THE EFFECTS OF REMOTE INSTRUCTION ON LEARNING LOSSES DURING THE COVID-19 PANDEMIC

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Abstract

The existing literature on the effect of the COVID-19 pandemic on elementary and secondary school learning losses finds that students have experienced greater learning losses than would be expected in a normal year, but the specific cause of these losses remains an open question. Researchers have demonstrated the existence of the learning losses among American students and explored the moderating effect of remote learning at the district level. In this study, I complement prior analysis by using the SafeGraph phone-tracking database as a proxy for school openness. This provides two advantages: first, a more precise estimation of openness, without having to resort to using the nebulous term "hybrid" to encapsulate all states between open and remote learning, and secondly, allowing for a school-level analysis, which is more granular than the district level.

The result of my study is a group of linear regression analyses of learning loss regressed on school openness with demographic, fiscal, and state fixed effects of approximately 7,500 schools in 10 states. The results of the analyses indicate that schools which were more open during the 2020-21 school year experienced significantly smaller learning losses in math, but that openness did not have a significant effect on English language arts learning loss when controls were included. Additionally, there were significant racial, economic, and state fixed effects, with schools that have higher percentages of black and Hispanic students, as well as higher percentages of students eligible for free and reduced-price lunch, experiencing larger learning losses. These results are consistent with prior literature suggesting that math skills suffer more than reading during periods in which school is not in session, and that racial minorities and students of low socioeconomic status are disproportionately harmed by interruptions to learning.

1 Introduction

America prides itself on being the "land of opportunity." Whether our country is truly the one where people are best able to pull themselves up by their bootstraps is debatable, but if that were the case, its catalyst would be our system of public education. Raj Chetty, a Harvard professor and pre-eminent scholar of economic opportunity, finds that elementary and secondary education act as the "great equalizer" in the United States, raising students from poor backgrounds to a place where they can compete with their peers (Reeves and Krause 2018). This is the platonic ideal for public education: a system which increases all students' potentials, but especially those who are disadvantaged to begin with. Therefore, a shock to a country's educational system presents a grave threat to opportunity, equality, and progress.

Education is crucial for human development as well as the economic fortunes of a nation (Kruss et al. 2015). Median wages of a nation correlate directly with the educational attainment of the nation's workforce (Berger and Fisher 2013). If every student in the United States achieved basic mastery by the standards of the National Assessment of Educational Progress[1], the country's gross domestic product (GDP) could increase by up to 14.6 percent (Eric A. Hanushek, Ruhose, and Woessmann 2015a). Educational achievement of a state predicts that state's economic growth over the past forty years (Eric A. Hanushek, Ruhose, and Woessmann 2015b). Additionally, higher educational achievement is associated with a diminished gender wage gap (Didier 2021).

The COVID-19 pandemic has caused devastating social and economic disruptions around the world, and the United States has not been exempted (Chriscaden 2020). Tens of millions of people have been threatened by poverty, the number of under-nourished people has soared to nearly one billion, and almost half of the global workforce is at risk of losing their livelihood (Chriscaden 2020). Education has been impacted by the pandemic as well (Goldberg 2021).

On March 12, 2020, Michigan became the first U.S. state to close its public schools.

[1] A nationwide assessment

By April 2, 2020, all fifty states and the District of Columbia had followed suit (Goldberg 2021). This began a period in which states used disparate approaches to education (Goldberg 2021). 87% of school districts expected teachers to "meet with their students" weekly at a minimum, while 40% of districts expected daily meetings (Hodgman, Sabatini, and Carminucci 2021). The 2019-20 school year ended without nationwide standardized testing, as the Trump administration granted a blanket waiver of the nationwide requirement to administer standardized tests mandated by the federal Every Student Succeeds Act (Perez Jr. 2021). During the 2020-21 school year, the U.S. leaned heavily on the decentralized nature of the educational system (Ferren 2021). While the majority of public schools in the United States had resumed in-person instruction by May 2021, nearly every district in the country utilized remote learning at some point during the 2020-21 school year (Ferren 2021).

Given the unusual nature of both the conclusion of the 2019-20 school year and the entirety of the 2020-21 school year, it is no surprise that the consensus in the extant literature is that students have experienced abnormally large learning losses (Ardington, Wills, and Kotze 2021; Bird, Castleman, and Lohner 2022; Borman 2020; Dorn et al. 2020; Dorn et al. 2021; Engzell, Frey, and Verhagen 2021; Kogan and Lavertu 2021; Kuhfeld et al. 2020; Malkus 2020; Bank 2020). Learning loss is defined as the phenomenon in which students have a specific or general loss of knowledge and skills or reverse their academic progress (*Learning Loss Definition* 2013). Learning loss is a common phenomenon, and its most commonly observed cause is summer vacation (*Learning Loss Definition* 2013). Generally, learning losses are quantified by students scoring below their prior scores on tested material (*Learning Loss Definition* 2013). In Fall 2020, students scored up to 33% below their 2019 scores (Dorn et al. 2020). These learning losses continued to compound over the course of the 2020-21 school year (Dorn et al. 2021).

One potential reason for the observed increase in the size of learning losses was the disruption from traditional instruction (Malkus 2020). Due to the decreased efficacy of remote learning, the poorest districts lost four full weeks of instruction from March 26 to May

29, 2020, equivalent to 12% of a school year and 41% of the period measured (Malkus 2020). Research prior to the COVID-19 pandemic have found remote learning to be fundamentally less effective than in-person instruction (Alpert, Couch, and Harmon 2016; Baum and M. McPherson 2019), and that finding has been replicated since the onset of the pandemic (Altindag, Filiz, and Tekin 2021; Kogan and Lavertu 2021). The deployment of remote learning as a substitute for in-person instruction has also raised concerns due to potential inequalities along racial and socioeconomic lines (Schwartz et al. 2020).

There are more potential factors behind the increased size of learning losses than the loss of in-person instruction and the utilization of in-person learning (Goldberg 2021). In May 2020, only two months into the pandemic, 29% of parents said that the pandemic was harming their child's mental health, with less-educated parents more likely to say so (Calderon 2020). Only 33% of parents said that their child could wait "as long as necessary" for the pandemic to end before experiencing negative mental health consequences (Calderon 2020). Rates of suicide ideation were significantly higher during the pandemic than before (Hill et al. 2021), there was a rise in eating disorders and other mental-health related emergency room visits for children (Leeb 2020), and there was a marked increase in both immediate family members losing a job (Jaeger et al. 2021) and parental bereavement among children (Kidman et al. 2021). Each of these factors may have negatively impacted students (Goldberg 2021).

It is important to better understand the impact of remote instruction on learning losses during COVID-19 in part because such pronounced learning losses may have far-reaching economic impact (Dorn et al. 2021; Eric A Hanushek and Woessmann 2020). One forecast predicted a reduction of $49,000 to $61,000 in lifetime earnings for each student affected by the pandemic, amounting to a total impact on the U.S. economy of $128 billion to $188 billion per year (Dorn et al. 2021). Another potential result of COVID-19-induced learning losses is a 3% reduction of income over each student's lifetime (Eric A Hanushek and Woessmann 2020). Either outcome would be troubling both for individuals and the entire nation (Goldberg 2021).

I seek to clarify the moderating effect of remote instruction on learning losses during the COVID-19 pandemic. I do so through the use of data from SafeGraph, a data company that aggregates anonymized location data from numerous applications in order to provide insights about physical places. By using SafeGraph's tracking data to compare the number of phones observed in schools in the 2020-21 school year versus the 2018-19 school year, I create a proxy for school openness during the 2020-21 school year. School openness serves as my independent variable on which I regress the school-level difference in standardized test proficiency rates between the 2018-19 and 2020-21 school years. I attempt to determine the impact of remote learning on learning loss, as well as the moderating effect of demographics and fiscal data. Through this analysis, I add to the literature on learning losses during the COVID-19 pandemic specifically and education-disrupting events more generally, as well as the literature on the efficacy of remote learning as a substitute for in-person instruction.

2 Literature Review

2.1 Learning Loss: Causes and Effects

Learning losses have been of interest to researchers in the field of education since their first documentation in 1906 (Quin 2017). A "learning loss" is defined as the phenomenon in which students have a specific or general loss of knowledge and skills or reverse their academic progress (*Learning Loss Definition* 2013). Common causes of learning loss include summer vacation, interruptions to formal education such as societal unrest or natural disaster, prolonged health concerns, and ineffective teaching (*Learning Loss Definition* 2013). The most commonly studied cause of learning loss is summer vacation, due to the frequency of summer vacation and its potentially harmful results (Cooper et al. 1996).

The dominant explanatory theory for learning loss is the "faucet theory" (Quin 2017). This theory posits that while all students attending the same school are exposed to identical learning resources, when students are at home, the "resource faucet" is shut off for some students and not for others (Entwisle, Alexander, and Olson 2001). Specifically, middle-class and upper-class children continue to make gains in the summer, while less affluent children actually lose ground (Entwisle, Alexander, and Olson 2001). This is because poor families are unable to provide the resources for their children that had been provided by the school during the school year (Entwisle, Alexander, and Olson 2001). Advantages conferred by middle- and upper-class parents upon their children that less affluent children were unable to obtain include physical resources such as books, games, and computers, but also elements of human, social, and psychological capital useful in making the home a more conducive learning environment (Entwisle, Alexander, and Olson 2001). Non-cognitive factors associated with stronger academic performance include academic behaviors such as organization and study habits, perseverance, including self-discipline and self-control, mindsets such as self-confidence, learning strategies, and social skills such as empathy and cooperation (Farrington et al. 2012). More highly-educated and wealthier parents are more likely to successfully instill these skills in their children outside of the classroom setting, thus giving their children an advantage within the school setting (Farrington et al. 2012).

Another potential cause of learning losses is the lack of a teacher-student relationship. The teacher-student relationship is one of the most powerful elements of the learning environment (Liberante 2012). The strength of a teacher-student relationship has a strong predictive association with multiple indicators of student success (Quin 2017). During the summer, or any other period of absence during which learning losses could develop, students do not have a teacher encouraging and directing their growth, which could lead to lower motivation and engagement in the learning process (Quin 2017). This decreased engagement could in turn lead to a lack of practice of learned skills, resulting in atrophy (Liberante 2012).

There are disagreements in the literature concerning the incidence and scope of learning losses. Estimates of the size of learning losses caused by summer vacation range from one month's worth of in-school learning (Cooper et al. 1996) to three months' worth of learning

(Kerry and Davies 1998). While some argue that measures of learning loss may be overstated due to different scaling of exams and variable exam difficulty between a fall exam and the spring exam taken prior (Hippel 2019; Hippel and Hamrock 2019), for the most part the existing literature is in agreement that at least some students do experience a backslide during the summer when they are away from school (Akers and Chingos 2012; Atteberry and McEachin 2020; Borman 2020; Cooper et al. 1996; Kerry and Davies 1998; Kuhfeld 2019; Quinn et al. 2016; Quin 2017).

Whether learning losses are shared equally across the variables of race, socioeconomic status, and prior academic performance is also an important topic. Some argue that summer learning losses are larger among Black and Latino students despite those same students learning less during the school year (Atteberry and McEachin 2020), while others find no difference in the size of summer learning losses among races (Cooper et al. 1996). The literature is in greater agreement when it comes to socioeconomic status, confirming the faucet theory's framework that less affluent students experience greater learning losses (Akers and Chingos 2012; McEachin and Atteberry 2017; Quin 2017).

In terms of prior academic performance, one study indicates that there is an increased incidence of learning loss among students who had made the greatest gains during the prior school year (Kuhfeld 2019). This finding raises questions about the validity of learning loss measurements, given that higher-achieving students suffering larger learning losses implies a cycle in which some students follow a mercurial path between scoring low on initial exams in the fall and high on exams in the spring (Kuhfeld 2019). One potential mechanism to explain this phenomenon is that measures of learning loss are inflated by students scoring below their true potential in the fall and testing better in the spring, rather than actually suffering learning losses to the degree indicated by the data (Kuhfeld 2019). The "mercurial path" finding is in agreement with the idea that lower-achieving groups consistently follow "steeper" learning trajectories throughout the school year, meaning that they start behind most other students, but learn at a faster rate, at least during the beginning of the school year (Quinn et al. 2016). These steeper learning trajectories appear to level out after the beginning of the school year, and in some cases reverse (Quinn et al. 2016).

Additionally, different subjects lead to disparate trends in learning loss. Learning losses are more common and pronounced in math than in reading (Akers and Chingos 2012; Cooper et al. 1996; Quinn et al. 2016). Potential explanations for this difference include the greater ease of practicing and maintaining reading skills compared to math skills and the fact that reading is a more conceptual-based knowledge than mathematics, and thus less susceptible to decay (Cooper et al. 1996).

New literature has attempted to determine what percentage of students experience summer learning loss. Atteberry and McEachin (Atteberry and McEachin 2020) find that while on the whole, students do lose ground in both math and language arts, this effect is driven by slightly more than half of students losing ground, while the remainder either maintain their level or learn more during the summer (Atteberry and McEachin 2020). Learning losses are a major concern because they can result in economic hardships (Dorn et al. 2021; Eric A Hanushek and Woessmann 2020; Jaume and Willén 2019; Kruss et al. 2015), which in turn are correlated with poor quality of life outcomes such as self-evaluation of health, lower incidences of sickness, and lower mortality(Jaume and Willén 2019; Kruss et al. 2015), as well as likelihood of marriage (Jaume and Willén 2019), wages (Berger and Fisher 2013) and job satisfaction (Jaume and Willén 2019). Any variable which impacts so many aspects of life is worth investigating, and the impact of learning loss on education marks learning loss as significant.

2.2 Learning Loss Induced by the COVID-19 Pandemic

There is already a significant body of work concerning learning loss induced by the COVID-19 pandemic. While there is broad agreement that the size of learning losses caused by the pandemic are larger than those experienced during a typical summer (Ardington, Wills, and Kotze 2021; Bird, Castleman, and Lohner 2022; Associates 2021; Donnelly and

Patrinos 2021; Dorn et al. 2020; Dorn et al. 2021; Engzell, Frey, and Verhagen 2021; Eric A Hanushek and Woessmann 2020; Kofoed et al. 2021; Kogan and Lavertu 2021; Kuhfeld et al. 2020; Bank 2020; Zierer 2021), a debate remains regarding the exact magnitude. Estimates range from 33% of a year of learning (Eric A Hanushek and Woessmann 2020) to 81% (Ardington, Wills, and Kotze 2021). On the optimistic end, one study found that third through eighth graders performed similarly in fall 2020 to their previous year's performance in reading, and were only 5-10% behind the previous year's performance in math (Kuhfeld et al. 2020). Less positive estimates showed that when tested in fall 2020, students had only learned 67% of the math and 87% of the reading that their age cohort had learned in the previous year (Dorn et al. 2020). Both of these outcomes are better than some initial forecasts had predicted, as one estimated that due to the truncated 2019-20 school year and general chaos caused by the pandemic, students would only have scored 63-68% of their typical English Language Arts test results and 37%-50% of their standard math outcomes. While not as dire as some expected, the impact of the pandemic on learning losses was considerable. Fewer students had reached grade-level competency in spring 2021 compared to past years in both reading and math (Associates 2021). Nearly twice as many students dropped one or more quintiles in the score distribution as was the case in fall 2019 (Kuhfeld et al. 2020). Other consequences of the pandemic included a decline in course completion, due to a rise in both course withdrawal and course failure (Bird, Castleman, and Lohner 2022).

Learning losses were observed among all age cohorts and around the world. Elementary school students (Ardington, Wills, and Kotze 2021; Associates 2021; Dorn et al. 2021; Engzell, Frey, and Verhagen 2021; Grewenig et al. 2021; Kogan and Lavertu 2021; Kuhfeld et al. 2020; Malkus 2020; Goldberg 2021) and college students (Bird, Castleman, and Lohner 2022; Jaeger et al. 2021) alike experienced academic setbacks. These learning losses were observed not only in the United States (Associates 2021; Dorn et al. 2021; Kogan and Lavertu 2021; Kuhfeld et al. 2020; Malkus 2020; Goldberg 2021), but also in South Africa (Ardington, Wills, and Kotze 2021), the Netherlands (Engzell, Frey, and Verhagen 2021), Germany (Grewenig et al. 2021), Spain, Australia, Sweden, Austria, Italy, and Mexico (Jaeger et al. 2021). Approximately 1.6 billion students were affected at the peak of school closures in March 2020, and by November 2020, 670 million students remained in countries enacting a full school closure policy (Luna-Bazaldua, Levin, and Liberman 2020). While each of these studies shows significant, widespread learning losses, none of them investigate the difference in the magnitude of learning losses between schools that took differing approaches in terms of offering a higher proportion of remote learning.

COVID-19-induced learning losses were not distributed evenly according to prior academic achievement, wealth, or race. Students who had achieved lower scores in the past showed both the largest learning losses (Kogan and Lavertu 2021) and the highest rates of course failure (Bird, Castleman, and Lohner 2022). Fewer students attending schools in lower-income zip codes were at grade level than in schools in higher-income zip codes (Associates 2021). There was also a racial gap in learning losses: fewer schools serving mostly Black, Hispanic, and Indigenous students are on grade-level compared to schools serving mostly White and Asian students (Associates 2021). Majority Black schools were one month behind majority White schools in math, and two months behind in reading (Dorn et al. 2021). Of eight studies reviewed in one analysis, only one found demographics to have a negligible effect (Donnelly and Patrinos 2021). COVID-19 deepened educational divides along lines of race, language, and learning disability (Goldberg 2021).

There are multiple potential causes of the inequality in observed learning losses. One major theme in the literature is that while the vast majority of schools utilized remote learning as a substitute for in-person instruction, the quality of remote instruction (Ferren 2021; Rickles et al. 2020) and the students' access to the remote instruction (Ferren 2021) was distributed unevenly. As of June 2020, only one in three school districts had communicated an expectation that teachers provide instruction while urban schools remained closed (Gross and Opalka 2020). Urban and suburban districts were significantly more likely than rural and small-town districts to communicate an expectation of instruction to their teachers, and the most affluent districts were more than twice as likely as districts with the highest concentrations of low-income students to require at least some teachers to provide live, synchronous instruction (Gross and Opalka 2020). During this same time period, spring 2020, 87% of school districts in the United States expected teachers to meet with their students weekly, whether remotely or in person (Hodgman, Sabatini, and Carminucci 2021). Again, there is a socioeconomic divide within this statistic, as 40% of low-poverty districts expected daily meetings, while only 28% of high-poverty districts expected the same (Hodgman, Sabatini, and Carminucci 2021). High-poverty districts were more likely to require teachers to "be available at scheduled times," meaning that the impetus to initiate meetings was on the student, rather than the teacher (Hodgman, Sabatini, and Carminucci 2021).

The inequality continued in the 2020-21 school year, including along racial lines: only 67% of districts where fewer than 15% of students were White had a remote learning option, while 90% of districts where at least 33% of students were White had a remote learning option (Harris 2021). As COVID-19 outbreaks had the ability to cause school closures, districts with a remote option were able to continue instruction, while districts without a remote option were forced to suspend instruction until the building was allowed to re-open (Harris 2021). Students living in districts with less educated adult populations, higher rates of single-parent households, and worse broadband access had teachers with lower rates of remote learning training (Malkus 2020).

In addition to the disparities in quality and access to remote learning, there were broader obstacles introduced by the pandemic that contributed to learning loss. Only 33% of parents said that their child could wait "as long as necessary" for the pandemic to end before experiencing negative mental health consequences (Calderon 2020). 45% of parents indicated that their child being separated from classmates and teachers was a major challenge (Calderon 2020). COVID-19 caused an increase of 17.5% to 20.2% in parental bereavement among children below the age of 17 (Kidman et al. 2021) and 28% of American students had a parent lose a job (Jaeger et al. 2021). Both of these are major stressors which could contribute to poor academic performance (Goldberg 2021). Mental fatigue was one of the most commonly reported responses to lockdowns, which makes sense given that it is caused by disruptions to one's routines and activities (Labrague and Ballad 2021). There was a rise in eating disorders and mental health-related emergency room visits for children aged 5-17 (Leeb 2020). These factors, combined with the uneven quality of remote instruction, created an environment ripe for learning loss.

2.2.1 The Oster et al. study

One study of learning loss during the COVID-19 pandemic merits a special mention. In November 2021, Clare Halloran, Emily Oster, Rebecca Jack, and James Okun published an NBER working paper titled "Pandemic Schooling Mode and Student Test Scores: Evidence from US States." This paper used virtually identical methodology and data sources to those which I had planned to use, to the point that I adjusted the data sources and methodology of my own study. Oster and her co-authors used data from the COVID-19 School Data Hub, a public database which they produced, to run difference-in-difference regressions at the district level for three groups of districts, separated into thirds by the share of the 2020-21 school year in which in-person learning was offered. The paper found that, while all states studied demonstrated an overall decline in proficiency rates between 2018-19 and 2020-21, districts which utilized in-person learning more frequently exhibited smaller learning losses. Specifically, the authors found that "moving a district from 0% to 100% access to in-person learning would mitigate test score loss by 10.1 percentage points in math and 3.7 percentage points in ELA," both highly significant.

Another notable observation from the Oster paper is the effect of participation changes on estimates of learning loss. "In all states, test participation was lower in the pandemic year than in previous years." (Halloran et al. 2021). The authors observe that test participation rates are lower in districts with higher rates of remote learning. Additionally, based on state reports, participation in 2021 standardized testing declined the most among more vulnerable groups such as low-SES students, English language learners, and others (Halloran et al. 2021). These groups typically perform worse on standardized tests than other student subgroups. This indicates that any estimate of learning loss between 2018-19 standardized tests and 2020-21 standardized tests will most likely be understated, as the observed scores from 2020-21 tests come disproportionately from higher-performing segments of the student population.

2.3 Historical Examples of Large-Scale Learning Losses Induced by Extended Interruptions of Education

The COVID-19 pandemic is not the first recorded incident in which students were forced to miss school for an extended period of time. Historical precedents for a period of time during which students missed school for months include teacher strikes, natural disasters, war, and protests. During World War II, Austrian and German children received less education than comparable children from non-war countries such as Switzerland and Sweden due to going to school for less time (Ichino and Winter-Ebmer 2004). The lack of schooling in Germany and Austria disrupted the trend of each birth year cohort achieving more years of educational attainment than the prior cohort, a trend which had been continuous for more than 20 years (Ichino and Winter-Ebmer 2004). The disruption of education caused by the war also led to a mass downturn in individual earnings for German and Austrian students at the time of the war, an economic hardship that was still felt in the 1980s at the cost of a 0.8% reduction in GDP (Ichino and Winter-Ebmer 2004).

Another example of widespread learning loss is labor unrest in Argentina (Jaume and Willén 2019). Argentina is the site of near-constant labor disputes, having hosted approximately 1,500 teacher strikes between 1983 and 2014 (Jaume and Willén 2019). According to a longitudinal study comparing students attending schools which had teachers strike with students at unaffected schools, the aggregate loss of earnings owed to the strikes is approximately $2.34 billion (Jaume and Willén 2019). In addition to the economic impact, affected students faced an increased likelihood of unemployment, occupational downgrading, lower family incomes, and marrying a less educated partner (Jaume and Willén 2019). Effects were even evident in the next generation, as children of former students affected by the strikes achieved worse test scores (Jaume and Willén 2019).

Other examples of large-scale learning loss are teacher strikes in New York City in 1968 and Belgium in 1990, resistance to desegregation in Norfolk, Charlottesville, and Warren County, Virginia, in 1958-59, and Hurricane Katrina in Louisiana in 2005 (Hippel 2020). In each of these situations, test scores fell by at least the equivalent of two months of learning (Hippel 2020). Additionally, students affected were more likely to repeat a grade and did not advance as far in higher education (Hippel 2020). If America had not attempted to cushion the impact of COVID-19 on students' education, we could almost certainly expect similar results for current students.

2.4 Remote Learning: Potential Costs and Benefits

In an effort to mitigate the potential hardships caused by similar extended absences, the American educational system relied on remote learning: nearly 93% of households with school-age children reported some form of remote learning in 2020 (McElrath 2020). The concept of remote instruction began with broadcast radio in the mid-1920s: one writer believed that "every home has the potentiality of becoming an extension of Harvard University." (Baum and M. McPherson 2019). However, such enthusiasm did not last long, and by 1931, the number of educational radio stations in the United States had fallen from 128 to 49, largely due to lack of interest and preference for music and comedy programs (Baum and M. McPherson 2019). A similar pattern occurred with the advent of television, as initial excitement about the potential of educational television programming gave way to an eventual decline due to the greater popularity of game shows, drama and comedy programs (Baum and M. McPherson 2019).

Since the inception of the internet, remote learning has once again found new life (Baum and M. McPherson 2019). In general, remote education provides an opportunity for schools to reach more students while simultaneously decreasing costs, but remote instruction has mixed results in terms of efficacy (M. S. McPherson and Bacow 2015). A study of college students showed that students who took a class remotely received higher grades than their in-person counterparts, but the relationship was reversed after accounting for instructor-specific factors (Altindag, Filiz, and Tekin 2021). This study suggests that online instruction is less effective than in-person instruction, and students had been receiving higher grades due to external factors such as the instructor's leniency in grading (Altindag, Filiz, and Tekin 2021). In fact, this study was able to quantify the grade inflation associated with remote learning: receiving an A was 7% more likely via remote learning than in-person, yet when the cohort of students took an identical test, the in-person students outperformed the remote students (Altindag, Filiz, and Tekin 2021). Other studies have similarly found superior learning outcomes for in-person students compared to remote students (Alpert, Couch, and Harmon 2016; Figlio, Rush, and Yin 2013; Kofoed et al. 2021). The negative impact of remote learning was especially evident among academically at-risk students (Kofoed et al. 2021).

One major difficulty of remote instruction is ensuring student engagement (Pazzaglia et al. 2016). Learning requires active engagement of the mind; it is not enough to simply sit in a room in which a teacher is speaking and giving demonstrations (Pazzaglia et al. 2016). Students who engaged for two or more hours per week had markedly better course outcomes than students who engaged for fewer than two hours per week (Pazzaglia et al. 2016). During remote courses, it is more difficult for a teacher to gauge classroom engagement and to hold students accountable for remaining engaged (Pazzaglia et al. 2016). Frequent and constructive student-instructor interaction, which is often missing in a remote setting, increases student satisfaction (Baum and M. McPherson 2019). Remote learning can lead to an absence of meaningful intrapersonal connections, contributing to weaker outcomes for students (Baum and M. McPherson 2019).

Remote learning requires a higher level of motivation on the part of the student to maintain engagement in the class (Grewenig et al. 2021). Students with lower initial achievement, lacking the support system that exists in a school setting, may not possess the knowledge and skill base necessary to make gains through self-regulated learning (Grewenig et al. 2021). If the student feels that their return to time invested is low enough, they will replace the time spent on school with more rewarding activities (Grewenig et al. 2021). This was demonstrated in Germany, where low-achieving students increased the amount of time spent on activities detrimental to education such as TV, computer games and social media at a rate much higher than that of high-achieving students (Grewenig et al. 2021).

During remote learning, only 15% of districts in the U.S. expected their elementary students to be receiving instruction for more than four hours per day, while 85% expected instructional time to dip under four hours - well below the pre-pandemic average of five instructional hours per day (Rickles et al. 2020). With this decrease in instructional time, negative outcomes are expected: in a randomized study, students receiving "compressed" lectures of one hour scored 3.2 points lower on a 100 point scale than students taking the same class but receiving information over two hour-long lecture periods (Joyce et al. 2015). Even cramming does not appear to be a reliable method for overcoming decreased instructional time.

During the COVID-19 pandemic, teachers, students, and families of students indicated difficulties with remote instruction (Hamilton, Kaufman, and Diliberti 2020; Marshall, Shannon, and Love 2020; Schwartz et al. 2020; Stelitano et al. 2020). Only four states and the District of Columbia required teachers to receive online instruction prior to teaching a K-12 course (Zweig and Stafford 2016), and only 7.6% of teachers had taught remotely prior to the onset of the pandemic (Marshall, Shannon, and Love 2020). Therefore, although the majority of teachers responding to a survey indicated that they had received some training in remote instruction during the pandemic, there were gaps in their expertise (Hamilton, Kaufman, and Diliberti 2020). In particular, teachers indicated difficulties pertaining to certain groups such as younger students (Marshall, Shannon, and Love 2020), students with disabilities and homeless students (Hamilton, Kaufman, and Diliberti 2020). Other common concerns indicated by teachers included incomplete curriculum coverage, focusing more than usual on review and less on new content, and inability to engage with students and assess their well-being (Hamilton, Kaufman, and Diliberti 2020).

Another major obstacle to remote learning was internet access (Schwartz et al. 2020). In districts where more than half of students were Black or Hispanic, the majority of district leaders ranked internet access as the greatest challenge (Schwartz et al. 2020). Only 30% of teachers in high-poverty schools reported that all of their students had access to the internet, while 83% of teachers in low-poverty schools reported that to be the case (Stelitano et al. 2020). Income also provides a proxy for the incidence of remote learning as from May 28 to June 2, 2020, 85.8% of households with incomes of $100,000 or more used online materials, while 76.5% in the $50,000-$99,999 range and 65.8% in the $49,999 or less range used online materials (McElrath 2020). Internet access was not only a major hurdle for remote instruction, but a driver of inequality.

2.5 What Else Effects Learning Loss? Potential Moderators

The quantity and quality of remote instruction, as well as the access to an internet connection, were not the only possible moderators of learning loss. Prior academic achievement acts as a moderator, as previously high-achieving students do not experience learning losses to the same degree as lower-achieving students (Altindag, Filiz, and Tekin 2021). In this case, prior academic achievement may be acting as a proxy for non-cognitive behaviors associated with success such as grit, tenacity, and belief in the value of academic work (Farrington et al. 2012). Students with better coping skills and personal resilience have demonstrated a superior ability to avoid lockdown-induced fatigue, which negatively affects academic performance (Labrague and Ballad 2021). Students with higher levels of socio-emotional skills have superior academic outcomes, including decreased learning losses (Salmela-Aro et al. 2021). Having coping strategies sufficient to deal with stressors helps students interpret information accurately rather than becoming overwhelmed, allowing them to focus their attention towards productive outlets such as education (Salmela-Aro et al. 2021). The idea of non-cognitive skills supporting learning loss prevention is confirmed by a study demonstrating that undergraduates who scored higher on traits such as agreeableness, conscientiousness, and openness to new experiences outperformed their peers on academic exams (Yu 2021).

Another potential moderator of COVID-19-induced learning losses lies in the family. Family support could act as a substitute for the teacher-student relationship (McElrath 2020). Given that teacher-student relationships are crucial to student engagement (Quin 2017), having a parent at home to motivate the student and ensure they are remaining engaged in their education could provide a large advantage in facilitating learning and thus decreasing learning loss. By April 2020, nationwide internet search intensity for both school- and parent-centered online learning resources had roughly doubled prior to pre-pandemic levels (Bacher-Hicks, Goodman, and Mulhern 2020). This suggests that families were getting involved in their children's education and seeking to provide support where it was lacking. Income acted as a proxy for level of familial engagement, as wealthier areas of the country saw substantially larger increases in search intensity (Bacher-Hicks, Goodman, and Mulhern 2020). While non-cognitive skills as well as familial income and engagement provide potential moderators to the size of learning losses, I focus my study on the incidence of remote education as a moderator. I achieve this analysis by using regression analyses to separate the impact of remote learning rate from alternative moderators.

3 Data and Methods

3.1 Data Sources

Standardized Test Scores. In order to perform this analysis, I use test scores from the 2018-19 school year and the 2020-21 school year. The U.S. Department of Education granted a blanket waiver of the standardized testing requirement of the Every Student Succeeds Act for the 2019-20 school year, so there is no set of standardized test scores from that year (Perez Jr. 2021). I analyze test scores for 3rd to 8th graders in my study, as did the Oster et al. study. My study builds on Oster et al.'s working paper, which analyzed 12 states: Colorado, Connecticut, Florida, Massachusetts, Minnesota, Nevada, Ohio, Rhode Island, Virginia, West Virginia, Wisconsin, and Wyoming. These states were selected based on three conditions:

1) at least 2 years of pre-pandemic test data demonstrating no pre-existing trend in test scores,

2) the same standardized testing program delivered in 2018-19 and 2020-21, and

3) a 2021 statewide standardized testing participation rate of at least 50%.

I removed two states included in the Oster et al. analysis from my own analysis. Ohio was excluded from my analysis because only district-level results were available, rather than school-level. Additionally, Virginia was excluded from my analysis because the number of students taking the exam in each school was unavailable, so I was unable to establish appropriate weights for my regression. Based on these conditions, I arrived at my final list for analysis:

1) a consistent testing program across 2018-19 and 2020-21,

2) a statewide standardized test participation rate of at least 50%,

3) school-level results available in both 2018-19 and 2020-21 including proficiency rate and number of students tested.

My final list of ten states is as follows: Colorado, Connecticut, Florida, Massachusetts, Minnesota, Nevada, Rhode Island, West Virginia, Wisconsin, and Wyoming. The states are indicated in green in Figure 1. Each of these states is in the Oster et al. study, but the exact schools included in the study may be different: first, because my regressions are run without filtering out schools with proficiency pre-trends, as the Oster et al. study did, and second, because a small number of schools were not included in the SafeGraph dataset, and were therefore removed from my study.

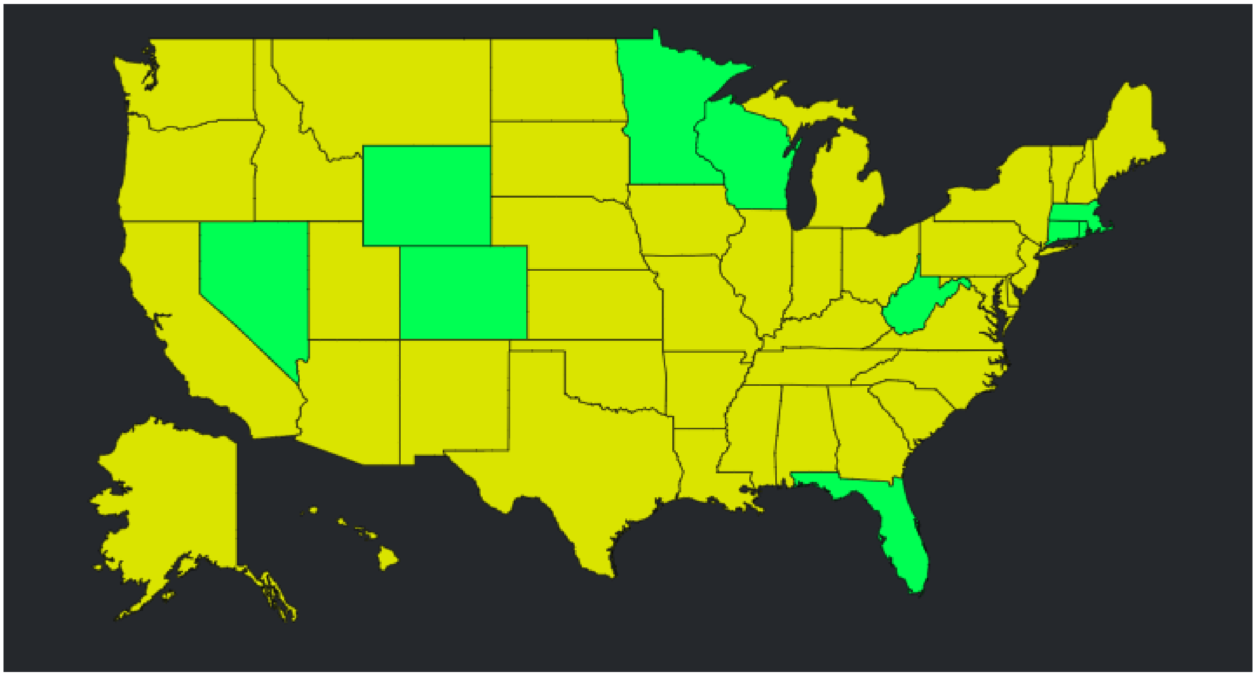


Figure 1: States Included in the Study

For each of these states, I retrieved test score data for both 2019 and 2021 from their state Department of Education's website. A list of the URLs from which test data was retrieved is included in Table 26, and a full table of the names of the assessments in my analysis is presented in Table 1.

After uploading the standardized assessment data files, they were cleaned to include only the relevant information. The measures included were percentage proficient and the number

State	Name of State Assessment
Colorado	Colorado Measures of Academic Success
Connecticut	Connecticut Smarter Balanced Assessment
Florida	Florida Standards Assessments
Massachusetts	Massachusetts Comprehensive Assessment System
Minnesota	Minnesota Comprehensive Assessments
Nevada	Smarter Balanced Assessment
Rhode Island	Rhode Island Comprehensive Assessment System
West Virginia	West Virginia General Summative Assessment
Wisconsin	Wisconsin Forward Exam
Wyoming	Wyoming Test of Proficiency and Progress

Table 1: State Assessment Names

of students completing the test, in order to establish weights for each school. I decided to collapse data across grades, meaning that age is not a variable considered in this study. This was because due to the Family Educational Rights and Privacy Act (FERPA), any potentially identifiable information is required to be masked in publicly available data files. Therefore, when the total number of proficient students in a grade was small enough,[2] the exact totals were masked by "¡n" or a similar non-numerical entry. These entries were less common when data was aggregated across grades for each school, as the total number of proficient students and total students tested was larger.

Free and Reduced Price Lunch Data. Free and reduced price lunch data was retrieved from the Common Core of Data, compiled by the National Center for Education Statistics (NCES)(*Common Core of Data (CCD)* 2022). Specifically, the data was retrieved from the Public Elementary/Secondary School Universe Survey, most recently administered in 2020-21. This means that the data aligns with the second year of standardized test results observed. This data was aggregated at the school level, meaning that it required little manipulation for the purposes of this study.

Students from families earning 130% or less of the federal poverty line qualify for free lunch, while students whose families earn between 130% and 185% of the federal poverty line qualify for reduced price lunch (Snyder and Musu-Gillette 2015). In my analysis, I aggregate students who qualify for free lunch and those who qualify for reduced price lunch. Free and reduced price lunch (FRPL) is a commonly used proxy for students' economic disadvantage in public schools, as it is often the only available indicator of student socioeconomic status (Snyder and Musu-Gillette 2015). One study suggests that while FRPL is a better indicator of student educational disadvantage than IRS-reported household income, it captures student poverty rates to a varying degree across schools, and is therefore an imprecise measure of school-level economic disadvantage (Domina et al. 2018). I have included FRPL data in my analysis, and discuss the matter further in the Discussion portion of the paper.

[2] The exact number was different by state, but generally between 6 and 10 students.

Demographic Data. Demographic data for this study is also retrieved from the National Center for Education Statistics' Common Core of Data, specifically the 2020-21 Public Elementary/Secondary School Universe Survey (*Common Core of Data (CCD)* 2022). This data was aggregated at the school level, and required little manipulation for the purposes of this study. The measures included in this survey were percentage White, percentage Black, percentage Hispanic, percentage Hawaiian/Pacific Islander, percentage Asian, percentage Native American, percentage Hawaiian, and percentage mixed race.

SafeGraph Data. The most unique dataset used in this study is the SafeGraph dataset. SafeGraph is a data company that aggregates anonymized location data from numerous applications in order to provide insights about physical places, via the SafeGraph Community. To enhance privacy, SafeGraph excludes census block group information if fewer than five devices visited an establishment in a month from a given census block group (*SafeGraph* 2022). In this study, I use SafeGraph's data to serve as an independent variable measuring the amount of foot traffic in schools. Theoretically, anybody carrying a cell phone will show up in SafeGraph's dataset. This allows me to compare the level of foot traffic in schools during the 2020-21 school year to the level of foot traffic in schools during the 2018-19 school year. I downloaded the "Elementary and Secondary Schools" dataset from SafeGraph, and filtered the dataset so that only the ten states in my analysis were included. I additionally filtered so that only schools with at least 10 visits in both the 2018-19 and the 2020-21 school year were included. This measure was taken to eliminate schools with unrealistically low numbers of visits, which could potentially lead to skewed data.

3.2 Data Manipulation

The SafeGraph dataset required fairly extensive manipulation prior to use. First, I had to decide whether to use visitors by week or visits by week as my independent variable. Each choice had potential benefits and drawbacks: using visits by month would give me a more accurate picture of traffic, as using visitors by month would lead to a person who entered the school once in a month being counted as equal to a person who visited the school every weekday. The potential downside of using visits rather than visitors is that visits could be more easily confounded, especially for schools in high-traffic areas such as cities where someone walking by the school would be more likely to appear in the dataset despite not entering the school. I decided to use visits instead of visitors, because the improved accuracy outweighed the potential pitfalls in my view.

The next step that I took was removing all data from the weekends and summers. In order to have an accurate picture of how "open" a school was, my goal was to determine the number of visits to that school during school hours. The most granular level of data was by the day, so I eliminated weekends for a start. Another question was which dates to include in my dataset as the "school year". In the United States, school calendars are set at local and state levels, so there is no standardized time frame for the school year (DeSilver 2019). I decided to count dates between August 1 and June 30 as the school year. This is a period of 10 months, which should capture almost all school days, with some summer days included on either end depending on whether a school began its year slightly earlier or later. I do not believe that including summer data biases my results, as visit counts are quite low on those days compared to days during the traditional school year.

A potential confound of my experiment is school buildings that are used for non-school purposes in addition to school activity. For example, a school which was used as a community center, either before or during the COVID-19 pandemic, would have inflated visit counts in comparison to school-related visits. However, this problem would be mitigated if the school continued to serve the same functions during the pandemic that it did prior to the pandemic: my variable of interest is the ratio of visits in the pandemic year to the non-pandemic year, so a school with proportionate usage pre- and inter-pandemic should not cause a problem.

Another step that I took was normalizing the SafeGraph dataset. According to SafeGraph, their data comes from a sample of phones, and the number of phones changes by the month. To account for this, I normalized my data by dividing each location's visit count by a ratio of the total number of phones in the dataset as compared to the first observed month, August 2018. At this point I had a dataset with an observation for each school, and variables for the school's state, the number of visits to the school by month, and a sum of the visits over the course of the school year. As a check, I made a plot of the total number of visits to schools by month in my dataset to see whether it aligned with the rhythm of the school year and the onset of the COVID-19 pandemic. Visits by month are plotted in Figure 2.

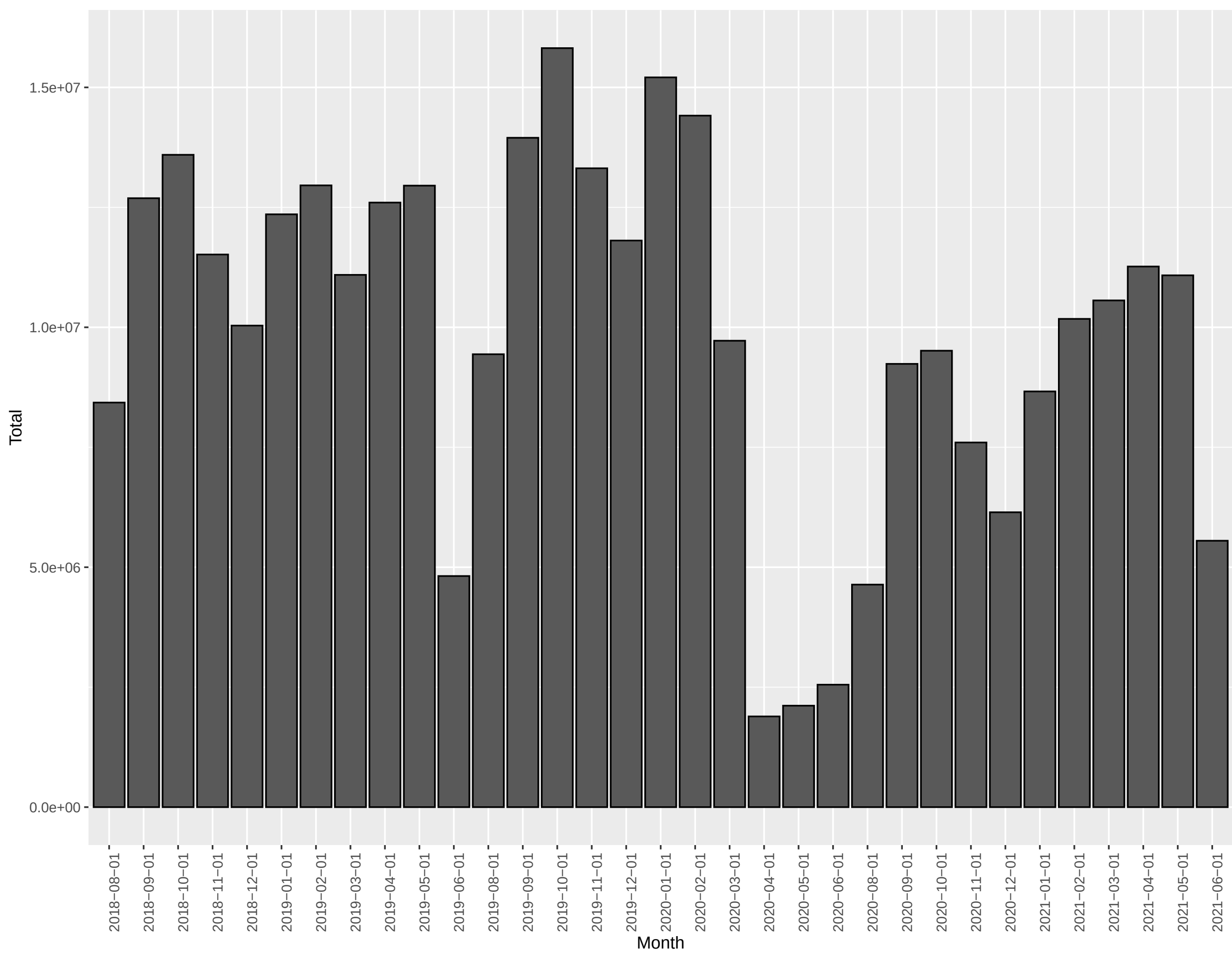


Figure 2: School Visits by Month, August 2018 - June 2021

With some outliers, this graph reflects the expected trends. The months of August and June which bookend each school year have fewer visits than October through May, due to the first half of August and the second half of June being non-school days for most places in the country. As expected, December has the lowest number of visits among months from September to May, because the holiday break from Christmas to New Year's Eve removes about one quarter of the month's school days for many schools. In addition to the expected summer and holiday trends, this graph aligns with what one would expect regarding the COVID-19 pandemic and school traffic. Given that the pandemic caused schools to close anywhere from March 12, 2020 at the earliest to April 2, 2020 at the latest, it makes sense that March 2020 shows a steep decline in traffic compared to February 2020 (Goldberg 2021). Likewise, it is logical that April 2020 is the least-trafficked month of any included in this sample. Not until September 2021 do schools' visit counts begin to approach normalcy, although they are still well below the levels of 2020 and 2019. This pattern remains throughout the 2020-21 school year, which reflects the fact that some schools were open, some were remote, and some incorporated a mixture of the two approaches.

With the SafeGraph dataset checked for logic, the next step was to remove duplicated schools. Unfortunately, none of my datasets had any distinguishing information beyond school name and state, so schools of the same name in the same state were impossible to distinguish. This would have caused an issue when combining datasets, as the key used to combine was a combination of the school name and state. Removing duplicated school names within the same state reduced the number of schools in all datasets by only 2.5%. I do not believe that removing schools with identical names in the same state biases the study in any systematic way.

After removing duplicated school names, I combined the SafeGraph dataset with the standardized test dataset as well as the demographic and FRPL datasets. Some schools did not have entries in each of these datasets, and these schools were removed from the analysis because I would be unable to perform a complete analysis of that school. My resulting dataset included 7,810 schools from my ten analyzed states, with the distribution indicated in Table 2.

This includes all schools with valid data for demographics, FRPL, and SafeGraph, as well

State	Number of Schools	Enrolled Students (2018-19)
Florida	2,092	1,427,768
Massachusetts	1,104	507,774
Minnesota	1,079	452,615
Wisconsin	1,183	428,245
Colorado	953	423,934
Connecticut	585	253,103
West Virginia	429	140,429
Wyoming	187	50,603
Rhode Island	118	43,412
Nevada	80	34,995

Table 2: Schools and Students in Sample by State

as *either* valid data for English-Language Arts (ELA) standardized testing *or* Mathematics standardized testing. 52 schools had valid ELA data but no valid math data, while 36 schools had valid math data but no valid ELA data. These schools were only included in the analyses for which they had valid data.

3.3 Measures

Openness. Percentage of remote instruction is the independent variable in my analysis. To establish a measure for openness, I use the 2018-19 school year as a baseline. I measure the percentage, as compared to the baseline of 2018-19, of capacity at which a school operated, *prior to testing*, in the 2020-21 school year. Therefore, I sum the visits to schools from August through March, and use that as the number of visits in the school year. While it is true that the school year lasts until anywhere from May to June, I am only interested in school operations that would have an effect on the standardized testing results measured for that year.

I sum the number of weekday visits to each school from the SafeGraph dataset from August through March for both 2018-19 and 2020-21. I then divide the visits in 2020-21 by the visits in 2018-19 and multiply by 100, which produces a measure of ”openness”. A school with the same number of visits in 2020-21 as in 2018-19 would receive a 100% for openness, while a school with half the visits in 2020-21 as in 2018-19 would receive a 50%, and a school with no visits in 2020-21 would receive a 0%.

One potential issue with this method is schools that had trends in enrollment regardless of the pandemic. For example, a school which lost 20% of its student population between 2018-19 and 2020-21 due to its town losing people would show an openness below 100% for the 2020-21 school year, even if it operated in-person at full capacity. To attempt to account for this, I created a measure of ”projected 2020-21 capacity”. This measure took the difference between the 2018-19 school visits and the 2019-20 school visits and extrapolated that difference to project the ”expected” number of school visits in 2020-21. Dividing the actual number of observed school visits in 2020-21 provided a measure of ”openness based on projected capacity.” A comparison of the basic openness measurement against the openness based on projected capacity measurement is demonstrated in Figure 3, and the formula is as follows:

$$O_{20-21} = \frac{\sum SV_{20-21}}{\sum SV_{19-20} + (\sum SV_{19-20} - \sum SV_{18-19})}$$

$$O_{20-21} = \frac{\sum SV_{20-21}}{\sum SV_{19-20}}$$

The projected openness method results in fewer schools having unrealistically high openness numbers. For this reason, I decided to use openness based on projected capacity as the default measure of openness in this study.

Next, I had to decide what to do with schools that had an openness value greater than 100%. Outside of random SafeGraph panel growth which was unaccounted for by the normalization process, the only way for a school to be above 100% openness during the 2020-21 school year was for the school's population to grow enough to compensate for the decrease in people in the building due to COVID. Options that I considered included filtering the dataset to schools with an openness value of 100% or lower, choosing a different, slightly

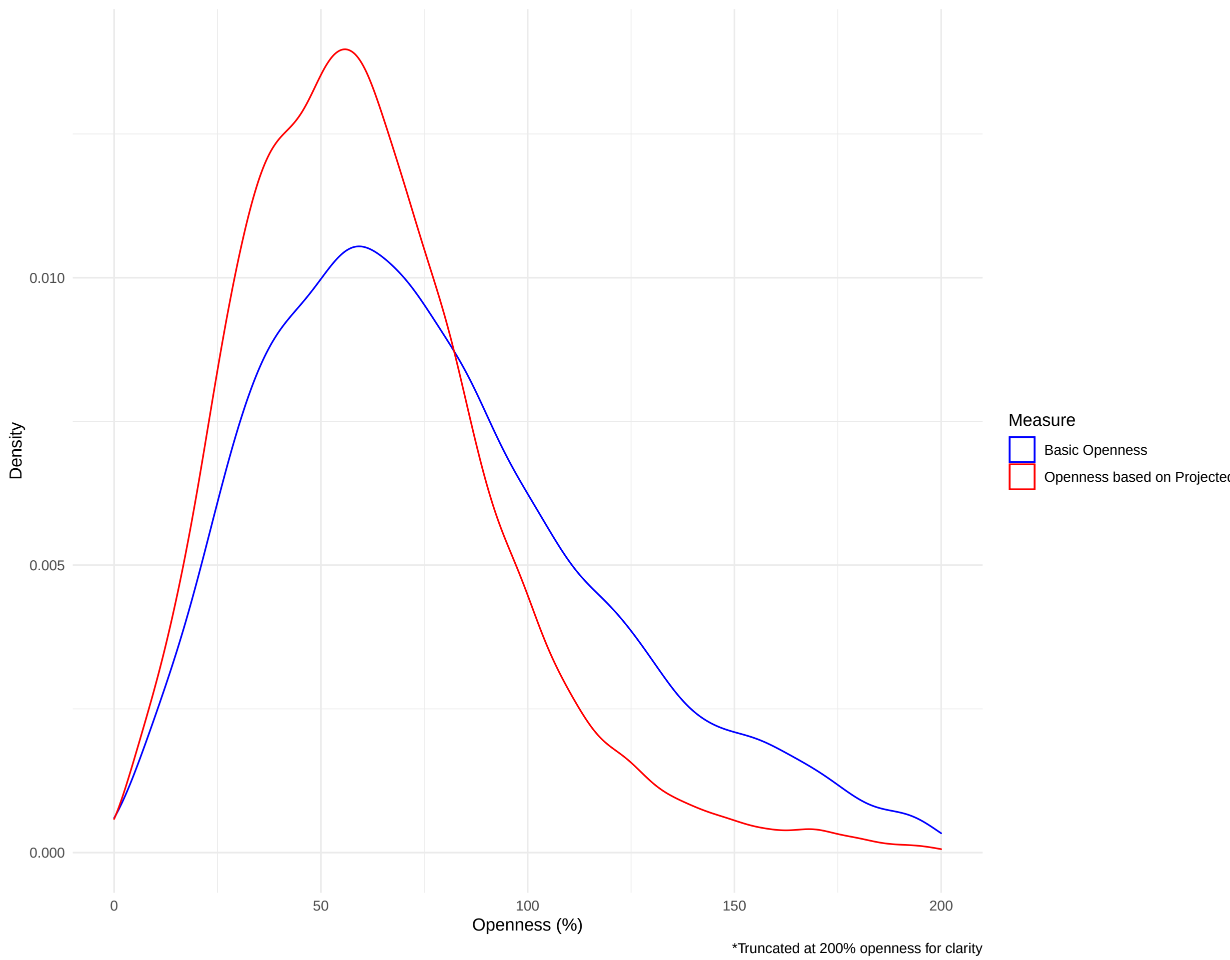


Figure 3: Comparison of Openness Measures

higher cutoff for openness, replacing values above 100% openness with 100% openness, or leaving the dataset as is. I decided against leaving the dataset as is: some values, such as one school with an openness of 2,771%, were completely illogical and clearly the result of a new school building opening or something similar. In the end, I have run regressions for three approaches: filtering the dataset at 100% openness, filtering the dataset at 150% openness, and replacing all openness values between 100% and 150% to reflect the theory that these schools were likely operating at full capacity during the 2020-21 school year, and their high openness numbers are due to random SafeGraph panel growth, or an inadequate panel size in the baseline year of 2018-19. There are only 212 schools excluded from the database by filtering out schools with openness values above 150%. A density plot of school openness

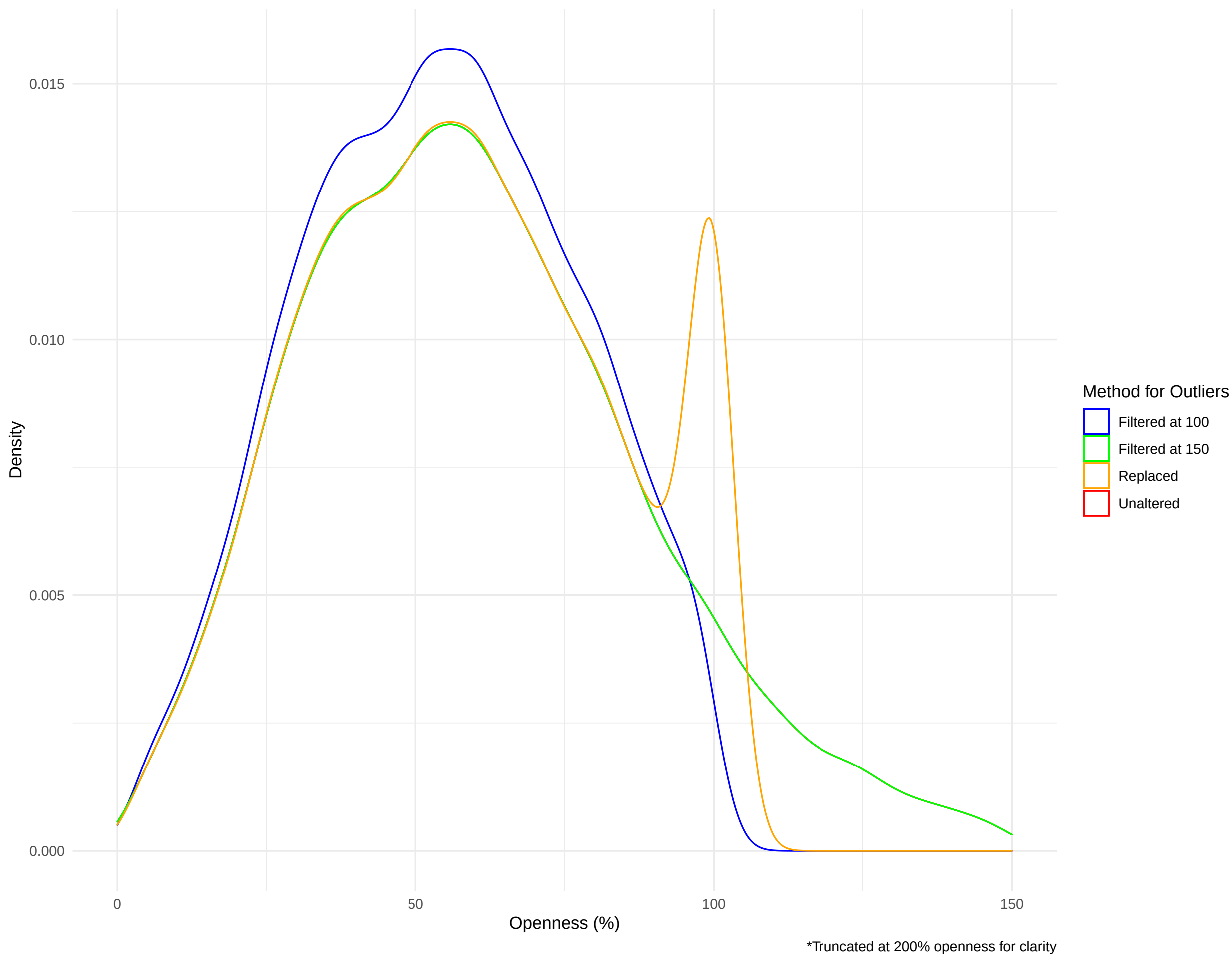


Figure 4: Comparison of Methods for Outliers

based on method of dealing with high openness scores is included in Figure 4.

Figure 4 shows that filtering at 100 and 150 have similar density plots from 0% to 100% openness. The replacement method also shows a similar trend, with the exception that it has a large cluster of schools at 100% openness, as a result of the 658 schools with openness values between 100% and 150% all being assigned openness values of 100%. The unaltered dataset is difficult to observe on the graph above, as it is almost perfectly aligned with the "filtered at 150" method. This makes sense because there are only 212 schools in the unaltered dataset that are not included in the "filtered at 150" dataset, and all of these schools have openness values above 150%, and therefore are not displayed on the graph. I will use the filtered at 100, filtered at 150, and replaced methods in all regressions involving openness.

2019 Percent Proficient. Percent proficient is the basis of the main dependent variable in my analysis. At the school level, this statistic indicates what percentage of students met the minimum requirement for proficiency for their state's standardized assessment. Given that these standards are determined by state, some states have more stringent requirements for proficiency than others. However, the within-school model of my analysis negates the potential for inter-state variation. It is important to note that cross-state comparisons of proficiency may not be valid, and intra-state proficiency measurements should be the primary focus of this study. In addition to percent proficient, I use the number of students taking the test for each school in order to establish weights. I use the 2019 testing numbers to establish the weights because pre-pandemic test participation is a better measure of school size than post-pandemic, when participation in standardized testing became much more variable.

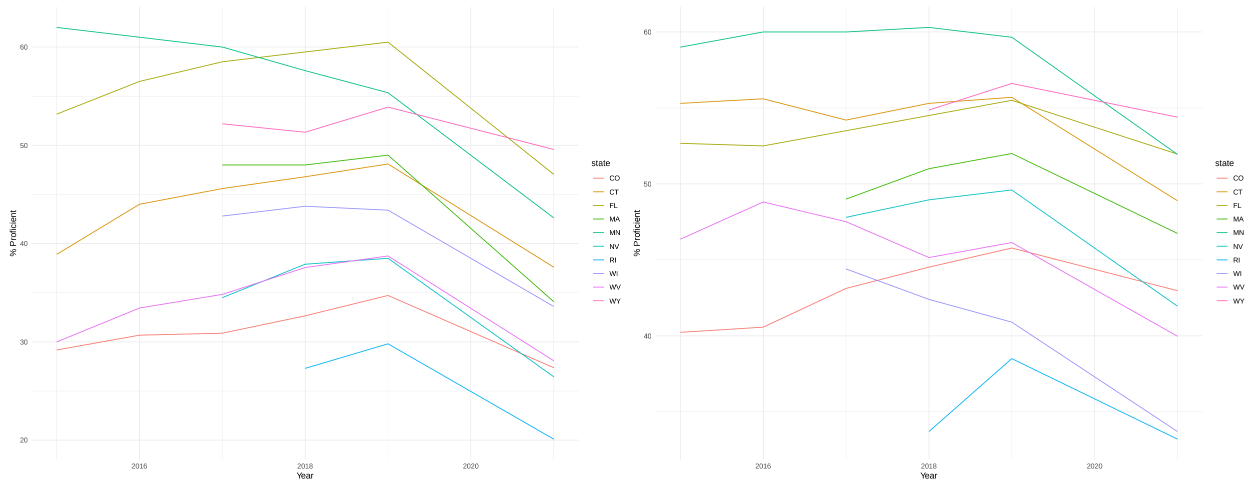
2021 Percent Proficient. While 2019 proficiency percentages will establish the baseline, 2021 proficiency percentages will provide me with a point of comparison.[3]

Learning Loss. The main dependent variable in my analysis, difference in proficiency, is calculated for each school. The first step is subtracting the percentage proficiency in 2019 from the percentage proficiency in 2021. This provides a negative value if the school had a lower proficiency percentage in 2021 than in 2019, and a positive value if the school had a higher proficiency percentage in 2021 than in 2019. I call this measure "learning loss", and its formula is given below.

$$LL = PP_{2021} - PP_{2019}$$

Every state experienced learning loss to some degree in Spring 2021, with some states experiencing more than others. Year-by-year proficiency percentages by state are shown in Figure 5. From 2015 to 2019, trends were variable: some states demonstrated a year-on-year

[3] It is important to note that the states in this study have been selected based on the condition that they used the same testing program in 2021 as in 2019.



(a) Math (b) ELA

Figure 5: Proficiency Trends by State, Math and ELA

increase in proficiency, some demonstrated a year-on-year decrease, and some were neutral. All states demonstrate a distinct drop-off between 2019 and 2021 in both math and ELA.[4]

However, the basic measure of learning loss could potentially lack context. There is potential for a large amount of school-to-school variation in learning loss based on the starting proficiency percentage. For example, a school with only 10% of students proficient before COVID can have a maximum learning loss of 10%. This would make that school appear to outperform a school which went from, for example, 70% proficiency to 50% proficiency, when in reality, the former school lost its entire proficient population, while the latter only lost 28%.

To normalize learning loss, I take the difference between 2019 proficiency percentage and 2021 proficiency percentage and divide it by the 2019 proficiency percentage. This normalizes the measure by school. I call this measure "scaled learning loss", and its formula is below. For the rest of the paper, I refer to the simpler calculation of learning loss as "unscaled."

[4] It should be noted that tests were not administered in Spring 2020, so the drop-off between 2019 and 2021 reflects a period twice as long as the standard inter-test period. Additionally, these graphs only cover the years for which the states included used the same testing regime that they administered in Spring 2021, which is why some states' data do not extend back as far as 2015.

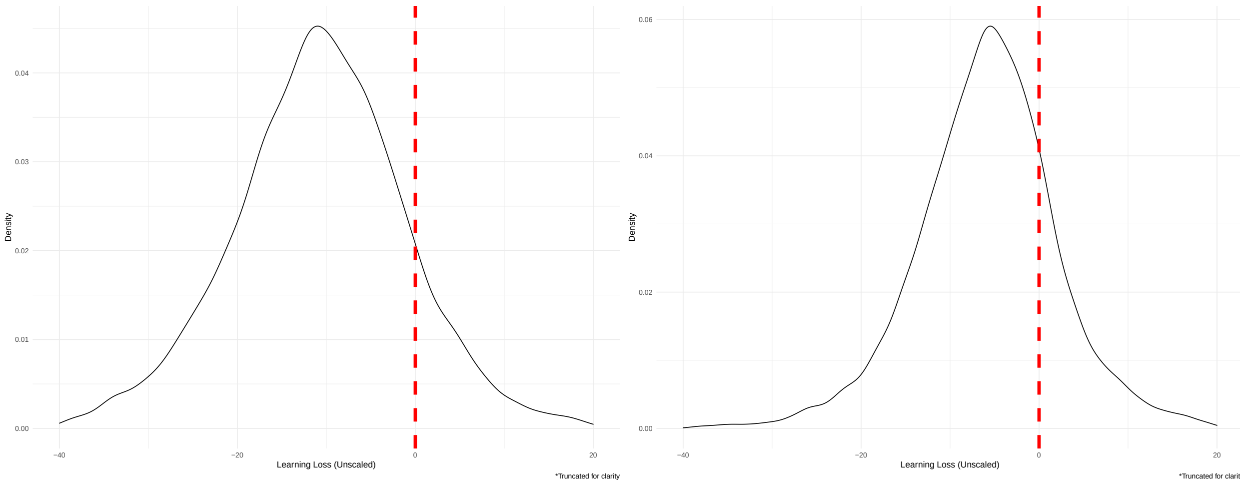
$$LL = \frac{PP_{2021} - PP_{2019}}{PP_{2019}}$$

Each of these measures has benefits and drawbacks. Overall, unscaled learning loss does a better job of demonstrating the sheer size of a school's learning loss, while scaled learning loss situates schools not in the same state in comparison to one another in a more accurate way. In the body of the study, I reference both unscaled and scaled learning loss. Regressions are run for both and are included in the regression tables section.

The counter-intuitive characteristic of learning loss is that a "negative learning loss" means that the school experienced learning loss, and had a lower proficiency percentage in 2021 than in 2019. Conversely, a "positive learning loss" indicates that the school as a whole did not exhibit learning loss, having a higher proficiency percentage in 2021 than in 2019. From this point forward in the study, I will refer to learning loss in more logical terms: a positive value indicating that a school experienced learning loss, meaning that they had a lower percentage proficiency in 2021 than in 2019.

As mentioned in the literature review, schools observed worse scores in 2021 as compared to 2019 almost across the board. Therefore, I would expect my measure of learning loss to be negative in most situations. This is supported by a quick check, as 87.38% of schools in the sample demonstrated learning loss in math, and 79.38% of schools in the sample demonstrated learning loss in ELA. The average unscaled learning loss was -0.1063, or 10.63 points out of 100, while in ELA it was -0.0578, or 5.78 points out of 100. Density plots of learning loss for both math and ELA are displayed in Figures 6 (Unscaled) and 7 (Scaled), along with box plots of learning loss by state for both subjects in Figures 8 (Unscaled) and 9 (Scaled).

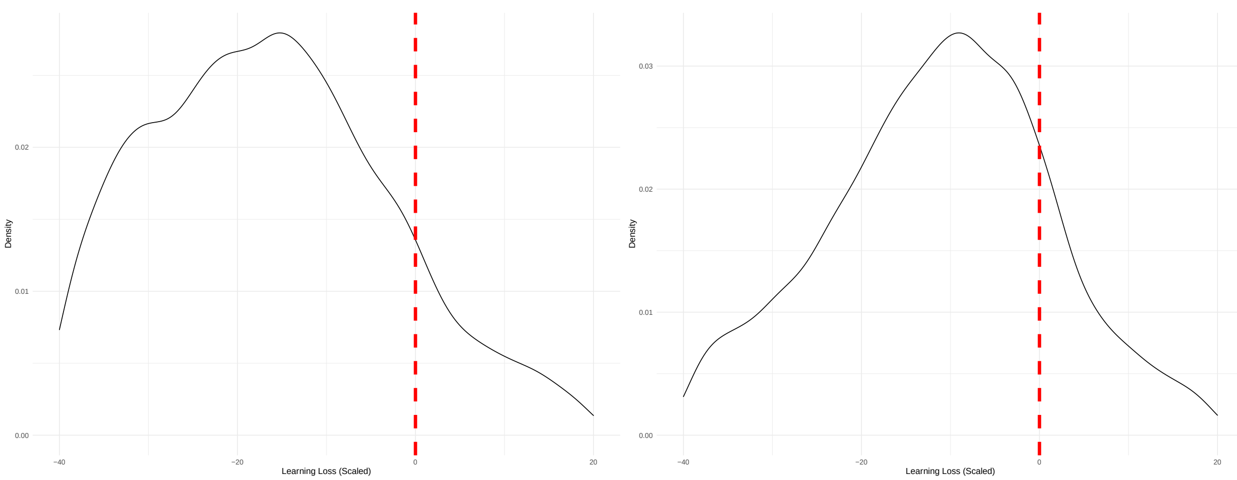
It is clear that there was widespread learning loss between 2019 and 2021. Every state experienced learning loss, with all ten in the study having a negative median value for learning loss. The median scaled learning loss in math was -23.50%, larger than the median ELA scaled learning loss of -10.78%.



(a) Math

(b) ELA

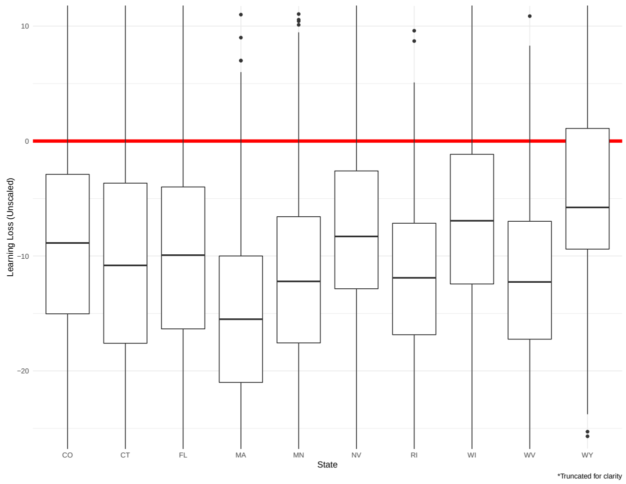
Figure 6: Density Plots, Math and ELA Learning Loss (Unscaled)



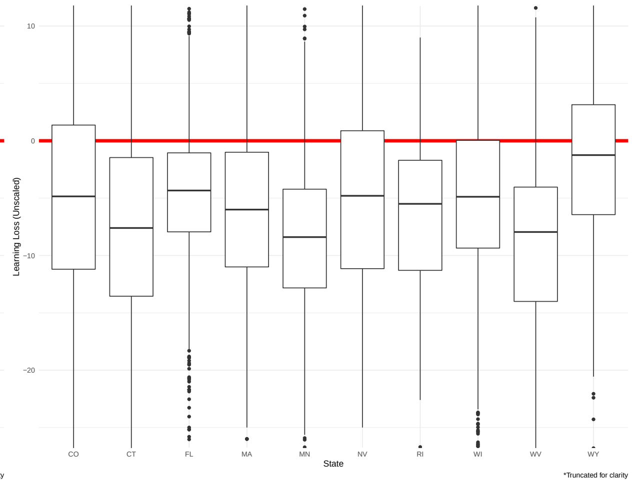
(a) Math

(b) ELA

Figure 7: Density Plots, Math and ELA Learning Loss (Scaled)

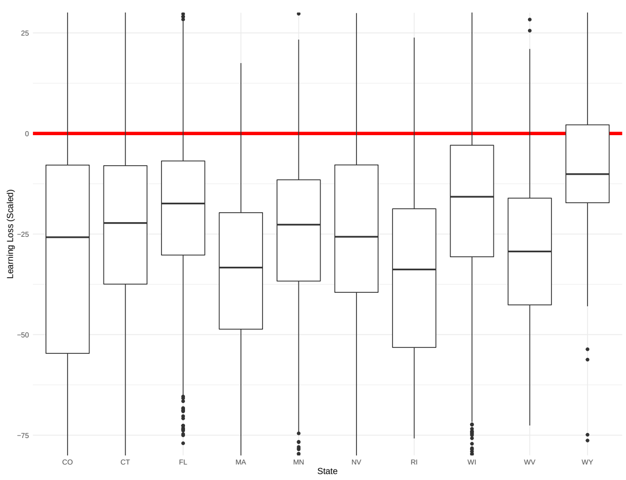


(a) Math

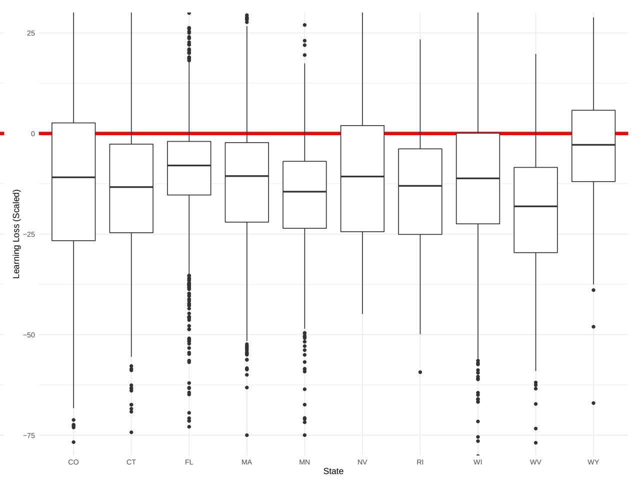


(b) ELA

Figure 8: Box Plots, Math and ELA Learning Loss (Unscaled)



(a) Math



(b) ELA

Figure 9: Box Plots, Math and ELA Learning Loss (Scaled)

Measure	Sample Average	U.S. Average	Sample States Average
Number of Students	4,138,635	49,753,676	7,967,422
Percentage FRPL Eligible	50.3	52.3	46.8
Percentage White	57.2	47.0	51.6
Percentage Black	12.5	15.1	13.5
Percentage Hispanic	21.6	27.2	25.8
Percentage Asian	3.5	5.3	4.2

Table 3: Descriptive Statistics for the Sample

Percentage Free and Reduced Lunch. I will use free and reduced price lunch eligibility by school as a proxy for the economic well-being of the school's students, in order to determine whether a school's economic well-being moderates the relationship between remote instruction and learning loss. In nine of the ten states in my study, the Common Core dataset included data for free and reduced price lunch. In Massachusetts, FRPL data was not reported. For Massachusetts, I substituted direct certification for FRPL eligibility. Any student belonging to a household that participates in Supplemental Nutrition Assistance Program (SNAP), Temporary Assistance for Needy Families (TANF), Food Distribution Program on Indian Reservations (FDPIR), as well as children who are migrant, homeless, in foster care, or in Head Start is "directly certified," and therefore categorically eligible to receive free meals at school.

Demographic Data. I will use demographic data in order to determine whether race moderates the relationship between remote instruction and learning loss. This information comes in the form of percentages. Summary statistics for my dataset are included in Table 3, along with United States averages.

There are also small percentages of Native American and Native Hawaiian students, but they are not represented in the sample enough to draw any conclusions. Based on a chi-square test, my sample is significantly different from both national averages and the average values of sample states when it comes to demographic data. In terms of the U.S. as a whole, my sample over-represents white students and under-represents all minorities. Part of this is due to state selection: when considering the average demographic information for only the states included in my sample, the disparities are smaller, but still statistically significant. This is something to keep in mind when interpreting the results of my study.

3.4 Analytic Methods

The main analysis in my study is a group of weighted linear regressions, half focusing on math and one focusing on ELA, of difference in proficiency on openness. The regressions include fixed effects of percentage free/reduced price lunch, percentages of white, black, Hispanic, and Asian students, and state factor variables. The weights in my regressions are established using the number of test-takers for each school in the 2019 and 2021 using the following equation, derived from the equation for the difference of two variances:

$$Var(\frac{\sum pp_{2021}}{n_{2021}} - \frac{\sum pp_{2019}}{n_{2019}}) = \frac{1}{\frac{1}{n_{2019}} - \frac{1}{n_{2021}}}$$

In the equation above, pp_{2021} represents the proficiency percentage in 2021, pp_{2019} represents proficiency percentage in 2019, n_{2021} represents the number of students tested in my sample in 2021, and n_{2019} represents the number of students tested in my sample in 2019. My regression also utilizes clustered standard errors by state in order to control for any potential heteroskedastic standard errors.

This analysis will determine whether there is a correlation between the percentage that a school was open in 2020-21 as compared to 2018-19 (as measured through comparing SafeGraph data for the two years) and the difference in proficiency percentage. A statistically significant positive correlation, for example, would suggest that the more open a school was in 2020-21, the higher their difference in proficiency, and thus the smaller their learning loss was between the two years. The model for my regression is as follows:

$$
\begin{gathered}
\text{Learning Loss} = \beta_0 + \beta_1 * \text{Openness} + \beta_2 * \text{Percentage FRPL}+ \\
\beta_3 * \text{Percentage White} + \beta_4 * \text{Percentage Black} + \beta_5 * \text{Percentage Hispanic}+ \\
\beta_6 * \text{Percentage Asian} + \beta_{7 \ldots 16} * \text{Colorado...Wyoming} \\
+ \beta_8 * \text{Connecticut}+ \\
\beta_9 * \text{Florida} + \beta_{10} * \text{Massachusetts} + \beta_{11} * \text{Minnesota}+ \\
\beta_{12} * \text{Nevada} + \beta_{13} * \text{Rhode Island} + \beta_{14} * \text{West Virginia}+ \\
\beta_{15} * \text{Wisconsin} + \beta_{16} * \text{Wyoming}
\end{gathered}
$$

I examine my independent variables for collinearity using the Variance Inflation Factor (VIF). There is the potential for collinearity, if two or more of the independent predictor variable in my regression are correlated with one another. To check for interaction effects, I run separate regressions for each demographic variable including an interaction term.

In addition to my main regressions, I examine the correlation between participation rate on the standardized test in 2021 and learning loss. I seek to determine whether schools with lower participation rates did systematically better or worse, which expands on a theory raised in the Oster et al. study: The observed standardized test data does not tell a complete story, as with participation rates much lower than usual, combined with observed trends in school attendance, it is likely that the sample of students taking standardized tests in 2021 is disproportionately high-achieving (Halloran et al. 2021). Finally, I analyze whether the correlation between remote instruction and learning loss is driven by the characteristics of remote schools, the effects on remote schools, or both.

4 Results

4.1 Main Regression

My first regression is a basic linear regression without any fixed effects. I wanted to get a brief look at what a naïve correlation between school openness and learning loss would show, without taking into account any potential confounds. I ran this regression in both math and ELA for each of the three outlier methods, for a total of six regressions. The unscaled results are presented in Tables 4 and 5, while the scaled results are presented in Tables 6 and 7.

The results demonstrate a correlation between school openness and learning loss, which is unsurprising. The direction of the correlation indicates that greater openness is associated with smaller levels of learning loss. For the naïve regression, the relationship is statistically significant to the 0.01 level for all three regressions for both subjects, both scaled and unscaled. However, the results of these naïve regressions should be taken with a grain of salt, as they may be overstating the impact of school openness.

Next, I add further potential explanatory variables to the regression. The results of six linear regressions of unscaled learning loss on openness, demographic data, and FRPL data are shown in Tables 8 and 9, while the regressions of scaled learning loss are displayed in Tables 10 and 11.

Tables 10 and 11 provide an idea of the model's results, but there is one more step to take with linear regressions. The nature of my analysis is that schools are clustered by state. Therefore, it is possible that there are characteristics of states that cause schools within that state to have closer learning loss values to one another than would be expected. For example, if a state had hypothetically cut its education budget and a large group of teachers had been laid off as a result, we would expect all schools from that state to show unnaturally high learning loss.

To examine the possibility of standard error clustering by state, I plotted the residuals against openness by state, and found no obvious evidence of state clustering. Heteroskedas-

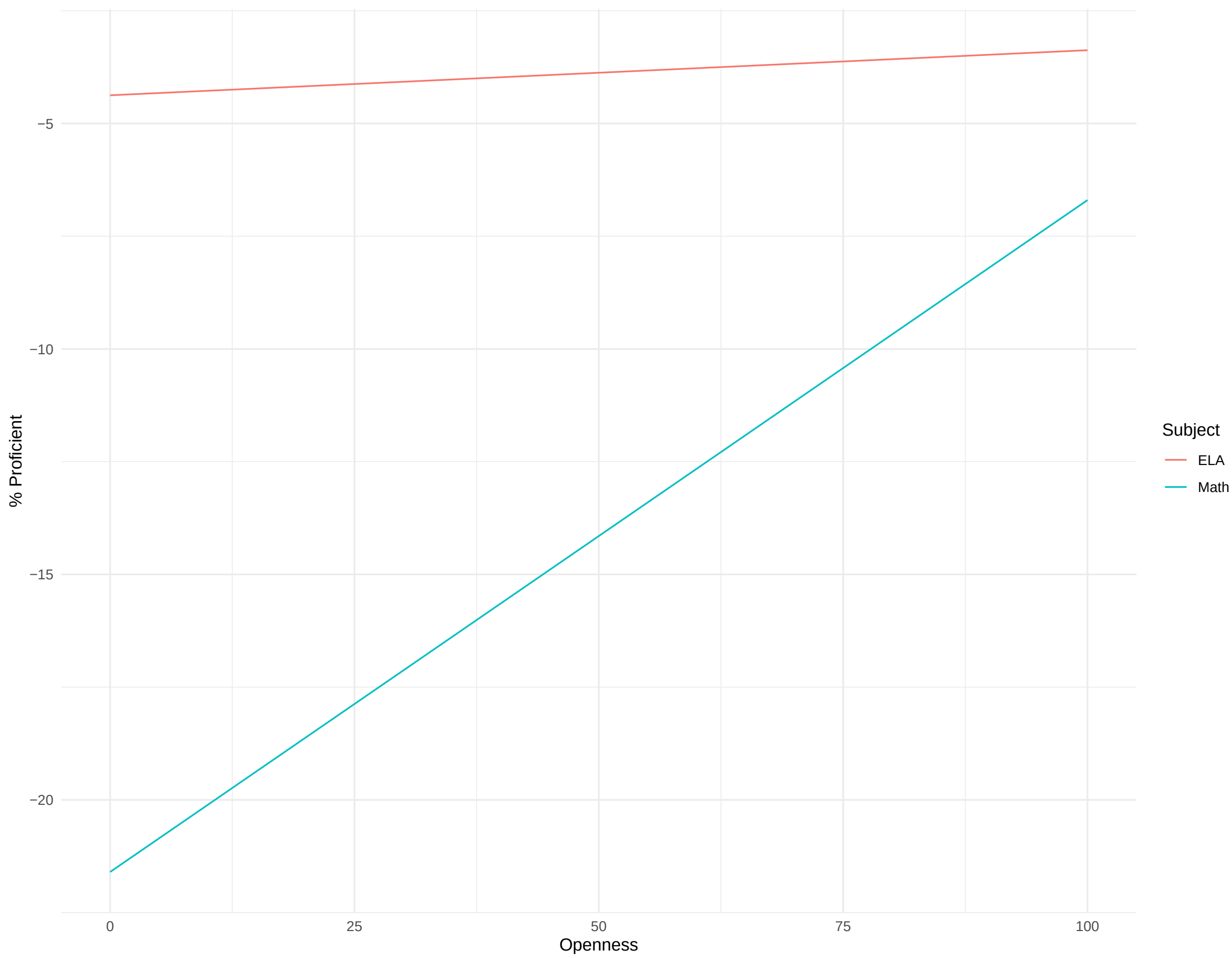
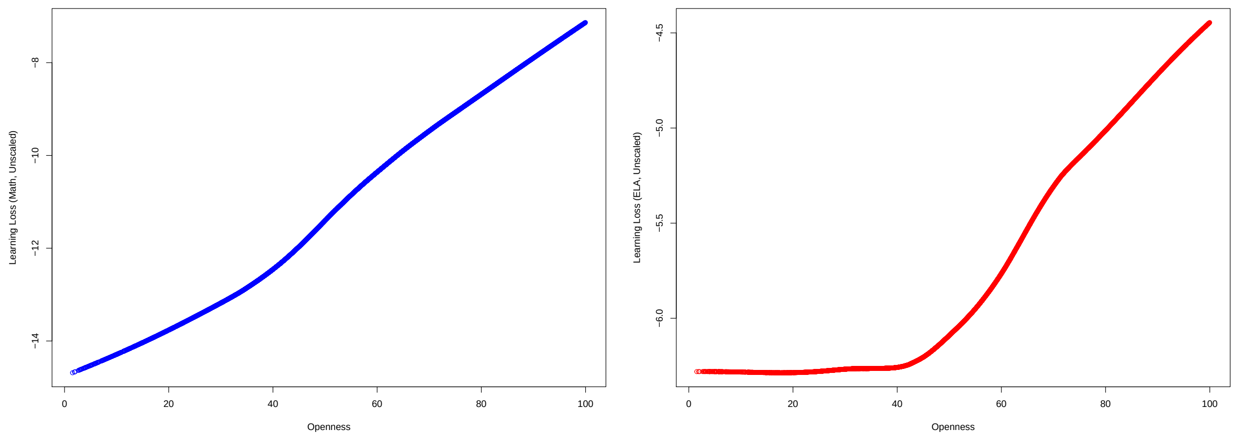


Figure 10: Linear Regression Results, Openness vs. Learning Loss

ticity plots are included in the appendix in Tables 27, 28, 29, 30, 31, and 32. In addition, I plotted residual histograms to see whether standard errors were normally distributed, and they are. Regardless of not finding any evidence of clustered standard errors, I adjusted the model to account for the potential of clustered standard errors using clustered covariance estimates from the ”sandwich” package in R. The results of the model with clustered covariance estimates by state are included for unscaled learning loss in Tables 12 and 13, and for scaled learning loss in Tables 14 and 15.

To complement the linear regressions, I use locally weighted smoothing (LOESS) in order to estimate a potential non-linear relationship between openness and learning loss. The ”lowess” function in R finds a curve of best fit without assuming any relationship between



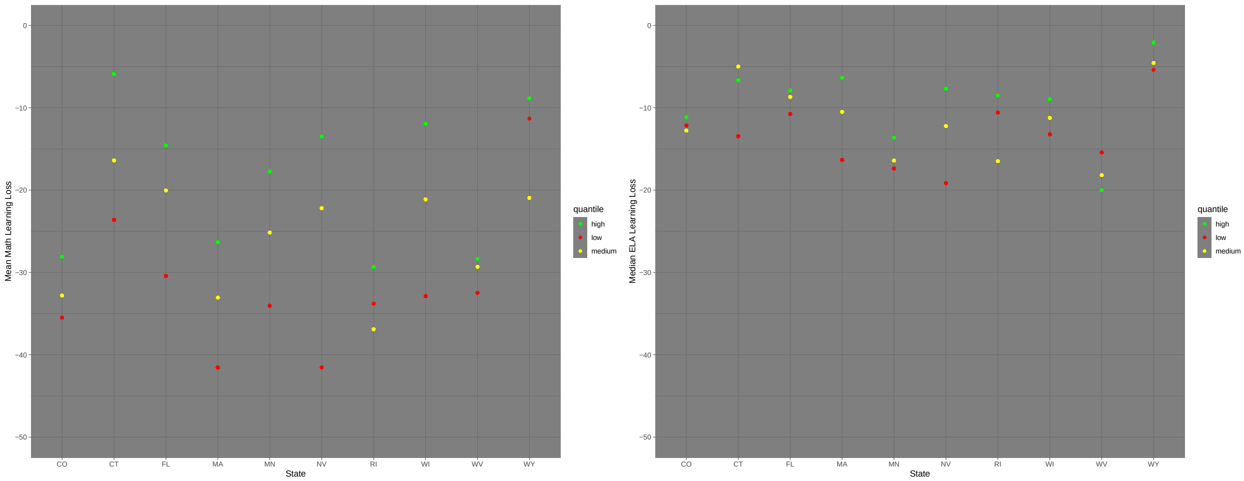
(a) Math

(b) ELA

Figure 11: LOESS Curves, Math and ELA

the two variables. LOESS does not provide an equation of best fit, but Figure 11 shows the LOESS curves for math and ELA.

The math LOESS curve is not far from linear, but the ELA LOESS curve is unusual. This smoothed curve demonstrates that the relationship between school openness and ELA learning loss is non-linear, following a concave upwards trajectory. A school which was 40% open during the 2020-21 school year would be expected to experience roughly the same learning loss as a school which was 0% open, but 40% openness serves as an inflection point after which expected learning loss decreases. This relationship is interesting, but the overall magnitude of the difference between a 0% open school and a 100% open school remains small and statistically insignificant.



(a) Math

(b) ELA

Figure 12: Median Learning Loss by State and Openness Group

4.2 Supplementary Analyses

It is apparent based on the regression results that openness correlates with learning loss for math, but is not correlated for ELA.[5] In addition, there are differential racial effects when it comes to math: higher percentages of black and Hispanic students are associated with a larger learning loss. Finally, having a greater proportion of FRPL eligible students is correlated with having a greater learning loss. There are additionally state fixed effects, but those likely have to do with the decentralized nature of the U.S. educational system. Each state had a unique response to the COVID-19 pandemic, and I do not examine these responses in this study.

To further investigate the relationship between openness and learning loss, I separate the data into states and split schools into three groups: low, medium, and high openness. These groups consist of schools that had openness scores between 0% and 33%, 34% and 66%, and 67% and 100%, respectively. The median learning loss for each state and group is shown in Figure 12.

The relationship between openness and learning loss in math is supported by these results:

[5] While the "100 method" of dealing with outliers for unscaled learning loss demonstrates a result significant at the 5% level, it is the only one of six regressions indicating a significant effect of openness on ELA learning loss, and so I do not believe it to be indicative.

in all ten states, the most open group had the least median learning loss of any group, and in seven of ten states, the least open group had the most median learning loss.

The relationship between openness and learning loss in ELA is less clear. In seven of ten studied states, the most open group had the least median learning loss, and in six of ten states, the least open group had the most median learning loss. Schools being closed has a strong detrimental effect on math, but that seems not to be the case in ELA.

I also investigate the correlation between racial minorities and learning loss. To do so, I separate the data into groups of low, medium, and high openness. These groups consist of schools that had openness scores between 0% and 33%, 34% and 66%, and 67% and 100%, respectively. Within each group, I regress the learning loss in math and ELA on the percentage of black and Hispanic students. The results of these regressions are shown in Tables 16 and 17.

The results of the regressions by type indicate no differential trends between school openness groups along racial lines. They do, however, indicate that FRPL eligible students experience larger learning loss in low-openness schools than in medium or high-openness schools, especially in math, where each 1% increase in school FRPL eligibility percentage is correlated with a greater expected learning loss by about one-quarter of a percent.

I make another attempt at investigating the relationship between race and learning loss by dividing my sample into deciles for each of % black, % Hispanic, and % Asian students, analyzing the bottom and top deciles for each race. I use ten quantiles instead of three because due to the predominately white nature of the sample, three quantiles resulted in schools being included in the "high" racial quantiles which actually had small percentages of that race. The resulting data regarding the deciles I examine is in Table 33 in the Appendix. I run a regression of learning loss on openness for each high and low deciles, with % FRPL eligible and state as controls. I attempt to find whether school openness has a greater impact in schools that are largely black, Hispanic, and Asian than it does in schools that have a small number of these students.

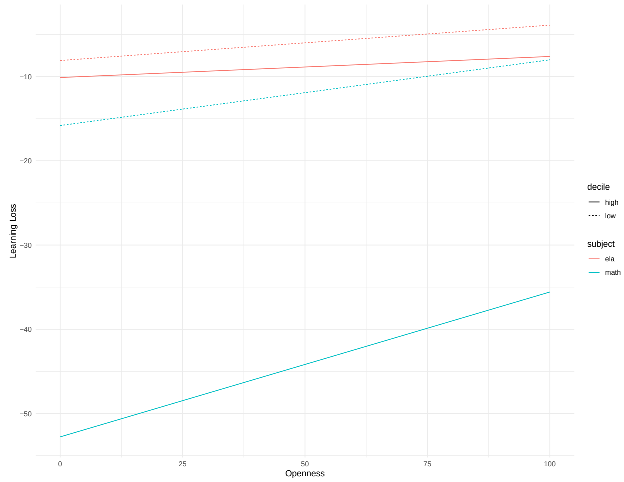


Figure 13: High and Low Black Deciles, Openness vs. Learning Loss

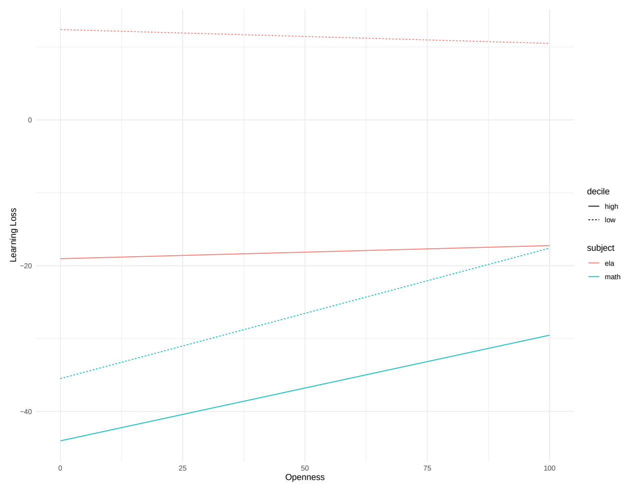


Figure 14: High and Low Hispanic Deciles, Openness vs. Learning Loss

The results of these models are shown in Tables 34, 35, and 36 in the Appendix. The openness coefficient and the intercept for each model are shown separately by race in Figures 13, 14, and 15.

These models show that there are a few significant differences in the relationship between openness and learning loss between schools that have high percentages of minority students and schools that have low percentages of minority students.

Additionally, for each demographic variable I run regressions investigating whether interaction effects are present, and to delineate between potential interaction effects and level effects. To do so, I multiply openness by each demographic variable to create an interaction

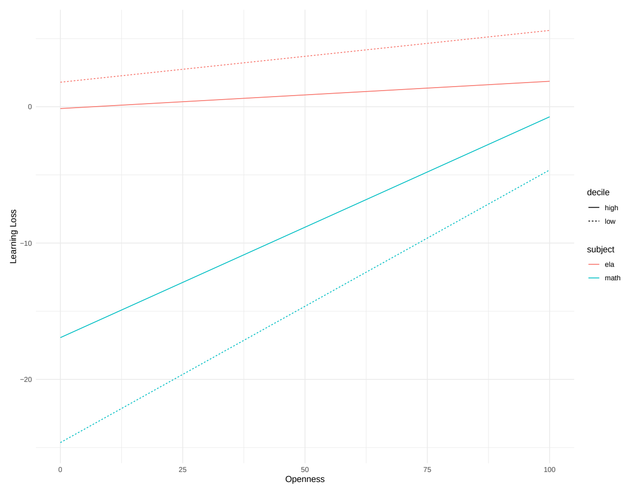


Figure 15: High and Low Asian Deciles, Openness vs. Learning Loss

term. I then run regressions for each demographic variable. For example, when investigating interaction effects for % Black, my independent variables are % Black, Openness, % Black * Openness, and % Black split into quintiles using the R function "quantcut". Results of these regressions are shown in Figure 21 for % Black, Figure 22 for % Hispanic, Figure 23 for % Asian, and Figure 24 for % FRPL eligible.

Investigating interaction effects through linear regression demonstrates that in most cases, there exists no interaction effect. The only interaction term which was highly significant was the interaction between % black and openness with respect to math learning loss. This indicates that schools being less open was correlated with larger learning losses when the schools in question had higher percentages of black students. In other words, this analysis confirms the interaction effect that I discovered earlier between % Black and school openness.

Additionally, I investigate the relationship between race and school openness, removing the learning loss element of the analysis. I want to find out whether schools with different demographic breakdowns have different trends in their openness over the course of the pandemic. The results of the regression are shown in Table 18.

Regressing openness on racial, FRPL, and state data is fairly revealing. Schools with higher percentages of minority students were significantly less open, and schools with higher percentages of FRPL eligible students were significantly more open. In this regression, the state fixed effects reveal that schools in Connecticut, Florida, Wisconsin, and Wyoming were significantly more open, while schools in Massachusetts and West Virginia were significantly less open.

Another relevant variable to investigate is FRPL eligibility. To do this, I split the dataset into three groups based on percentage FRPL eligibility. These groups consist of schools that had openness scores between 0% and 33%, 34% and 66%, and 67% and 100%, respectively, and I label them low-poverty, medium-poverty, and high-poverty schools, respectively. In my sample there are 2,404 low-poverty schools, 2,530 medium-poverty schools, and 1,910 high-poverty schools. For each of these groups, I run a separate regression of learning loss on openness, with demographic and state factors for both math and ELA. The results of these six regressions are in Tables 19 and 20.

Unsurprisingly, high-poverty schools have a higher baseline learning loss than low- or medium-poverty schools, which have similar baseline learning loss values. This is true for both math and ELA, although the magnitude of the scores themselves and the gap between high- and medium-poverty schools is signficantly larger for math. With respect to math, a baseline high-poverty school is predicted to have a scaled learning loss of 41.608%, while a medium-poverty school is predicted to have a scaled learning loss of 25.315% and a low-poverty school is predicted to have a scaled learning loss of 26.203%. For ELA, a high-poverty school's predicted baseline scaled learning loss is 12.911%, while the same values for a medium- and a low-poverty school are 7.848% and 8.000%, respectively. The differences in baselines are the most noteworthy result of these regressions, as there are not any novel trends in other areas.

My final analysis is an investigation into whether participation rate on the 2021 standardized testing is correlated with learning loss. Many states have noted that testing data from 2021 should not be analyzed closely because of low participation rates. Indeed, 2019 participation rates are comparatively low: in my sample, the mean 2019 participation rate was 94.9%, while the mean 2021 participation rate was 79.6%. I attempt to discover if there is a systematic bias to the low participation rates.

If participation rate is correlated with learning loss, it demonstrates that the group of students who took the test in 2021 is not representative. For example, if schools with lower participation rates experienced more learning loss than schools with higher participation rates, then it likely demonstrates that the students taking the test in the schools with low participation rates are disproportionately members of a population who scores lower than average at baseline, and therefore the true magnitude of learning loss is overstated by my analysis. Conversely, if schools with lower participation rates experienced less learning loss than schools with higher participation rates, it likely demonstrates that the students taking the test in the schools with low participation rates are disproportionately members of a population who score higher than average, and the true magnitude of learning loss is understated by my analysis.

In this analysis as for many others in this study, I run separate analyses for math and ELA. To determine 2021 participation rate, I divide the number of scores on the 2021 standardized test by the number of students reported as enrolled in grades 3-8 at the school, according to the National Center for Education Statistics' Common Core of Data. The results of the regression of learning loss on participation rate, with demographic data, FRPL eligibility, and state as controls, is shown in Table 25. Regressing participation rate reveals many correlations which will be discussed in the analysis of results section.

5 Regression Tables

Table 4: Naïve Regression Results (Math, Unscaled)

	Dependent variable:		
	Unscaled Learning Loss (Math)		
Outlier Method:	(100)	(150)	(Replace)
Openness	0.104***	0.086***	0.097***
	(0.005)	(0.004)	(0.004)
Constant	−16.797***	−16.000***	−16.494***
	(0.254)	(0.225)	(0.237)
Observations	6,946	7,628	7,628
R^2	0.070	0.067	0.072
Adjusted R^2	0.070	0.067	0.072
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5: Naïve Regression Results (ELA, Unscaled)

	Dependent variable:		
	Unscaled Learning Loss (ELA)		
Outlier Method:	(100)	(150)	(Replace)
Openness	0.032***	0.024***	0.028***
	(0.004)	(0.003)	(0.003)
Constant	−7.331***	−7.007***	−7.166***
	(0.198)	(0.177)	(0.186)
Observations	6,968	7,654	7,654
R^2	0.012	0.009	0.010
Adjusted R^2	0.011	0.009	0.010
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6: Naïve Regression Results (Math, Scaled)

	Dependent variable:		
	Scaled Learning Loss (Math)		
Outlier Method:	(100)	(150)	(Replace)
Openness	0.304^{***}	0.247^{***}	0.279^{***}
	(0.012)	(0.010)	(0.010)
Constant	-39.717^{***}	-37.185^{***}	-38.679^{***}
	(0.663)	(0.590)	(0.620)
Observations	6,861	7,507	7,507
R^2	0.088	0.081	0.087
Adjusted R^2	0.088	0.081	0.087
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 7: Naïve Regression Results (ELA, Scaled)

	Dependent variable:		
	Scaled Learning Loss (ELA)		
Outlier Method:	(100)	(150)	(Replace)
Openness	0.083^{***}	0.063^{***}	0.071^{***}
	(0.010)	(0.008)	(0.009)
Constant	-15.165^{***}	-14.279^{***}	-14.695^{***}
	(0.544)	(0.483)	(0.509)
Observations	6,883	7,535	7,535
R^2	0.010	0.008	0.009
Adjusted R^2	0.010	0.008	0.009
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 8: Main Regression Results (Math, Unscaled & Without Clustered Standard Errors)

	Dependent variable:		
	Unscaled Learning Loss (Math)		
Outlier Method:	(100)	(150)	(Replace)
Openness	0.065*** (0.005)	0.051*** (0.004)	0.059*** (0.004)
% Black	−0.052*** (0.008)	−0.056*** (0.007)	−0.054*** (0.007)
% Hispanic	−0.049*** (0.006)	−0.054*** (0.006)	−0.052*** (0.006)
% Asian	0.016 (0.016)	0.007 (0.015)	0.009 (0.015)
% FRPL Eligible	−0.005 (0.006)	−0.004 (0.006)	−0.005 (0.006)
CT	−2.402*** (0.541)	−2.037*** (0.524)	−2.086*** (0.523)
FL	−1.367*** (0.449)	−0.977** (0.432)	−1.112** (0.433)
MA	−7.121*** (0.475)	−6.970*** (0.464)	−6.938*** (0.463)
MN	−6.160*** (0.498)	−6.003*** (0.483)	−6.016*** (0.483)
NV	−1.511 (1.063)	−1.062 (1.026)	−1.095 (1.025)
RI	−3.936*** (1.004)	−3.747*** (0.978)	−3.764*** (0.977)
WI	−0.100 (0.500)	0.152 (0.483)	0.114 (0.483)
WV	−5.303*** (0.674)	−5.180*** (0.651)	−5.176*** (0.650)
WY	0.764 (1.069)	1.193 (0.889)	1.278 (0.886)
Constant	−9.940*** (0.518)	−9.411*** (0.489)	−9.779*** (0.497)
Observations	6,946	7,628	7,628
R^2	0.150	0.150	0.152
Adjusted R^2	0.148	0.149	0.150
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 9: Main Regression Results (ELA, Unscaled & Without Clustered Standard Errors)

	Dependent variable:		
	Unscaled Learning Loss (ELA)		
Outlier Method:	(100)	(150)	(Replace)
Openness	0.012^{***} (0.004)	0.008^{**} (0.003)	0.009^{**} (0.004)
% Black	-0.011^{*} (0.006)	-0.013^{**} (0.006)	-0.012^{**} (0.006)
% Hispanic	-0.017^{***} (0.005)	-0.018^{***} (0.005)	-0.018^{***} (0.005)
% Asian	0.016 (0.012)	0.012 (0.012)	0.013 (0.012)
% FRPL Eligible	-0.025^{***} (0.005)	-0.023^{***} (0.005)	-0.023^{***} (0.005)
CT	-2.361^{***} (0.433)	-1.827^{***} (0.423)	-1.833^{***} (0.423)
FL	1.142^{***} (0.355)	1.490^{***} (0.345)	1.469^{***} (0.346)
MA	-1.969^{***} (0.383)	-1.603^{***} (0.376)	-1.592^{***} (0.377)
MN	-4.219^{***} (0.399)	-3.864^{***} (0.391)	-3.861^{***} (0.390)
NV	−0.813 (0.854)	−0.282 (0.832)	−0.284 (0.832)
RI	−1.054 (0.772)	−0.626 (0.758)	−0.622 (0.758)
WI	−0.228 (0.401)	0.107 (0.390)	0.104 (0.390)
WV	-2.593^{***} (0.540)	-2.284^{***} (0.526)	-2.277^{***} (0.526)
WY	2.787^{***} (0.857)	2.910^{***} (0.719)	2.918^{***} (0.717)
Constant	-4.093^{***} (0.421)	-4.285^{***} (0.399)	-4.361^{***} (0.407)
Observations	6,968	7,654	7,654
R^2	0.073	0.068	0.068
Adjusted R^2	0.071	0.066	0.066
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 10: Main Regression Results (Math, Scaled & Without Clustered Standard Errors)

	Dependent variable:		
	Scaled Learning Loss (Math)		
Outlier Method:	(100)	(150)	(Replace)
Openness	0.149*** (0.012)	0.121*** (0.010)	0.138*** (0.011)
% Black	−0.239*** (0.018)	−0.245*** (0.018)	−0.241*** (0.018)
% Hispanic	−0.177*** (0.015)	−0.187*** (0.014)	−0.182*** (0.014)
% Asian	0.044 (0.038)	0.034 (0.038)	0.039 (0.038)
% FRPL Eligible	−0.195*** (0.013)	−0.185*** (0.013)	−0.186*** (0.013)
CT	6.336*** (1.325)	6.991*** (1.291)	6.886*** (1.290)
FL	16.757*** (1.098)	17.176*** (1.062)	16.885*** (1.065)
MA	−7.506*** (1.161)	−7.339*** (1.138)	−7.260*** (1.137)
MN	−1.292 (1.215)	−0.975 (1.187)	−1.015 (1.186)
NV	1.743 (2.467)	2.744 (2.398)	2.671 (2.396)
RI	−8.865*** (2.439)	−8.413*** (2.386)	−8.453*** (2.384)
WI	4.818*** (1.225)	5.472*** (1.190)	5.384*** (1.189)
WV	−5.533*** (1.638)	−5.268*** (1.590)	−5.264*** (1.589)
WY	10.538*** (2.594)	11.259*** (2.184)	11.492*** (2.177)
Constant	−21.599*** (1.270)	−20.798*** (1.205)	−21.614*** (1.225)
Observations	6,861	7,507	7,507
R^2	0.261	0.253	0.254
Adjusted R^2	0.259	0.252	0.253
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 11: Main Regression Results (ELA, Scaled & Without Clustered Standard Errors)

	Dependent variable:		
	Scaled Learning Loss (ELA)		
Outlier Method:	(100)	(150)	(Replace)
Openness	0.010 (0.011)	0.005 (0.009)	0.006 (0.010)
% Black	-0.084^{***} (0.016)	-0.088^{***} (0.015)	-0.087^{***} (0.015)
% Hispanic	-0.087^{***} (0.013)	-0.088^{***} (0.012)	-0.088^{***} (0.012)
% Asian	-0.027 (0.034)	-0.030 (0.033)	-0.030 (0.033)
% FRPL Eligible	-0.112^{***} (0.012)	-0.108^{***} (0.011)	-0.108^{***} (0.011)
CT	0.227 (1.182)	1.365 (1.145)	1.361 (1.145)
FL	7.199^{***} (0.967)	7.730^{***} (0.931)	7.714^{***} (0.933)
MA	-3.405^{***} (1.042)	-2.678^{***} (1.015)	-2.670^{***} (1.015)
MN	-5.470^{***} (1.084)	-4.785^{***} (1.053)	-4.783^{***} (1.053)
NV	-0.796 (2.204)	0.302 (2.132)	0.301 (2.132)
RI	-3.093 (2.085)	-2.193 (2.027)	-2.190 (2.027)
WI	-0.932 (1.093)	-0.188 (1.056)	-0.190 (1.056)
WV	-5.174^{***} (1.460)	-4.517^{***} (1.409)	-4.511^{***} (1.409)
WY	6.480^{***} (2.310)	6.755^{***} (1.934)	6.758^{***} (1.930)
Constant	-4.375^{***} (1.149)	-4.904^{***} (1.081)	-4.960^{***} (1.102)
Observations	6,883	7,535	7,535
R^2	0.083	0.079	0.079
Adjusted R^2	0.081	0.077	0.077
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 12: Main Regression Results (Math, Unscaled & With Clustered Standard Errors)

	Dependent variable:		
	Unscaled Learning Loss (Math)		
Outlier Method:	(100)	(150)	(Replace)
Openness	0.065*** (0.012)	0.051*** (0.007)	0.059*** (0.009)
% Black	−0.052** (0.021)	−0.056*** (0.018)	−0.054*** (0.018)
% Hispanic	−0.049*** (0.013)	−0.054*** (0.012)	−0.052*** (0.011)
% Asian	0.016 (0.035)	0.007 (0.037)	0.009 (0.037)
% FRPL Eligible	−0.005 (0.007)	−0.004 (0.007)	−0.005 (0.007)
CT	−2.402*** (0.115)	−2.037*** (0.149)	−2.086*** (0.143)
FL	−1.367*** (0.365)	−0.977*** (0.332)	−1.112*** (0.321)
MA	−7.121*** (0.250)	−6.970*** (0.254)	−6.938*** (0.255)
MN	−6.160*** (0.312)	−6.003*** (0.304)	−6.016*** (0.300)
NV	−1.511*** (0.051)	−1.062*** (0.043)	−1.095*** (0.046)
RI	−3.936*** (0.218)	−3.747*** (0.210)	−3.764*** (0.207)
WI	−0.100 (0.279)	0.152 (0.264)	0.114 (0.262)
WV	−5.303*** (0.341)	−5.180*** (0.284)	−5.176*** (0.278)
WY	0.764 (0.514)	1.193*** (0.452)	1.278*** (0.454)
Constant	−9.940*** (0.466)	−9.411*** (0.391)	−9.779*** (0.393)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 13: Main Regression Results (ELA, Unscaled & With Clustered Standard Errors)

	Dependent variable:		
	Unscaled Learning Loss (ELA)		
Outlier Method:	(100)	(150)	(Replace)
Openness	0.012** (0.005)	0.008 (0.006)	0.009 (0.006)
% Black	−0.011 (0.015)	−0.013 (0.013)	−0.012 (0.013)
% Hispanic	−0.017 (0.014)	−0.018 (0.014)	−0.018 (0.014)
% Asian	0.016 (0.023)	0.012 (0.022)	0.013 (0.022)
% FRPL Eligible	−0.025*** (0.006)	−0.023*** (0.006)	−0.023*** (0.006)
CT	−2.361*** (0.124)	−1.827*** (0.113)	−1.833*** (0.114)
FL	1.142*** (0.245)	1.490*** (0.228)	1.469*** (0.230)
MA	−1.969*** (0.121)	−1.603*** (0.138)	−1.592*** (0.137)
MN	−4.219*** (0.255)	−3.864*** (0.259)	−3.861*** (0.259)
NV	−0.813*** (0.038)	−0.282*** (0.036)	−0.284*** (0.035)
RI	−1.054*** (0.174)	−0.626*** (0.181)	−0.622*** (0.180)
WI	−0.228 (0.255)	0.107 (0.255)	0.104 (0.255)
WV	−2.593*** (0.469)	−2.284*** (0.459)	−2.277*** (0.459)
WY	2.787*** (0.286)	2.910*** (0.334)	2.918*** (0.318)
Constant	−4.093*** (0.511)	−4.285*** (0.540)	−4.361*** (0.540)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 14: Main Regression Results (Math, Scaled & With Clustered Standard Errors)

	Dependent variable:		
	Scaled Learning Loss (Math)		
Outlier Method:	(100)	(150)	(Replace)
Openness	0.149*** (0.017)	0.121*** (0.016)	0.138*** (0.017)
% Black	−0.239*** (0.028)	−0.245*** (0.025)	−0.241*** (0.026)
% Hispanic	−0.177*** (0.037)	−0.187*** (0.039)	−0.182*** (0.040)
% Asian	0.044 (0.146)	0.034 (0.151)	0.039 (0.149)
% FRPL Eligible	−0.195*** (0.050)	−0.185*** (0.046)	−0.186*** (0.046)
CT	6.336*** (0.932)	6.991*** (0.934)	6.886*** (0.932)
FL	16.757*** (0.907)	17.176*** (0.877)	16.885*** (0.882)
MA	−7.506*** (1.276)	−7.339*** (1.267)	−7.260*** (1.271)
MN	−1.292 (1.351)	−0.975 (1.379)	−1.015 (1.383)
NV	1.743*** (0.556)	2.744*** (0.536)	2.671*** (0.539)
RI	−8.865*** (0.968)	−8.413*** (1.021)	−8.453*** (1.032)
WI	4.818*** (1.053)	5.472*** (1.120)	5.384*** (1.127)
WV	−5.533*** (0.666)	−5.268*** (0.772)	−5.264*** (0.788)
WY	10.538*** (0.947)	11.259*** (1.247)	11.492*** (1.204)
Constant	−21.599*** (2.878)	−20.798*** (2.764)	−21.614*** (2.805)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 15: Main Regression Results (ELA, Scaled & With Clustered Standard Errors)

	Dependent variable:		
	Learning Loss (ELA)		
Outlier Method:	(100)	(150)	(Replace)
Openness	0.010 (0.012)	0.005 (0.014)	0.006 (0.015)
% Black	-0.084^{***} (0.026)	-0.088^{***} (0.023)	-0.087^{***} (0.023)
% Hispanic	-0.087^{*} (0.050)	-0.088^{*} (0.052)	-0.088^{*} (0.051)
% Asian	-0.027 (0.029)	-0.030 (0.032)	-0.030 (0.032)
% FRPL Eligible	-0.112^{***} (0.020)	-0.108^{***} (0.017)	-0.108^{***} (0.017)
CT	0.227 (0.562)	1.365^{**} (0.547)	1.361^{**} (0.550)
FL	7.199^{***} (0.390)	7.730^{***} (0.378)	7.714^{***} (0.364)
MA	-3.405^{***} (0.592)	-2.678^{***} (0.589)	-2.670^{***} (0.582)
MN	-5.470^{***} (1.171)	-4.785^{***} (1.172)	-4.783^{***} (1.173)
NV	-0.796^{**} (0.335)	0.302 (0.323)	0.301 (0.320)
RI	-3.093^{***} (0.670)	-2.193^{***} (0.691)	-2.190^{***} (0.691)
WI	-0.932 (1.108)	-0.188 (1.131)	-0.190 (1.134)
WV	-5.174^{***} (1.452)	-4.517^{***} (1.491)	-4.511^{***} (1.490)
WY	6.480^{***} (1.112)	6.755^{***} (1.337)	6.758^{***} (1.295)
Constant	-4.375^{***} (1.669)	-4.904^{***} (1.695)	-4.960^{***} (1.646)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 16: Regression for High, Medium, and Low-Openness Schools (Math)

	Dependent variable:		
	Learning Loss (Math)		
Openness Group:	Low	Medium	High
% Black	−0.239***	−0.277***	−0.221***
	(0.039)	(0.027)	(0.035)
% Hispanic	−0.182***	−0.209***	−0.179***
	(0.034)	(0.021)	(0.030)
% Asian	−0.037	0.178***	−0.184*
	(0.067)	(0.054)	(0.107)
% FRPL Eligible	−0.251***	−0.172***	−0.130***
	(0.031)	(0.019)	(0.024)
CT	6.383**	5.636***	9.940***
	(2.611)	(1.863)	(3.036)
FL	18.427***	19.182***	13.329***
	(2.196)	(1.576)	(2.468)
MA	−7.609***	−9.178***	−4.007
	(1.965)	(1.711)	(3.170)
MN	−3.477	−0.985	−0.119
	(2.299)	(1.760)	(2.774)
NV	−8.451*	4.386	10.923*
	(4.924)	(3.275)	(6.198)
RI	−3.534	−12.159***	−8.312
	(4.576)	(3.331)	(6.177)
WI	1.542	4.740***	7.263***
	(2.394)	(1.818)	(2.670)
WV	−3.502	−6.146***	−7.988**
	(4.325)	(2.193)	(3.515)
WY	15.503	9.959	10.836***
	(11.855)	(6.626)	(3.480)
Constant	−14.964***	−15.022***	−11.486***
	(1.929)	(1.617)	(2.589)
Observations	1,348	3,323	2,160
R^2	0.266	0.222	0.120
Adjusted R^2	0.259	0.219	0.115
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 17: Regression for High, Medium, and Low-Openness Schools (ELA)

	Dependent variable:		
	Learning Loss (ELA)		
Openness Group:	Low	Medium	High
% Black	−0.091***	−0.115***	−0.043*
	(0.032)	(0.026)	(0.024)
% Hispanic	−0.131***	−0.070***	−0.102***
	(0.027)	(0.021)	(0.021)
% Asian	−0.069	0.024	−0.148**
	(0.055)	(0.055)	(0.075)
% FRPL Eligible	−0.122***	−0.099***	−0.096***
	(0.025)	(0.019)	(0.016)
CT	−2.940	1.118	2.162
	(2.281)	(1.846)	(2.036)
FL	9.653***	7.501***	5.174***
	(1.943)	(1.532)	(1.602)
MA	−5.638***	−2.310	1.945
	(1.795)	(1.684)	(2.137)
MN	−5.594***	−6.008***	−4.645**
	(2.038)	(1.732)	(1.838)
NV	−4.513	−0.179	2.078
	(4.133)	(3.316)	(4.336)
RI	−2.315	−6.985**	3.401
	(3.846)	(3.372)	(4.326)
WI	−1.644	−1.004	−0.765
	(2.115)	(1.798)	(1.763)
WV	−2.822	−4.670**	−8.512***
	(3.648)	(2.183)	(2.389)
WY	2.825	4.543	6.665***
	(9.863)	(6.770)	(2.373)
Constant	−1.944	−4.832***	−3.619**
	(1.764)	(1.580)	(1.697)
Observations	1,347	3,323	2,160
R^2	0.140	0.060	0.084
Adjusted R^2	0.131	0.057	0.078
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 18: Openness Regressed on Demographic, FRPL, and State Data

	Dependent variable:
	Openness
% Black	-0.439^{***} (0.017)
% Hispanic	-0.437^{***} (0.014)
% Asian	-0.458^{***} (0.037)
% FRPL Eligible	0.200^{***} (0.013)
CT	7.906^{***} (1.150)
FL	19.245^{***} (0.844)
MA	-4.693^{***} (0.967)
MN	-0.321 (1.031)
NV	3.551 (2.441)
RI	-2.166 (2.420)
WI	5.088^{***} (1.035)
WV	-5.010^{***} (1.520)
WY	28.264^{***} (2.615)
Constant	51.259^{***} (0.859)
Observations	6,844
R^2	0.260
Adjusted R^2	0.259
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 19: Regression for High, Medium, and Low-Poverty Schools (Math)

	Dependent variable:		
	Learning Loss (Math)		
Poverty Group:	High	Medium	Low
Openness	0.133***	0.115***	0.166***
	(0.027)	(0.019)	(0.020)
% Black	−0.311***	−0.287***	−0.143**
	(0.029)	(0.030)	(0.063)
% Hispanic	−0.210***	−0.187***	−0.181***
	(0.028)	(0.022)	(0.037)
% Asian	−0.299***	0.122	0.404***
	(0.080)	(0.077)	(0.057)
CT	14.066***	4.889**	3.654**
	(3.561)	(2.142)	(1.832)
FL	27.797***	11.903***	9.467***
	(2.382)	(1.717)	(1.836)
MA	−3.288	−14.994***	−7.493***
	(3.019)	(1.902)	(1.634)
MN	6.507*	−3.684*	−2.836*
	(3.512)	(1.915)	(1.721)
NV	12.667**	0.055	−12.488**
	(5.751)	(3.137)	(5.127)
RI	−0.183	−16.844***	−6.428*
	(7.123)	(3.745)	(3.352)
WI	5.411	1.973	4.344**
	(3.331)	(1.937)	(1.734)
WV	4.842	−10.013***	−10.819***
	(4.234)	(2.159)	(3.632)
WY	16.974**	9.613***	7.474*
	(8.229)	(3.441)	(4.062)
Constant	−41.608***	−25.315***	−26.203***
	(3.409)	(2.078)	(1.813)
Observations	1,921	2,538	2,402
R^2	0.265	0.282	0.150
Adjusted R^2	0.260	0.278	0.145
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 20: Regression for High, Medium, and Low-Poverty Schools (ELA)

	Dependent variable:		
	Learning Loss (ELA)		
Poverty Group:	High	Medium	Low
Openness	−0.023	−0.012	0.048***
	(0.021)	(0.019)	(0.017)
% Black	−0.119***	−0.126***	−0.020
	(0.023)	(0.030)	(0.054)
% Hispanic	−0.104***	−0.097***	−0.085***
	(0.022)	(0.021)	(0.031)
% Asian	−0.153**	−0.057	0.142***
	(0.064)	(0.077)	(0.049)
CT	−3.372	3.260	−1.322
	(2.821)	(2.201)	(1.604)
FL	11.035***	7.088***	2.495
	(1.856)	(1.758)	(1.568)
MA	−4.975**	−5.012**	−3.361**
	(2.401)	(1.975)	(1.436)
MN	−3.613	−4.869**	−6.857***
	(2.781)	(1.971)	(1.507)
NV	−4.650	2.032	−5.295
	(4.614)	(3.208)	(4.498)
RI	0.740	−6.954*	−1.750
	(4.490)	(3.786)	(2.941)
WI	1.423	−0.306	−3.027**
	(2.640)	(1.994)	(1.517)
WV	−6.081*	−5.472**	−5.059
	(3.358)	(2.218)	(3.188)
WY	8.027	8.278**	2.943
	(6.516)	(3.501)	(3.567)
Constant	−12.911***	−7.848***	−8.000***
	(2.690)	(2.165)	(1.615)
Observations	1,937	2,543	2,403
R^2	0.107	0.070	0.036
Adjusted R^2	0.101	0.065	0.031
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 21: Interaction Effects Regression (Percentage Black)

	Dependent variable:	
	Unscaled Learning Loss (Math)	Unscaled Learning Loss (ELA)
	(1)	(2)
% Black	-0.028^{*}	-0.009
	(0.015)	(0.011)
% Black * Openness	-0.046^{**}	-0.013
	(0.023)	(0.018)
2nd % Black Quintile	0.002	
	(0.004)	
3rd % Black Quintile	-0.001	
	(0.004)	
4th % Black Quintile	0.001	
	(0.004)	
2nd % Black Quintile		0.006^{**}
		(0.003)
3rd % Black Quintile		0.010^{***}
		(0.003)
4th % Black Quintile		0.011^{***}
		(0.003)
5th % Black Quintile	0.007	0.014^{***}
	(0.005)	(0.004)
Openness	0.089^{***}	0.027^{***}
	(0.005)	(0.004)
Constant	-0.157^{***}	-0.079^{***}
	(0.004)	(0.003)
Observations	7,628	7,654
R^2	0.074	0.012
Adjusted R^2	0.073	0.011
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 22: Interaction Effects Regression (Percentage Hispanic)

	Dependent variable:	
	Unscaled Learning Loss (Math)	Unscaled Learning Loss (ELA)
	(1)	(2)
% Hispanic	-0.045^{***}	0.0002
	(0.013)	(0.010)
% Hispanic * Openness	-0.020	-0.009
	(0.017)	(0.013)
2nd % Hispanic Quintile	0.010^{***}	
	(0.003)	
3rd % Hispanic Quintile	0.017^{***}	
	(0.004)	
4th % Hispanic Quintile	0.019^{***}	
	(0.004)	
5th % Hispanic Quintile	0.026^{***}	
	(0.007)	
2nd % Hispanic Quintile		0.011^{***}
		(0.003)
3rd % Hispanic Quintile		0.016^{***}
		(0.003)
4th % Hispanic Quintile		0.015^{***}
		(0.003)
5th % Hispanic Quintile		0.011^{**}
		(0.005)
Openness	0.087^{***}	0.026^{***}
	(0.005)	(0.004)
Constant	-0.163^{***}	-0.081^{***}
	(0.004)	(0.003)
Observations	7,628	7,654
R^2	0.075	0.015
Adjusted R^2	0.074	0.014
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 23: Interaction Effects Regression (Percentage Asian)

	Dependent variable:	
	Unscaled Learning Loss (Math)	Unscaled Learning Loss (ELA)
	(1)	(2)
% Asian	−0.035	−0.042*
	(0.032)	(0.025)
% Asian * Openness	−0.087	−0.030
	(0.065)	(0.052)
2nd % Asian Quintile	−0.004	
	(0.004)	
3rd % Asian Quintile	0.007*	
	(0.004)	
4th % Asian Quintile	0.003	
	(0.004)	
2nd % Asian Quintile		0.007**
		(0.003)
3rd % Asian Quintile		0.014***
		(0.003)
4th % Asian Quintile		0.011***
		(0.003)
5th % Asian Quintile	0.013***	0.020***
	(0.005)	(0.004)
Openness	0.090***	0.028***
	(0.004)	(0.003)
Constant	−0.164***	−0.081***
	(0.004)	(0.003)
Observations	7,628	7,654
R^2	0.071	0.014
Adjusted R^2	0.070	0.013
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 24: Interaction Effects Regression (Percentage FRPL Eligible)

	Dependent variable:	
	Unscaled Learning Loss (Math)	Unscaled Learning Loss (ELA)
	(1)	(2)
% FRPL Eligible	−0.028	−0.010
	(0.020)	(0.015)
% FRPL Eligible * Openness	−0.026*	−0.007
	(0.015)	(0.012)
2nd % FRPL Eligible Quintile	0.005	
	(0.004)	
3rd % FRPL Eligible Quintile	0.011*	
	(0.006)	
4th % FRPL Eligible Quintile	0.007	
	(0.009)	
5th % FRPL Eligible Quintile	0.016	
	(0.013)	
2nd % FRPL Eligible Quintile		−0.002
		(0.003)
3rd % FRPL Eligible Quintile		0.001
		(0.005)
4th % FRPL Eligible Quintile		−0.002
		(0.007)
5th % FRPL Eligible Quintile		0.003
		(0.010)
Openness	0.099***	0.028***
	(0.008)	(0.006)
Constant	−0.156***	−0.066***
	(0.005)	(0.004)
Observations	7,628	7,654
R^2	0.073	0.011
Adjusted R^2	0.072	0.011
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 25: Participation Rate Regression

	Dependent variable:	
	Participation Rate	
	Math	ELA
Learning Loss (Math)	0.063*** (0.007)	
Learning Loss (ELA)		−0.008 (0.007)
Openness	0.135*** (0.008)	0.138*** (0.007)
% Black	−0.139*** (0.012)	−0.182*** (0.011)
% Hispanic	−0.053*** (0.010)	−0.055*** (0.009)
% Asian	−0.221*** (0.024)	−0.165*** (0.022)
% FRPL Eligibility	0.029*** (0.009)	−0.018** (0.008)
CT	46.959*** (0.764)	48.821*** (0.678)
FL	47.051*** (0.595)	58.966*** (0.518)
MA	59.093*** (0.646)	58.912*** (0.574)
MN	46.031*** (0.684)	47.212*** (0.609)
NV	54.724*** (1.596)	55.637*** (1.420)
RI	53.291*** (1.586)	53.970*** (1.343)
WI	46.253*** (0.688)	47.440*** (0.611)
WV	47.272*** (1.000)	48.367*** (0.889)
WY	51.546*** (1.725)	52.964*** (1.531)
Constant	33.297*** (0.728)	32.610*** (0.632)
Observations	6,861	6,883
R^2	0.621	0.711
Adjusted R^2	0.620	0.711
Note:		*p<0.1; **p<0.05; ***p<0.01

6 Discussion

6.1 Analysis of Results

My model was effective in demonstrating the relationship between school openness and learning loss. The first important thing to note is that in my main regression, shown in Tables 14 and 15, both math and ELA have a highly significant constant term. This means that without factoring in independent variables, the average school experienced significant learning loss last year. I demonstrated this in Figures 6 and 8, and it is confirmed by the regression results: a constant term of between -20 and -22 for math, and between -4 and -5, depending on the method of dealing with outliers, indicates a baseline scaled learning loss of 20-22% in math and 4-5% in ELA.

These results are consistent with the literature not only in demonstrating learning loss, but the fact that learning losses were greater in math than they were in ELA. This aligns with the theory that "learning losses are more common and pronounced in math than in reading" (Akers and Chingos 2012). The mechanism for this difference is the greater ease of practicing reading skills at home as compared to math skills (Cooper et al. 1996).

In addition to the constant term, the openness term in my regressions is notable. It is differential between math and ELA, with math having a statistically significant value of between 0.121 and 0.149, and ELA having smaller and insignificant values. This indicates that the more open a school was, the smaller learning loss that school incurred in math, while it had no effect on ELA learning loss. These results, demonstrated in Figure 10, are rather striking: the regression indicates that a school which was 0% open during the 2020-21 school year would be expected to experience a scaled learning loss of 21.599%, while a school which was 100% open, all other characteristics being equal, would be expected to experience a scaled learning loss of only 6.699%.

Additionally, the main regression demonstrates the significant impacts of race on the size of learning loss. Schools with higher percentages of Black and Hispanic students experience significantly more learning loss, and this finding applies to both math and ELA. When investigating race and learning loss further, I find few differential trends. Low-, medium-, and high-openness schools each have similar significant racial effects for both math and ELA. This indicates that Black and Hispanic students suffered during the pandemic regardless of whether their school re-opened quicker than most or not.

An investigation into openness itself revealed significant trends. Higher percentages of Black, Hispanic, and Asian students were all linked with significantly lower percentages openness. Based on the model with results in Table 18, a school with 0% Black, Hispanic, or Asian students is predicted to have been 51.259% open during the 2020-21 school year. Meanwhile, a school with 100% Black students is predicted to have been only 7.359% open, a school with 100% Hispanic students is predicted to have been only 7.559% open, and a school with 100% Asian students is predicted to have been only 5.459% open. These results are remarkable, and likely reflect the fact that most minority populations are concentrated in cities, where schools were more likely to have remained remote for longer during the 2020-21 school year (DiMarco 2022).

Examining schools with the highest percentages of Black students also reveals a few trends. Schools in the top decile of percentage Black students were significantly more impacted by openness than schools in the bottom decile of percentage Black students. At a baseline high-percentage Black school, the difference between 0% openness and 100% openness was a decline in learning loss of 17.2%, while for a baseline low-percentage Black school, the difference between 0% openness and 100% openness was only 7.8%. This difference is illustrated by Figure 13 and in Table 34. The significant difference between the effect of openness on high- and low-percentage Black schools indicates that in-person instruction is especially impactful on Black students, and they are a group who is most at risk from a large-scale closing of schools.

Another notable difference in racial regression results is the baseline: schools in the top decile of percentage of Black students were predicted to have a baseline learning loss of 52.776% in math, while students in the bottom decile of Black students were predicted to have a baseline scaled learning loss of only 15.812%. This is a massive and significant difference. Hispanic students had a smaller baseline difference: the decile of schools with the highest percentage of Hispanic students experienced a baseline learning loss of 44.031%, while the decile of schools with the lowest percentage of Hispanic students experienced a baseline loss of 35.487%.

Schools with a high percentage of Asian students experienced smaller than average learning loss, and benefited greatly from school openness. The decile of schools with the highest percentage of Asian students was expected to have a learning loss of only 4.637% in a school that was 100% open during the 2020-21 school year, as compared to an expected learning loss of 24.637% in a school that was 0% open during the 2020-21 school year.

FRPL eligibility, used as a proxy for poverty, demonstrates the differential impact of the pandemic on education along lines of wealth. To begin with, as Table 18 demonstrates, a higher percentage of FRPL eligibility is correlated with a higher openness. This means that based on my model, poorer schools were more likely to be in-person during the pandemic. This is surprising, and directly conflicts with the findings of Goldhaber et al., who found that high-poverty schools spent between 3 and 9 more weeks remote during the 2020-21 school year, depending on the state (Goldhaber et al. 2022). I believe that the reason for the difference between their findings and my own is my smaller sample size: the Goldhaber et al. study used 49 states and Washington, D.C., while I only included 10 states in my sample. My states are generally somewhat rural, and therefore, FRPL eligibility in my study is more likely to represent rural poverty, rather than urban poverty. Goldhaber et al. notes that accounting for population density and urbanicity decreases the gap between high-poverty schools and others, which also supports my theory that my paper happens to focus more on rural than on urban poverty.

As for the regressions in which I split my data into groups based on FRPL eligibility, there are notable takeaways. For both math and ELA, the high-poverty group had a markedly higher baseline learning loss. This is consistent with the "faucet theory" from educational literature: students of lower socioeconomic status suffer more away from school than at school, because while they are at school, the "faucet" of resources is turned on for every student equally, while at home, the faucet is often shut off for low-SES children. While the magnitudes were greater across the board for math than for ELA, both subjects saw the high-poverty group experience a baseline learning loss nearly double that of the medium-poverty group. Another interesting point is that for both math and ELA, low-poverty schools actually experienced a greater baseline learning loss than medium-poverty schools, although the differences were negligible. This indicates that the biggest gap is between high- and medium-poverty schools, while medium- and low-poverty schools are virtually indistinguishable in terms of baseline learning loss.

The final notable piece of my study is examining participation rate and its relationship with learning loss. My regression, the results of which are in Table 25, indicates that a higher participation rate correlates significantly with smaller math learning loss, higher school openness, lower percentages of all minority students, a slightly percentage of FRPL eligibility, and lots of state effects. The correlation between participation rate and smaller learning loss indicates that schools with higher participation rates generally outperformed schools with lower participation rates, all else being equal. This suggests that the students missing from the sample in schools with low participation rates would increase those districts' scores, which indicates that the magnitude of learning loss, at least in math, is potentially slightly overstated in this study.

6.2 Caveats and Limitations

Any relationship between participation rate and learning loss deserves further investigation, as a low participation rate could bias the results of the study if the students missing from the sample were systematically higher- or lower-scoring on standardized assessments. In general, if participation rate correlates with a larger learning loss, it indicates that the districts with lower participation rates are missing scores from their lowest-scoring students, and vice versa if participation rate correlates with a smaller learning loss.

My regression, the results of which are in Table 25, indicates that a higher participation rate correlates significantly with smaller math learning loss, higher school openness, lower percentages of all minority students, a slightly percentage of FRPL eligibility, and lots of state effects. The correlation between participation rate and smaller learning loss indicates that schools with higher participation rates generally outperformed schools with lower participation rates, all else being equal. This suggests that the students missing from the sample in schools with low participation rates would increase those districts' scores, which indicates that the magnitude of learning loss, at least in math, is potentially slightly overstated in this study.

However, participation rate is also correlated with significantly lower proportions of Black and Hispanic students, who in general tended to score lower on these standardized assessments. Overall, the evidence from this study seems to indicate that learning loss in math may be slightly over-estimated, but there are nuances that cannot be explored using school-level data.

Having more granular standardized test data would have improved this study. Firstly, when analyzing school-level data, I cannot actually assign scores to individuals who are or are not White, Black, Hispanic, Asian, or FRPL eligible. I can only use the percentages of the school that fall in these categories, which may or may not be representative of the students who actually took the 2021 standardized test. This is a limitation of this study: while I can correlate participation rate with demographic variables and make inferences, I cannot say with certainty whether Black, Hispanic, and Asian students were less likely to participate in the exam.

In addition to student-level data, I would have liked to have been able to analyze differential trends involving students' grade level. At a younger age, the knowledge you receive at school is more foundational, and the growth each year is higher. However, the brain is more plastic at a young age, which makes more easier informational uptake. Therefore, I would be interested to see whether the sheer amount of information missed would result in larger learning losses for younger children, or whether the greater ability for informational uptake would result in smaller learning losses.

Another limitation of this study is the representativeness of the sample. My study only covers ten states, and the U.S. educational system is highly decentralized. It is very likely that with more data fed to it, the model would give different results. This is a choice that I had to make based on data availability. The Goldhaber et al. study uses student-level data from 49 states, and is certainly more representative of real trends than my study.

As with all correlational studies, my study cannot determine causality. The past two years have been a time of massive upheaval and stress for many people. It is unlikely that receiving remote instruction as opposed to in-person instruction is the sole factor in determining a student's learning loss.

Another slight issue with my study is the use of percentage proficiency as my instrument in determining learning loss. Percentage proficiency only reflects the number of students in a sample who are above a certain cut score. This means that there is ample potential for growth and learning loss, both above and below the proficiency cut score, that would not show up on a measure of percentage proficiency. For example, if a state has a proficiency cut score of 70, and a student scores 95 in 2019 and 75 in 2021, that student has experienced learning loss. However, the student would not show up in my measure of learning loss, as he qualifies as proficient in both 2019 and 2021.

My study rests on the reliability of the SafeGraph phone tracking dataset. While I have no doubt that their company is largely accurate, there is some potential for inaccuracy in using cell phone visits to a school as a measure of school openness. For one thing, not every person in a school will have a phone, even when the school is operating at full capacity. Imagine a school in which no students had a cell phone, and every teacher had one. If that school switched to fully remote learning, but the teachers still came to the school building to use Zoom, for example, my measure of school openness would be 100%, which would clearly be inaccurate. Given that my sample of standardized testing was 3rd to 8th graders, it is difficult to estimate how accurate cell phone tracking is as a method of tracking openness.

Another potential problem with SafeGraph's dataset was the panel growth. I normalized the data based on the total number of phones in SafeGraph's panel as it updated by the month. However, this cannot account for disproportionate panel growth in a certain locale. There is nothing to be done to account for random growth, but it is unlikely that random growth affected the results of my study in any systematic way.

6.3 Implications

My study provides a strong suggestion that schools should seriously consider the benefits and drawbacks of transitioning to remote learning. Given what we know about the importance of education for economic as well as quality-of-life reasons, a full cost-benefit analysis of remote learning in the future should include an understanding that remote learning will lead to large setbacks which will have potentially long-lasting effects. Some instances may still be worth transitioning to remote learning, but the decision must be made deliberately.

Additionally, my study suggests the need to address population subgroups differently when it comes to educational relief. Notably, the high-poverty group suffered much greater learning losses than even the medium-poverty group. Therefore, distribution of aid should be sure to focus on the schools with the highest percentages of FRPL-eligible students in order for the relief to have the greatest possible impact. Schools with high percentages of Black and Hispanic students were also disproportionately affected by remote learning, both in terms of incidence and impact: high-Black and high-Hispanic districts were remote more often, and high-Black districts especially suffered worse setbacks from being remote.

Once aid is distributed, my study offers a potential avenue for spending the funds: ensuring that in a future disruptive event, in-person instruction will be able to continue. Equipping schools with sufficient ventilation or similar safety measures may be the most effective use of aid in terms of future payoff.

With respect to the literature surrounding learning loss and the COVID-19 pandemic, my study adds to a growing body of research suggesting that students suffered severe consequences for remote learning. My study proposes SafeGraph's cell phone tracking database as a viable measurement for school openness. Finally, my study provides some clarity to the commonly used and fairly nebulous term "hybrid": the grey area between in-person and remote instruction.

7 Conclusion

My observational study used standardized testing data from ten states and a cell phone tracking database to analyze the effects of remote learning on learning loss. Linear regressions with fixed effects were used to analyze the school-level data to observe how the relationship between school openness and learning loss is moderated by demographic, fiscal, and place effects. The study also did supplementary analyses involving race, poverty, and testing participation rates.

My study found that in these ten states, school openness was highly correlated with decreased learning loss: the less remote a school, the smaller their learning loss, and the more remote a school, the larger their learning loss. Additionally, my study observed differential racial and fiscal effects: Black and Hispanic students had disproportionately large learning losses, which are a result of both increased levels of remote learning and greater negative impact of remote learning on those populations. The study also found that school FRPL eligibility is strongly correlated with increased learning loss, despite schools with higher FRPL eligibility being less remote. This indicates that high-poverty students are more deeply impacted by the negative effects of remote learning.

Future work in this area should use student-level data, as well as further investigating the suitability of the SafeGraph cell phone tracking dataset as a measure of school openness.

In addition, future quantitative work in education should continue to monitor the outcomes of the cohort of children in school during the COVID-19 pandemic in order to gain a better understanding of long-term consequences of interruptions to education.

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A Appendix

State	URL from which Test Data Retrieved
Colorado	https://www.cde.state.co.us/assessment
Connecticut	https://portal.ct.gov/SDE/Student-Assessment/Main-Assessment/Student-Assessment
Florida	https://www.fldoe.org/accountability/assessments/k-12-student-assessment/results/
Massachusetts	https://www.doe.mass.edu/mcas/
Minnesota	https://education.mn.gov/mde/fam/tests/
Nevada	http://nevadareportcard.nv.gov/di/main/assessment
Rhode Island	https://www.ride.ri.gov/instructionassessment/assessment/assessmentresults.aspx
West Virginia	https://wvde.us/assessment/
Wisconsin	https://dpi.wi.gov/assessment/forward/data
Wyoming	https://edu.wyoming.gov/for-district-leadership/state-assessment/student-assessments/

Table 26: State Assessment URLs

Table 27: Variance Inflation Factor values for Math Model (100 Outlier Method)

	GVIF	Df	GVIF^(1/(2*Df))
openness2021_projected	1.363	1	1.167
pct_black	1.828	1	1.352
pct_hispanic	2.146	1	1.465
pct_asian	1.135	1	1.065
pct_frpl	2.296	1	1.515
as.factor(state)	2.251	9	1.046

Table 28: Variance Inflation Factor values for Math Model (150 Outlier Method)

	GVIF	Df	GVIF^(1/(2*Df))
openness2021_projected	1.364	1	1.168
pct_black	1.770	1	1.330
pct_hispanic	2.037	1	1.427
pct_asian	1.141	1	1.068
pct_frpl	2.246	1	1.499
as.factor(state)	2.199	9	1.045

Table 29: Variance Inflation Factor values for Math Model (Replace Outlier Method)

	GVIF	Df	GVIF^(1/(2*Df))
openness2021_projected	1.388	1	1.178
pct_black	1.779	1	1.334
pct_hispanic	2.056	1	1.434
pct_asian	1.143	1	1.069
pct_frpl	2.245	1	1.498
as.factor(state)	2.227	9	1.045

Table 30: Variance Inflation Factor values for ELA Model (100 Outlier Method)

	GVIF	Df	GVIF^(1/(2*Df))
openness2021_projected	1.360	1	1.166
pct_black	1.825	1	1.351
pct_hispanic	2.150	1	1.466
pct_asian	1.135	1	1.065
pct_frpl	2.267	1	1.506
as.factor(state)	2.182	9	1.044

Table 31: Variance Inflation Factor values for ELA Model (150 Outlier Method)

	GVIF	Df	GVIF^(1/(2*Df))
openness2021_projected	1.361	1	1.167
pct_black	1.769	1	1.330
pct_hispanic	2.042	1	1.429
pct_asian	1.141	1	1.068
pct_frpl	2.218	1	1.489
as.factor(state)	2.131	9	1.043

Table 32: Variance Inflation Factor values for ELA Model (Replace Outlier Method)

	GVIF	Df	GVIF^(1/(2*Df))
openness2021_projected	1.384	1	1.177
pct_black	1.777	1	1.333
pct_hispanic	2.062	1	1.436
pct_asian	1.143	1	1.069
pct_frpl	2.217	1	1.489
as.factor(state)	2.157	9	1.044

Decile	Low Black	High Black	Low Hispanic	High Hispanic	Low Asian	High Asian
Low Value (%)	0	100	0	56.94	0	9.34
High Value (%)	0.33	33.27	2.01	99.56	0	98.36

Table 33: Relevant Demographic Data for High and Low Racial Deciles

Table 34: High and Low Percentage Black Deciles Model Regression Results

	Dependent variable:			
	Learning Loss (Math)		Learning Loss (ELA)	
Decile:	High	Low	High	Low
Openness	0.172***	0.078	0.025	0.042
	(0.045)	(0.053)	(0.037)	(0.037)
% FRPL Eligible	−0.272***	−0.331***	−0.107**	−0.207***
	(0.051)	(0.047)	(0.042)	(0.032)
CT	29.944**	11.013**	1.642	2.044
	(14.089)	(5.496)	(11.604)	(3.898)
FL	36.249***	13.052**	4.653	13.835***
	(13.408)	(5.200)	(11.004)	(3.512)
MA	8.978	−11.258***	−10.930	−3.353
	(13.792)	(4.044)	(11.355)	(2.876)
MN	20.547	−0.207	−6.424	−3.619
	(13.863)	(3.409)	(11.415)	(2.384)
NV		5.208		6.341
		(5.632)		(3.981)
RI	−8.328	−8.198	−22.900	14.249
	(23.225)	(14.502)	(19.652)	(10.287)
WI	7.975	5.735*	0.534	1.894
	(14.064)	(3.329)	(11.583)	(2.338)
WV	43.195	1.470	39.813	1.564
	(32.659)	(4.108)	(27.710)	(2.833)
WY		12.384**		7.571**
		(5.442)		(3.847)
Constant	−52.776***	−15.812***	−10.115	−8.097***
	(13.893)	(4.365)	(11.417)	(3.112)
Observations	686	687	688	689
R^2	0.182	0.126	0.055	0.099
Adjusted R^2	0.171	0.111	0.043	0.085
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 35: High and Low Percentage Hispanic Deciles Model Regression Results

	Dependent variable:			
	Learning Loss (Math)		Learning Loss (ELA)	
Decile:	High	Low	High	Low
Openness	0.145***	0.179***	0.018	−0.019
	(0.043)	(0.035)	(0.028)	(0.030)
% FRPL Eligible	−0.173***	−0.369***	−0.071***	−0.206***
	(0.036)	(0.039)	(0.024)	(0.033)
CT	17.578***		−2.807	−24.412
	(5.099)		(3.457)	(36.963)
FL	26.019***	24.412**	14.423***	−5.272
	(3.071)	(9.571)	(2.120)	(36.370)
MA	−9.456**	6.131	−7.868***	−18.077
	(3.818)	(8.669)	(2.643)	(36.300)
MN	2.215	12.594	−8.930	−20.656
	(11.454)	(8.642)	(7.795)	(36.253)
NV	9.726		−8.709*	
	(7.696)		(5.241)	
RI	−5.369	15.724	4.202	−3.158
	(17.826)	(11.335)	(6.283)	(36.810)
WI	−8.194	18.937**	−11.845**	−12.651
	(6.916)	(8.767)	(4.699)	(36.270)
WV		16.499*		−15.226
		(8.691)		(36.240)
WY		−10.963		−27.499
		(12.677)		(37.071)
Constant	−44.031***	−35.487***	−19.043***	12.400
	(4.504)	(8.567)	(3.063)	(36.349)
Observations	686	687	688	689
R^2	0.325	0.173	0.292	0.105
Adjusted R^2	0.316	0.162	0.283	0.092
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 36: High and Low Percentage Asian Deciles Model Regression Results

	Dependent variable:			
	Learning Loss (Math)		Learning Loss (ELA)	
Decile:	High	Low	High	Low
Openness	0.162***	0.200***	0.040*	0.038
	(0.027)	(0.049)	(0.024)	(0.058)
% FRPL Eligible	−0.420***	−0.379***	−0.207***	−0.317***
	(0.023)	(0.047)	(0.020)	(0.056)
CT	0.938	61.912***	−6.489**	183.916***
	(3.488)	(13.697)	(3.085)	(16.531)
FL	12.552***	15.532***	1.446	10.257*
	(3.399)	(5.085)	(2.975)	(5.829)
MA	−4.330	−7.866	−6.977**	−3.626
	(3.197)	(6.016)	(2.838)	(7.123)
MN	−1.239	4.995	−7.260**	−6.984
	(3.309)	(5.091)	(2.938)	(5.918)
NV		13.625		−1.862
		(13.158)		(16.283)
RI	−14.324**	−17.485	−14.434**	−17.625
	(7.012)	(20.608)	(5.794)	(24.939)
WI	3.674	8.801*	−3.226	−2.594
	(3.434)	(5.237)	(3.044)	(6.110)
WV	16.667	5.278	−4.249	−1.643
	(11.901)	(5.061)	(10.598)	(5.889)
WY		17.385**		4.135
		(7.169)		(8.431)
Constant	−16.937***	−24.637***	−0.132	1.799
	(3.333)	(5.909)	(2.980)	(7.067)
Observations	686	687	688	689
R^2	0.448	0.172	0.209	0.201
Adjusted R^2	0.441	0.159	0.198	0.188
Note:				*p<0.1; **p<0.05; ***p<0.01