examination of the impact of closure policies on attendance rates, shedding light on the differential effects between districts that opted for in-person instruction versus those that remained closed. The pandemic influenced a significant shift in education with widespread school closures during the 2020-21 academic year. These closures marked a decline in school attendance rates compared to previous years, with a significant difference in attendance rates compared to districts that opted for in-person instruction instead of those that remained closed (Vidal et al., 2023). For instance, those who chose in-person instruction experienced lower rates of absenteeism than those who remained in remote learning settings during the transition period to a different instructional model (Vidal et al., 2023). While schools have since reopened, attendance rates continue to lag pre-pandemic levels, especially with low-income Black and Hispanic students (Vidal et al., 2023). While the pandemic impacted absenteeism, the recovery since then has been quite stark as, in its aftermath, the number of chronically absent students has doubled from about fifteen percent in 2018-2019 to around thirty percent in 2021-2022 (Dee, 2023). This increase in absenteeism is not state-specific but widespread, and the data available for each state suggest an increase in absenteeism (Dee, 2023). Furthermore, the disparities in levels of chronic absenteeism across racial, ethnic, and socioeconomic lines widened as well (Dee, 2023).

While we are undoubtedly in the early days of research on the effects of the COVID lockdowns—especially with respect to its effects on education—we could look to other similar unexpected school closures elsewhere. Müller and Goldenberg find that unexpected closures disproportionately hurt students from lower socio-economic backgrounds—although how exactly depends on the length of closure and how available alternative education is (2020). However, that access can, in turn, be dependent on their socio-economic background as twice as many children in middle class households spent £100 on online learning than those in working class homes—thus, finding that online learning widens the socio-economic gap in education between those who can and cannot access the online tools. Furthermore, they find that parents with higher levels of education feel more comfortable than their less educated counterparts in assisting with their children’s schoolwork. Müller and Goldenberg conclude, lastly, that while online learning seemed to be effective during the pandemic, it was dependent on whether students could access the online learning in the first place and how much support they received.

Data

Chronic Absenteeism Data:

While the federal government requires states to produce statistics on their levels of chronic absenteeism, *how* they are reported (i.e., aggregated, by school/district/county/etc.) is up to each individual state, so there is no single source for chronic absenteeism data that is consistent across states. The literature indicates that the age of the student does affect their level of chronic absenteeism, but the trade off in terms of lost observations to collect school level data (there were fewer states with school level data) was too large for this project. Ultimately, we decided to focus on district level chronic absenteeism across as many states as possible. To determine which states were possible to research we went to all state Departments of Education to see if they had district level data on absenteeism for 2017-2022. While 25 states seemingly had a subset of the data we were looking for, only 11 had the *entire* span of the years we were interested in. Furthermore, of those 11, three (California, New Mexico, and Utah) proved too difficult to aggregate for this project (something future researchers could look to correct). Ultimately, we were left with eight states for this study: Colorado, Georgia, Illinois, Maine, Massachusetts, North Dakota, Oregon, and Tennessee. Which, as we will show, exhibited variation in both the length and modality of their lockdowns.

In-Person/Hybrid/Virtual Learning Data:

As our literature review indicated, the length of the school closure affects students' academic outcomes. Therefore, we needed data on the length and modality of learning during the COVID-19 pandemic. Luckily, however, Brown economist Emily Oster had been collecting such data already through her *COVID-19 School Data Hub*, which included the percent of the '20/'21 school year school districts spent in-person, online, or in hybrid. We took this data and mapped it to the districts we had chronic absenteeism data on to begin to create our dataset.

Demographic Data:

Lastly, we were able to use the census tracts associated with our school districts to gather tract-level census data for the year 2020 that we would aggregate and average for our districts. We used racial, school expenditure, and household makeup data from the 2020 Decennial Census and education and income data from the American Community Survey (ACS) dataset. Ultimately, we were left with 1,884 districts that had complete data.

Findings

Figure 3 shows remarkable variation across the races featured in our data set for some states but not others. “White” was excluded to denote the prevalence of other races within the school districts of these states since chronic absenteeism is shown to impact those who are non-white disproportionately. Only Georgia and Tennessee feature a higher concentration of Blacks than other states, while Colorado, Oregon, and Illinois have a higher Latino concentration. While these numbers may appear significant, there is still a dominant White population within each state, which is expected. Moreover, none of the states seem to have much of an American Indian population, with the average median percentage of American Indians across the eight states being 0.01%. Along with the American Indian population, it seems that Asians, Hawaiians, and other Pacific Islanders have significantly low population proportions as well.

The differences in education these data display in Figure 4 is similar across most states and educational attainment percentages for each variable differ. However, since we are interested in how less educated parents influence chronic absenteeism, it is essential to see visible differences between the “some college” and “bachelor’s” variables, which there is. Figure 5 also shows variation in income across all the states. However, like with education, we are interested in examining the effects of lower income on chronic absenteeism rates. Thus, the fact that most of the states have median incomes that are either above or below $50,000 indicates promise within these data regarding variability.

Aside from socioeconomic correlates of chronic absenteeism, Figures 2,6, and 7 address the changes that remote and hybrid learning introduced to the education landscape and its presence as a catalyst for higher chronic absenteeism rates. The average percentage of chronic absenteeism for the 2018-19 school year constitutes the "pre-COVID" measure, and "post-COVID" is for the 2021-22 school year in Figure 2. For each of these eight states, there is a visible increase in the chronic absenteeism rate that almost doubles in some cases, highlighting the pandemic's significant impact.

Figure 6 shows the differences in each of the state's learning models with significant variability across states in terms of which states were either completely virtual, hybrid, a mixture of the two, or remained in person. The state with the lowest median virtual and hybrid share is North Dakota, which did not change to any hybrid or online learning model and remained in-person. Aside from North Dakota, the two states that have relatively lower median virtual and hybrid shares been Colorado and Georgia. Oregon and Tennessee exhibit opposite behavior as these are the two states with the highest median virtual and hybrid shares, which are close to 1; in other words, of the select school districts within Oregon and Tennessee, a significant majority went virtual. Finally, states like Maine, Massachusetts, and Illinois seem to fall somewhere in the middle, suggesting more heterogeneous measures. These data suggest significant variations across seven states that greatly supplement our understanding of COVID-19's impacts on chronic absenteeism. Finally, Figure 7 explores the potential effect of a virtual learning model on chronic absenteeism; how do chronic absenteeism rates respond as the percentage of virtual learning increases? The correlation plot shows a slightly upward-sloping line suggesting that virtual learning is associated with increased virtual learning and higher absenteeism rates as a fair assumption.

Methodology

We use OLS regressions to identify virtual and hybrid learning's effects on chronic absenteeism while controlling for school district and community factors. Our first model investigated the increase in chronic absenteeism during COVID and, thus, we'll refer to it as our Difference Model. We calculated the post-COVID change by taking the difference between the 21/22 chronic absenteeism rate and the mean rate during the '17/'18 and '18/'19 school years. This difference will be our dependent variable, and from *Table 3*, you can see that the mean increase was 11%. The difference is given in percentage points (i.e., its range is between 0 and 1). Our independent variables of interest are percent of the '20/'21 school year completed using virtual and hybrid learning methods—although we are mainly interested in the effect of *fully* virtual learning. These, too, (along with all other percentage variables) are given in percentage points. Next, we controlled for the variables that past literature indicated affected whether a student was chronically absent. Thus, in total, the Difference model was as follows:

$$\begin{aligned}
&\mathrm{ChronAbsRateDiff}_i \\
&= \beta_0 + \beta_1 \mathrm{ShareVirtual}_i + \beta_2 \mathrm{ShareHybrid}_i + \beta_3 \mathrm{PctNonWhite}_i \\
&+ \beta_4 \mathrm{MedianHouseholdIncome}_i + \beta_5 \mathrm{PctWithOtherRelative}_i \\
&+ \beta_6 \mathrm{PctSingleMotherWithChild}_i + \beta_7 \mathrm{PctBachelorsOrAbove}_i + \beta_8 \mathrm{ExpendPerPupil}_i + \epsilon_i
\end{aligned}$$

We also included regressions with a subset of these variables and one with the following interaction terms:

$$\begin{aligned}
&\beta_9 \mathrm{ShareVirtual}_i \cdot \mathrm{PctBachelorsOrAbove}_i + \beta_{10} \mathrm{ShareVirtual}_i \cdot \mathrm{ExpendPerPupil}_i \\
&+ \beta_{11} \mathrm{ShareVirtual}_i \cdot \mathrm{PctSingleMotherWithChild}_i
\end{aligned}$$

For our second model, we wanted to investigate the level of chronic absenteeism prior to COVID's disruption and, thus, will be referred to as our Pre-Pandemic Model. To do so, we ran a nearly identical model minus the virtual and hybrid variables, but with '18/'19 chronic absenteeism as the dependent variable. Therefore, the Pre-Pandemic Model's mathematical representation:

$$\begin{aligned}
&\text{ChronAbsRate}'18/'19_i \\
&= \beta_0 + \beta_1 \text{PctNonWhite}_i + \beta_2 \text{MedianHouseholdIncome}_i + \beta_3 \text{PctWithOtherRelative}_i \\
&+ \beta_4 \text{PctSingleMotherWithChild}_i + \beta_5 \text{PctBachelorsOrAbove}_i + \beta_6 \text{ExpendPerPupil}_i + \epsilon_i
\end{aligned}$$

Where, in both models, the subscript "i" refers to an individual school district in one of our eight states.

Results

Our Pre-Pandemic Model attempts to explain a given district's level of chronic absenteeism in a "normal" setting (i.e., not in the immediate aftermath of a global pandemic). Our Difference Model, on the other hand, attempts to explain the change in chronic absenteeism following the COVID-19 school closures where in-person instruction was replaced with virtual. Therefore, looking at the results in tandem tells a story of how one variable affects the general level of chronic absenteeism and whether it exacerbated or mitigated chronic absenteeism during the subsequent school closures. The results of the Difference Model are given in *Table 1* and its associated elasticities are given in *Table 2*. For our analysis of our Difference Model, we will concern ourselves with the results coming from the "Interactions" regression in prior tables as that is the complete model detailed in the Methodology section above. The results of the Pre-Pandemic Model are shown in *Table 4* were, similarly, we will mainly be looking at the results of the "Max" regression. We note that, when looking across our differing models, virtual, hybrid, income, education, and expenditure's effects are robust across the models.

From the Difference Model, looking at virtual learning (which from *Table 3* averaged 13.6% of the '20/'21 school year across all our districts), we get a coefficient on the *share_virtual* term of 0.148 which is statistically significant beyond the 99% confidence level. The coefficient implies that going fully virtual for an entire school year would result in a 14.8 percentage point *increase* in the pre- to post-pandemic level of chronic absenteeism. From the elasticities table, that translates into meaning that a 1% increase in the proportion of the school year spent using virtual learning results in a 0.18% increase in the change of chronic absenteeism. Hybrid learning (which was 40.4% of the school year of our districts) had a coefficient of 0.006 which was *not* statistically different from zero at the 95% confidence level.

Therefore, we cannot conclude that substituting hybrid learning for in-person learning leads to a change in a school district's chronic absenteeism level. The lack of consistency in the definition of hybrid learning is (i.e., the number of days/hours a given student is receiving in-person vs. virtual instruction) may drive this null result.

Prior literature often mentioned both race and income's effects on whether a student ended up chronically absent. To test for the same relationship, we included income and the percent of a school district that is non-white in our regression. The mean for each variable according to our summary stats were 19.9% non-white and $70,671 for median income. The coefficient on *pct_non_white* in our Difference Model was -0.051 which was *not* significant at the 95% confidence level. The coefficient on income was, however, significant beyond the 95% confidence level with a value of -0.0004. That coefficient implies that an $1,000 dollar increase in the median household income in each district would result in a 0.0004 percentage point *decrease* in the respective school district's change in chronic absenteeism rate going from pre- to post-COVID all else equal. From our Pre-Pandemic Model a similar story is told. The coefficient on *pct_non_white* is insignificant with a value of -0.023. And although the value is insignificant, its sign is of interest as it runs counter to the past literature. Furthermore, like the Difference Model, income's effect *is* significant beyond the 99% confidence level with a magnitude of -0.001—implying a $1,000 increase in a district's median household income would result in 0.001 percentage point decrease in its *level* of chronic absenteeism all else equal.

Next, we looked at how family structure influenced both the level of pre-pandemic chronic absenteeism and the change after COVID. Our two variables investigating that effect were the percent of the school district's population that had other relatives living with them and the percent of single mothers with children actively living with them. The mean values of the two variables in our dataset were 3.25% and 4.13% respectively. In our Difference Model, other relatives' effect was both significant beyond the 99% confidence level and massive in magnitude with a value of 1.03—implying a 1 percentage point increase in the percent of school district's population that lives with another relative would result in a 0.010 percentage point increase in the change in chronic absenteeism resulting from COVID all else equal. In our Pre-Pandemic Model, the other relative's effect is significant beyond the 99% confidence level, too, with a slightly smaller value of 0.618—implying a 1 percentage point increase in the percent of school district's population that lives with another relative would result in a 0.006 percentage point increase in the district's *level* of absenteeism all else equal The two figures imply that, on average, living with another relative has a negative effect on chronic absenteeism. However, during COVID the negative effect was aggravated—possibly due to parents having to attend to relatives rather than to their children's learning. In the Difference Model, the single mother effect was insignificant at the 95% confidence level with a magnitude of 0.317. Its sign is positive, however, indicating a negative effect like other relative's effect. In the Pre-Pandemic Model, however, the value *is* significant beyond the 99% confidence level with a extremely large magnitude of 0.970—implying that a 1 percentage point increase in the percent of a given school district's population that are single mothers with children at home would lead to a 0.010 percentage point increase in the district's level of chronic absenteeism.

Finally, we investigated how the percent of a school district's population that received some college degree and the given school district's expenditure to pupil ratio affected both the level of pre-pandemic chronic absenteeism and change in chronic absenteeism from pre- to post-COVID. In both the Difference Model and Pre-Pandemic Model, a college degree's effect was insignificant with values of -0.012 and 0.008 respectively. One plausible explanation is that the income correlated with a college degree is the true driving factor of chronic absenteeism, not the degree itself. Next, expenditure per pupil had very similar results in both our Difference Model and Pre-Pandemic Model with a value of 0.003 for both. Both statistics are statistically significant beyond the 99% confidence level. The values imply that a $1,000 increase in a district's expenditure per pupil would result in a 0.003 percentage point *increase* in the *change* in chronic absenteeism and a 0.003 percentage point increase in the *level* of chronic absenteeism. We would expect this value's sign to be negative, but it is positive. We suspect some omitted variable bias, but what exactly is omitted is probably dependent on how our eight states fund their school districts. Further reasoning for the negative sign is that income and education's effects are already explaining most of the variation. However, expenditure's interaction term is much more in line with what we expect.

Some of the most interesting results are found in the interactions. From *Table 1* we can see that, while not statistically significant, the interaction term between the share of the school year spent in virtual learning and the percent of college degree holders is negative at -0.0653. This is exactly what the literature would have us expect. Faced with the pandemic, parents with college degrees felt much more equipped to help with their children's virtual learning, and that is exactly the interaction term implies: that share of a school district's population holding a college degree *mitigates* the negative effect of virtual learning on absenteeism.

Next, the interaction between virtual learning and expenditure is also negative while being significant at the 95% confidence level. Again, the previous literature found that virtual learning is more effective when students have the resources necessary to access online learning and higher expenditures per pupil would indicate a higher likelihood of having devices like a Chromebook so students can attend virtual class rather than having to compete over a family laptop. And, lastly, the interaction between the proportion of single mothers to the share of virtual was statistically insignificant. However, it too was negative, implying the possibility that the unique circumstances of the COVID lockdowns meant that the generally negative effect single mothers have on absenteeism was mitigated because they were able to stay home during the pandemic to help their children.

Conclusion

This paper attempted to examine and quantify the variables that cause chronic absenteeism and which—in tandem with the virtual/hybrid learning—contributed to the average 11% increase in chronic absenteeism following the COVID-19 pandemic. Past literature pointed to racial, education, income, and family structure as determinants. However, many of these papers had a much more limited scope than what we were attempting to do. Therefore, there were serious questions as to whether the previous trends of such an idiosyncratic decision would show up in higher level aggregated data (i.e., school districts across states). However, many such trends we maintained: We found statistically significant evidence that income decreases chronic absenteeism. Single mothers and other relatives significantly increased the level of chronic absenteeism in each district. Furthermore, while not statistically significant, interaction terms implied that more educated parents were better equipped to help their children with virtual learning, school spending mitigated virtual learning's harm, and family structure is less important during a lockdown.

However, we did find some relationships that contradicted past literature. For example, minority racial groups were shown to have higher levels of chronic absenteeism, but we found the opposite to be true with the percent of non-white being negatively correlated with both the level of chronic absenteeism and the change during COVID. Furthermore, we expected school expenditures to help chronic absenteeism, but we found statistically significant evidence that they increased the level and change in chronic absenteeism. We expect that expenditure's effect is most likely due to omitted variable bias, but it is still of note. These contradictions may be the result of our data investigating 1,884 school districts across eight states whereas most of the prior literature looked at smaller geographic areas, such as a single state or school district.

However, the focus of our research was to discover what effect virtual learning had on chronic absenteeism—and here we saw our most interesting result. We found that virtually learning's effect was statistically significant, implying that a 1% increase in virtual learning led to 0.18% increase in the change in chronic absenteeism. Such a result is even more concerning when considering chronic absenteeism's persistence over time and implications on future socioeconomic outcomes. Therefore, policymakers should be wary of the belief that they can freely substitute virtual learning for in-person instruction.

Implications – Benefit-Cost Analysis

One motivation behind our research was to allow for better benefit-cost analysis when—inevitably—another pandemic or similar event requires the consideration of school closures. To demonstrate this, we will perform a simple retroactive benefit-cost analysis of the COVID-19 pandemic school closures and their effect on chronic absenteeism. Research by the Oregon Department of Education indicates that 12th graders who attend less than 90% of classes (i.e., chronically absent) graduate at only a 75% clip—a 16% decrease from those who attend 90% or more. Therefore, using our Difference Model, policymakers could have inputted different combinations of the percent of the school year they anticipated to be online and in hybrid. For example, if they predicted a quarter of the year would be virtual and another quarter to be hybrid, our model would have predicted a 13.1% increase in chronic absenteeism (assuming average values for all other variables).

Next, the census estimates that there were 17 million high schoolers in the 2021, 13.1% of which (2,227,000 high schoolers) will become chronically absent who would not have previously. Of those, 16% will, thus, not get a high school degree—that is, 356,320 high schoolers will enter the labor force without high school degrees they otherwise would have had except for the school closures. The Bureau of Labor Statistics estimates that in 2022 those without a high school degree earn $171 per week less than those with a high school degree which translates to a loss of income of roughly $8,900 per year. Therefore, assuming a constant income loss across time and retirement at 65, those highschoolers would have lost $418,300 each—a total loss in income of $149 billion.

A University of Michigan study estimates that closing the economy saved between 4.9 and 9.7 million quality-adjusted life years (i.e., years in perfect health). They further estimate that between 2.1 and 8.9 million quality-adjusted life years were lost due to the economic downturn associated with closing the economy. Note that there *is* an overlap between their estimates which implies that COVID lockdowns might have—on net—*lost* quality-adjusted life years. However, for the sake of our analysis, let's assume that their median predictions were true. Therefore, 7.3 million quality-adjusted life years would have been saved and 5.5 million would have been lost. Therefore, on net, the all lockdowns (i.e., not just school closures, but travel restrictions and all other closures) saved 1.8 million quality-adjusted life years. Thus, assuming a median income of $70,000, lockdowns saved $126 billion in earnings.

Therefore, taking the two estimates together, changing schooling modality to 25% virtual and 25% hybrid would have lost $149 billion to save $126 billion—that is, doing so would have resulted in an estimated $23 billion *loss* in income.

Obviously, a lot of assumptions were made to come to such estimates. However, such estimates were not even possible when policymakers were first faced with the challenges that COVID presented. There was no estimated effect that suddenly closing in-person learning for virtual instruction would have on chronic absenteeism. Thus, while there is much to improve upon in our research (i.e., the districts available, and precision of demographic estimates), it is a step in the right direction.

Additional Findings

An unexplored avenue in this research are the differences in absenteeism among grade levels. Since the literature suggests that grade levels experience absenteeism at different rates, this motivates further examination among the differences in chronic absenteeism rates between grade levels and whether virtual learning impacts these variables differently.

Unfortunately, only three of the eight states could be used for this portion of the study due to the limitations of the other five data sets that lacked grade-level information. The new data set contained 893 observations from Illinois, Oregon, and Tennessee and each separated school districts by “elementary school” and “high school”. Additionally, the same census demographic information as before is applied to each of the respective school districts.

Before the regression analysis, two visuals of the data were created to assess the difference in absenteeism rates between elementary school and high school. In Figure 9, it appears that although we see an increase in absenteeism rates for both elementary schools and high schools from pre-covid to post-covid, elementary schools have higher rates post-covid, which could mean that virtual learning impacted elementary school students differently than high school students. This would be consistent with another research, e.g.… the (Eklund et al., 2020) suggests that chronic absenteeism is worse among high school students. Figure 10 supplements this story with a correlation plot showing a steeper line for elementary school in the change of chronic absenteeism as virtual learning increases. These figures suggest that virtual learning impacts elementary school students differently than high school students.

To examine this, we employed a similar methodology as before, using OLS regressions to identify virtual learning’s effects on chronic absenteeism while controlling for school district and community factors, only this time separating elementary and high schools. In the pre-covid models shown in tables 5 and 7, we see consistency with both *Figure 9* and the literature where high school chronic absenteeism rates are higher than elementary school, as suggested by the higher “share_virtual” coefficient, which is significant at the 99% level. These differences suggest that before COVID-19, as other school districts transitioned to other learning modules, the effect on chronic absenteeism was higher across the five regressions for high school students than for elementary school students. We are now looking at our post-covid estimates, ie. *In Table 6 and Table 8*, we see an inverse relationship where now, as virtual learning increases, the effect of chronic absenteeism is higher across the five regressions for elementary school students than for high school students. It should be noted that all the post-covid elementary school regressions are significant at the 99% level; however, only the first three post-covid high school regressions are significant at the 95% level, with the final two regressions not having statistical significance; thus, this behavior cannot be generalized across all the regressions, but only the first three, unlike the pre-covid regressions.

These regressions demonstrate a possible difference in how virtual learning impacted elementary schools. Therefore, to isolate this relationship, we created a binary indicator variable where "high school" is coded as one and "elementary school" as zero. Then, a linear regression model with an interaction term between "gradelvl" and "share_virtual" was used to examine if the impact of virtual learning on absenteeism rates differs by grade level. Then, after including a plethora of potential confounders, here is the model:

$$
\begin{aligned}
&\text{abs\_rate\_diff} \\
&= \beta_0 + \beta_1 \text{gradelvl\_indicator} + \beta_2 \text{share\_virtual} + \beta_3 (\text{gradelvl\_indicator} \times \text{share\_virtual}) \\
&+ \beta_4 \text{expend\_per\_pupil} + \beta_5 \text{median\_household\_income\_in\_thousands} \\
&+ \beta_6 \text{median\_housing\_costs\_in\_hundreds} + \beta_7 \text{pct\_non\_white} + \beta_8 \text{pct\_bachelors\_or\_above} \\
&+ \beta_9 \text{pct\_married\_with\_children} + \beta_{10} \text{pct\_single\_mother\_with\_children} \\
&+ \beta_{11} \text{pct\_with\_other\_relatives} + \beta_{12} \text{pct\_institutionalized} +
\end{aligned}
$$

The results of *Table 9* indicate that while "share_virtual" has a significant positive effect on "abs_rate_diff," there is no statistically significant interaction between "gradelvl" and "share_virtual." This suggests that the effect of virtual learning on absenteeism rates does not differ significantly between high school and elementary school students. This conclusion conflicts with findings in the literature section that imply that chronic absenteeism has almost a compounding effect in high school when experienced in elementary schools; in other words, a pattern that carries over and worsens over time. Since we found statistically significant evidence that suggests the pandemic led to a percentage increase in chronic absenteeism, it implies that not all of the effects of chronic absenteeism translate into a pandemic-type disruption, thus assuming that high schools would have a more significant difference in chronic absenteeism than elementary schools was far-reaching and shows that the effects of the pandemic are beyond the literature within the magnitude of this small sample of district and state variation.

Appendix

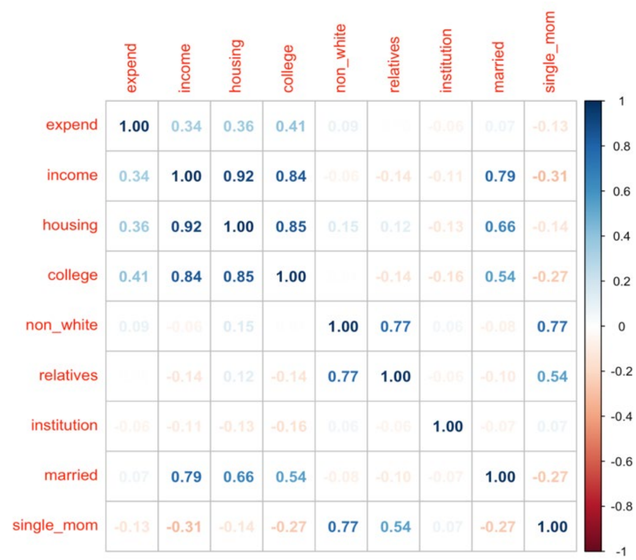


Figure 1

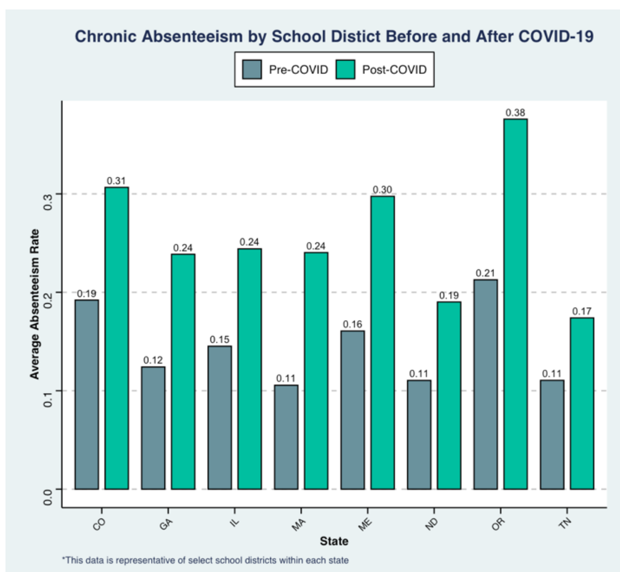


Figure 2

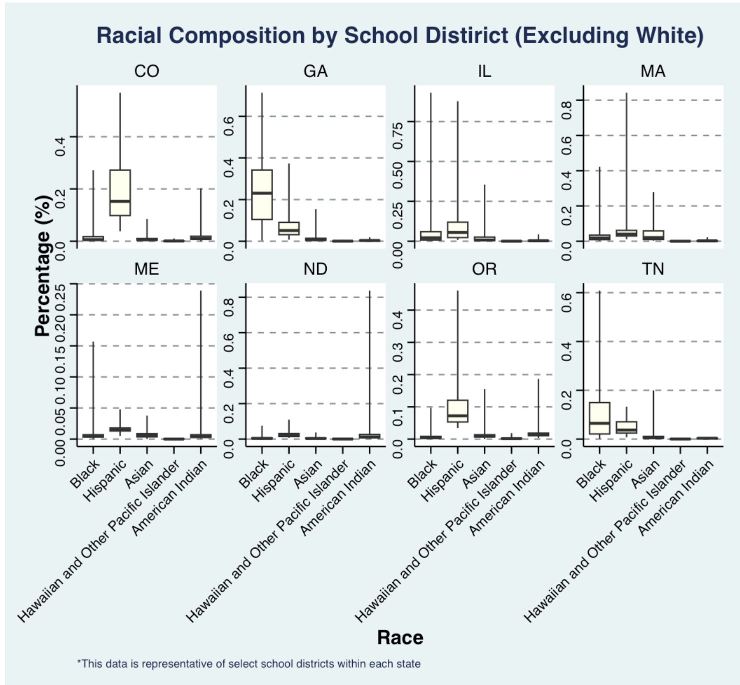


Figure 3

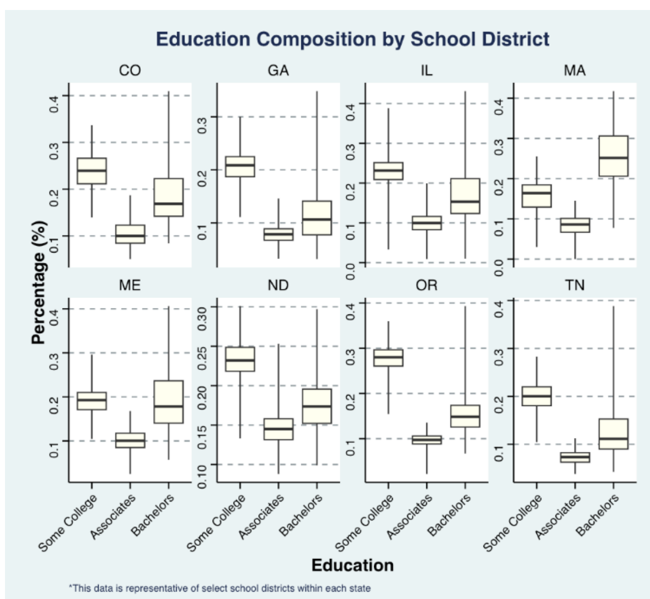


Figure 4

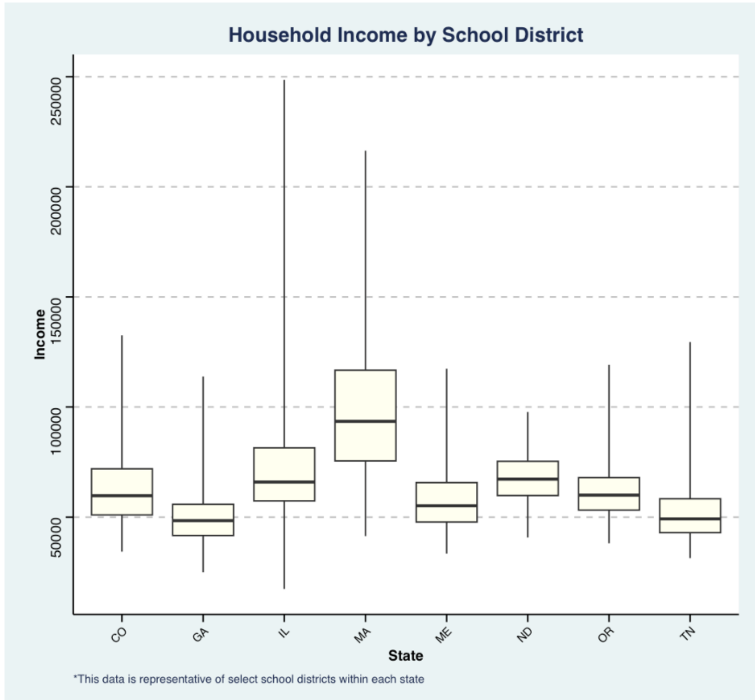


Figure 5

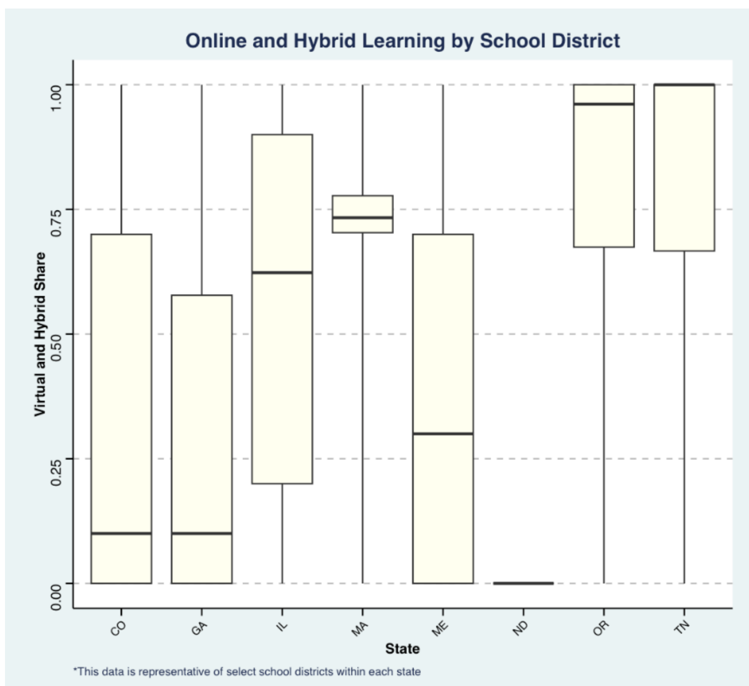


Figure 6

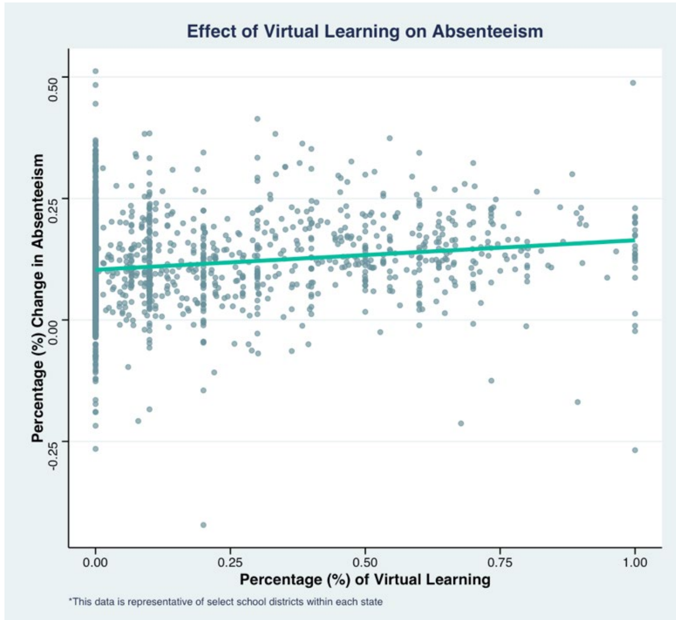


Figure 7

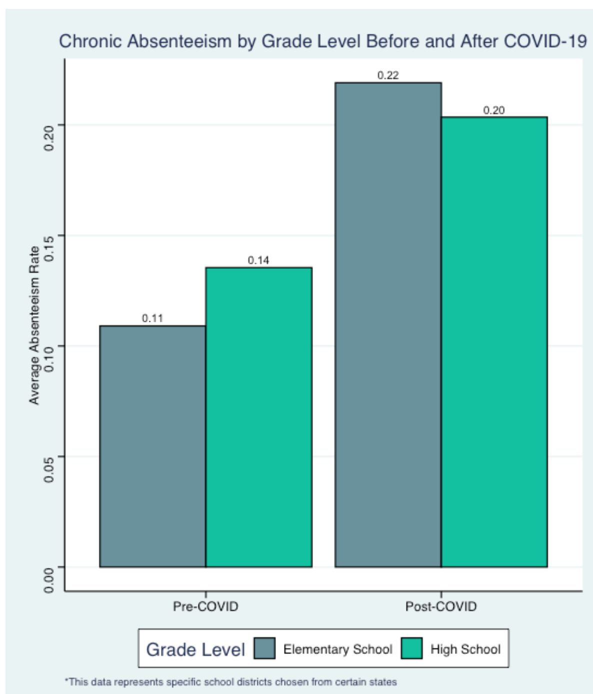
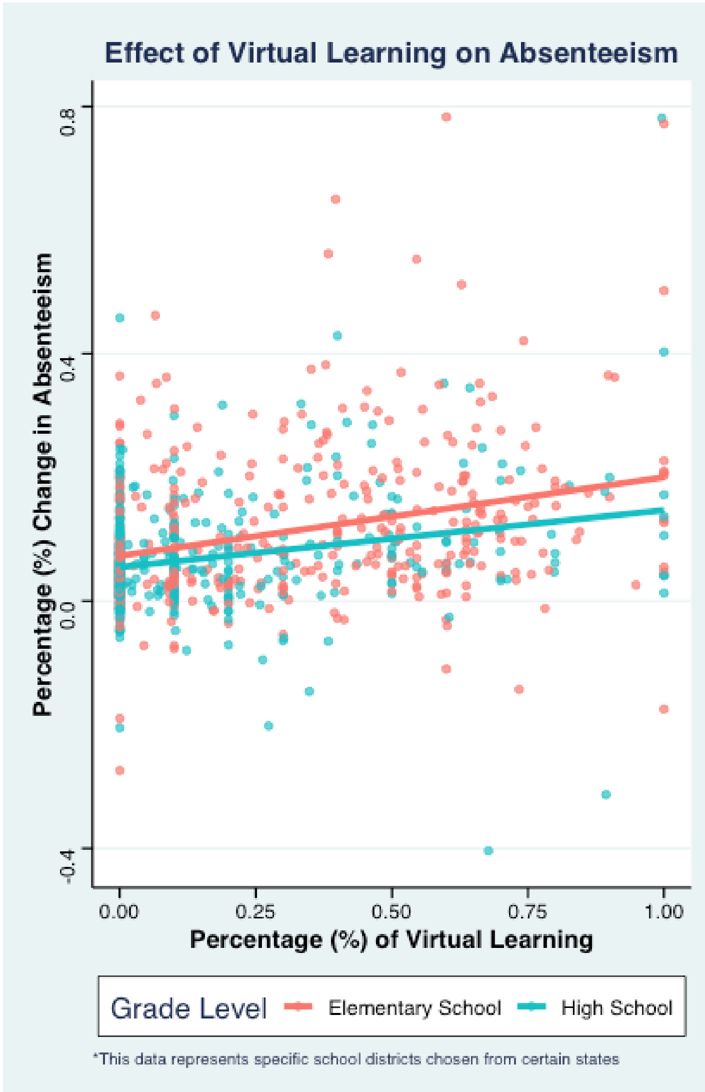


Figure 8



Effect of Virtual Learning on Absenteeism
Percentage (%) Change in Absenteeism
0.8
0.4
0.0
-0.4
0.00
0.25
0.50
0.75
1.00
Percentage (%) of Virtual Learning
Grade Level
Elementary School
High School
*This data represents specific school districts chosen from certain states

Figure 9

	Simple	Medium	Max	Interactions
(Intercept)	0.12568 ***	0.10602 ***	0.066221 ***	0.051812 ***
	(0.0063928)	(0.011197)	(0.012447)	(0.013818)
share_virtual	0.058667 ***	0.049499 ***	0.045715 ***	0.1476 ***
	(0.010427)	(0.0106)	(0.010498)	(0.03679)
share_hybrid	0.0082926	0.0035215	0.006939	0.0063443
	(0.0060242)	(0.006166)	(0.0061677)	(0.0062479)
pct_non_white	0.032842 *	-0.02011	-0.051786	-0.051037
	(0.014049)	(0.027289)	(0.028447)	(0.028448)
median_household_income_in_thousands	-0.00041782 ***	-0.00036663 ***	-0.00041799 **	-0.00044615 **
	(7.5718e-05)	(8.6559e-05)	(0.00013877)	(0.00014062)
pct_with_other_relatives		0.96621 ***	1.0664 ***	1.0274 ***
		(0.22633)	(0.23181)	(0.2351)
pct_single_mother_with_children		-0.039557	0.18766	0.31715
		(0.18201)	(0.18645)	(0.22106)
pct_bachelors_or_above			-0.022238	-0.012289
			(0.025555)	(0.027976)
expend_per_pupil			0.0023204 ***	0.0028571 ***
			(0.0003314)	(0.000396)
share_virtual:pct_bachelors_or_above				-0.065353
				(0.066075)
share_virtual:expend_per_pupil				-0.0033439 *
				(0.0013733)
share_virtual:pct_single_mother_with_children				-0.36737
				(0.31754)
N	1884	1884	1884	1884
R2	0.055422	0.06521	0.089141	0.093724

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 1: Difference Model Regression Results

variable	simple	medium	max	interactions
share_virtual	0.0700619	0.0591133	0.0545940	0.1762716
share_hybrid	0.0293976	0.0124839	0.0245991	0.0224908
pct_non_white	0.0572960	-0.0350830	-0.0903448	-0.0890375
median_household_income_in_thousands	-0.2589472	-0.2272189	-0.2590537	-0.2765025
pct_other_relatives	NA	0.2753019	0.3038367	0.2927447
pct_single_mother_with_children	NA	-0.0143314	0.0679866	0.1149034
pct_bachelors_or_above	NA	NA	-0.0564632	-0.0312041
expend_per_pupil	NA	NA	0.3741107	0.4606583

Table 2: Elasticities Calculated from Each Regression

	vars	n	mean	sd	min	max	range	se
chron_abs_rate_diff	1	1884	1.140298e-01	8.897010e-02	-0.4255000	4.915000e-01	9.17000e-01	0.0020498
share_virtual	2	1884	1.361771e-01	2.354903e-01	0.0000000	1.000000e+00	1.00000e+00	0.0054254
share_hybrid	3	1884	4.042398e-01	3.430484e-01	0.0000000	1.000000e+00	1.00000e+00	0.0079034
pct_non_white	4	1884	1.989335e-01	1.722278e-01	0.0270000	9.750000e-01	9.48000e-01	0.0039679
median_household_income	5	1884	7.067067e+04	2.679263e+04	17391.0000000	2.485710e+05	2.31180e+05	617.2695068
pct_with_other_relatives	6	1884	3.249060e-02	1.471130e-02	0.0090000	1.038333e-01	9.48333e-02	0.0003389
pct_single_mother_with_children	7	1884	4.131230e-02	1.965200e-02	0.0090000	3.030000e-01	2.94000e-01	0.0004528
pct_bachelors_or_above	8	1884	2.895326e-01	1.538199e-01	0.0340000	9.180000e-01	8.84000e-01	0.0035438
expend_per_pupil	9	1884	1.838504e+01	6.660724e+00	0.6799107	7.287611e+01	7.21962e+01	0.1534550

Table 3: Summary Stats of Regression Variables

	Simple	Medium	Max
(Intercept)	0.19186 ***	0.15901 ***	0.10918 ***
	(0.0050411)	(0.0090831)	(0.0099209)
pct_non_white	0.11359 ***	0.033792	-0.022537
	(0.0094243)	(0.021066)	(0.021718)
median_household_income_in_thousands	-1.0611e-06 ***	-9.1926e-07 ***	-1.1213e-06 ***
	(6.0581e-08)	(6.8167e-08)	(1.1049e-07)
pct_with_other_relatives		0.40831 *	0.61804 ***
		(0.17812)	(0.17817)
pct_single_mother_with_children		0.61575 ***	0.96967 ***
		(0.14552)	(0.14655)
pct_bachelors_or_above			0.0080153
			(0.020165)
expend_per_pupil			0.0028038 ***
			(0.00026274)
N	1884	1884	1884
R2	0.2028	0.21117	0.25844

*** p < 0.001; ** p < 0.01; * p < 0.05.

Table 4: Pre-Pandemic Model Regression Results

	Dependent variable:				
	abs_rate_18_19				
	(1)	(2)	(3)	(4)	(5)
share_virtual	0.092***	0.093***	0.090***	0.152***	0.082
	(0.016)	(0.017)	(0.016)	(0.049)	(0.068)
share_hybrid	0.023	0.025	0.020	0.021	0.023
	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)
pct_non_white	0.008	-0.050	-0.090	-0.088	-0.102
	(0.024)	(0.056)	(0.061)	(0.061)	(0.062)
median_household_income_in_thousands	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
pct_with_other_relatives		0.418	0.587	0.596	0.663
		(0.456)	(0.489)	(0.489)	(0.497)
pct_single_mother_with_children		0.412	0.627	0.532	0.301
		(0.395)	(0.417)	(0.422)	(0.485)
pct_bachelors_or_above			0.037	0.052	0.049
			(0.062)	(0.063)	(0.081)
expend_per_pupil			0.002**	0.002**	0.003*
			(0.001)	(0.001)	(0.001)
share_virtual:median_household_income_in_thousands				-0.00000	
				(0.00000)	
share_virtual:pct_bachelors_or_above					0.006
					(0.132)
share_virtual:expend_per_pupil					-0.003
					(0.003)
share_virtual:pct_single_mother_with_children					0.894
					(0.617)
Constant	0.159***	0.129***	0.103***	0.098***	0.111***
	(0.015)	(0.030)	(0.032)	(0.032)	(0.037)
Observations	435	435	435	435	435
R^2	0.191	0.193	0.205	0.209	0.212
Adjusted R^2	0.183	0.182	0.190	0.192	0.191
Residual Std. Error	0.084 (df = 430)	0.084 (df = 428)	0.084 (df = 426)	0.084 (df = 425)	0.084 (df = 423)
F Statistic	25.303*** (df = 4; 430)	17.068*** (df = 6; 428)	13.749*** (df = 8; 426)	12.452*** (df = 9; 425)	10.321*** (df = 11; 423)
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 5: Pre-Pandemic Model Regression Results (Elementary School)

	Dependent variable:				
	abs_rate_diff				
	(1)	(2)	(3)	(4)	(5)
share_virtual	0.137***	0.110***	0.111***	0.205***	0.309***
	(0.021)	(0.021)	(0.021)	(0.063)	(0.088)
share_hybrid	0.028	0.020	0.018	0.020	0.011
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
pct_non_white	-0.028	0.097	0.167**	0.169**	0.173**
	(0.032)	(0.072)	(0.079)	(0.079)	(0.080)
median_household_income_in_thousands	-0.00000***	-0.00000***	-0.00000*	-0.00000	-0.00000**
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
pct_with_other_relatives		0.952	0.387	0.402	0.279
		(0.588)	(0.630)	(0.629)	(0.639)
pct_single_mother_with_children		-1.818***	-2.174***	-2.316***	-1.653***
		(0.509)	(0.537)	(0.543)	(0.624)
pct_bachelors_or_above			-0.203**	-0.181**	-0.171*
			(0.080)	(0.081)	(0.103)
expend_per_pupil			0.001	0.001	0.004**
			(0.001)	(0.001)	(0.002)
share_virtual:median_household_income_in_thousands				-0.00000	
				(0.00000)	
share_virtual:pct_bachelors_or_above					-0.114
					(0.169)
share_virtual:expend_per_pupil					-0.006
					(0.004)
share_virtual:pct_single_mother_with_children					-1.136
					(0.793)
Constant	0.147***	0.196***	0.199***	0.192***	0.143***
	(0.020)	(0.039)	(0.041)	(0.041)	(0.048)
Observations	435	435	435	435	435
R^2	0.146	0.193	0.207	0.211	0.217
Adjusted R^2	0.138	0.182	0.192	0.195	0.197
Residual Std. Error	0.112 (df = 430)	0.109 (df = 428)	0.108 (df = 426)	0.108 (df = 425)	0.108 (df = 423)
F Statistic	18.334*** (df = 4; 430)	17.100*** (df = 6; 428)	13.875*** (df = 8; 426)	12.657*** (df = 9; 425)	10.655*** (df = 11; 423)
Note:					$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 6: Difference Model Regression Results (Elementary School)

	Dependent variable:				
	abs_rate_18_19				
	(1)	(2)	(3)	(4)	(5)
share_virtual	0.142***	0.144***	0.145***	0.209***	0.375***
	(0.025)	(0.025)	(0.026)	(0.066)	(0.083)
share_hybrid	0.045***	0.045***	0.046***	0.045***	0.037**
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
pct_non_white	0.268***	0.007	-0.003	-0.001	-0.024
	(0.035)	(0.073)	(0.083)	(0.083)	(0.085)
median_household_income_in_thousands	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
pct_with_other_relatives		1.011	1.097	1.179*	1.415**
		(0.631)	(0.694)	(0.698)	(0.698)
pct_single_mother_with_children		2.109***	2.122***	2.033***	2.195***
		(0.418)	(0.433)	(0.441)	(0.623)
pct_bachelors_or_above			0.031	0.042	0.058
			(0.083)	(0.084)	(0.092)
expend_per_pupil			-0.0003	-0.0003	0.002**
			(0.001)	(0.001)	(0.001)
share_virtual:median_household_income_in_thousands				-0.00000	
				(0.00000)	
share_virtual:pct_bachelors_or_above					-0.001
					(0.179)
share_virtual:expend_per_pupil					-0.011***
					(0.003)
share_virtual:pct_single_mother_with_children					-0.152
					(0.696)
Constant	0.220***	0.097***	0.101***	0.089**	0.049
	(0.019)	(0.033)	(0.035)	(0.037)	(0.042)
Observations	458	458	458	458	458
R^2	0.404	0.436	0.436	0.438	0.453
Adjusted R^2	0.399	0.429	0.426	0.426	0.439
Residual Std. Error	0.105 (df = 453)	0.102 (df = 451)	0.102 (df = 449)	0.102 (df = 448)	0.101 (df = 446)
F Statistic	76.829*** (df = 4; 453)	58.132*** (df = 6; 451)	43.462*** (df = 8; 449)	38.761*** (df = 9; 448)	33.553*** (df = 11; 446)
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 7: Pre-Pandemic Model Regression Results (High School)

	Dependent variable:				
	abs_rate_diff				
	(1)	(2)	(3)	(4)	(5)
share_virtual	0.057***	0.053**	0.050**	0.064	-0.023
	(0.021)	(0.021)	(0.021)	(0.055)	(0.070)
share_hybrid	-0.018	-0.018	-0.020	-0.020	-0.017
	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)
pct_non_white	0.100***	0.097	0.022	0.022	0.025
	(0.029)	(0.062)	(0.070)	(0.070)	(0.072)
median_household_income_in_thousands	-0.00000***	-0.00000***	-0.00000***	-0.00000***	-0.00000***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
pct_with_other_relatives		0.596	1.137*	1.155**	0.948
		(0.530)	(0.579)	(0.583)	(0.589)
pct_single_mother_with_children		-0.378	-0.174	-0.193	-0.056
		(0.351)	(0.362)	(0.369)	(0.526)
pct_bachelors_or_above			0.152**	0.154**	0.160**
			(0.069)	(0.070)	(0.078)
expend_per_pupil			0.001	0.001	-0.001
			(0.001)	(0.001)	(0.001)
share_virtual:median_household_income_in_thousands				-0.00000	
				(0.00000)	
share_virtual:pct_bachelors_or_above					-0.098
					(0.151)
share_virtual:expend_per_pupil					0.006**
					(0.003)
share_virtual:pct_single_mother_with_children					-0.214
					(0.587)
Constant	0.096***	0.103***	0.097***	0.094***	0.111***
	(0.015)	(0.027)	(0.029)	(0.031)	(0.035)
Observations	458	458	458	458	458
R^2	0.122	0.129	0.139	0.139	0.147
Adjusted R^2	0.114	0.117	0.124	0.122	0.126
Residual Std. Error	0.086 (df = 453)	0.086 (df = 451)	0.085 (df = 449)	0.085 (df = 448)	0.085 (df = 446)
F Statistic	15.722*** (df = 4; 453)	11.135*** (df = 6; 451)	9.070*** (df = 8; 449)	8.054*** (df = 9; 448)	6.968*** (df = 11; 446)
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 8: Difference Model Regression Results (High School)

	Dependent variable:
	abs_rate_diff
gradelvl_indicator	-0.007
	(0.009)
share_virtual	0.084***
	(0.019)
expend_per_pupil	0.00001
	(0.001)
median_household_income_in_thousands	-0.00000
	(0.00000)
median_housing_costs_in_hundreds	0.0001
	(0.00004)
pct_non_white	0.004
	(0.054)
pct_bachelors_or_above	-0.043
	(0.058)
pct_married_with_children	-0.480***
	(0.129)
pct_single_mother_with_children	-0.840***
	(0.318)
pct_with_other_relatives	1.398***
	(0.500)
pct_institutionalized	0.171
	(0.130)
gradelvl_indicator:share_virtual	-0.019
	(0.026)
Constant	0.163***
	(0.029)
Observations	893
R^2	0.201
Adjusted R^2	0.190
Residual Std. Error	0.097 (df = 880)
F Statistic	18.430*** (df = 12; 880)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 9: Interaction Regression Results

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