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Projecting the potential impacts of COVID-19 school closures on academic achievement

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Abstract

With 55 million students in the United States out of school due to the COVID-19 pandemic, education systems are scrambling to meet the needs of schools and families, including planning how best to approach instruction in the fall given students may be farther behind than in a typical year. Yet, education leaders have little data on how much learning has been impacted by school closures. While the COVID-19 learning interruptions are unprecedented in modern times, existing research on the impacts of missing school (due to absenteeism, regular summer breaks, and school closures) on learning can nonetheless inform projections of potential learning loss due to the pandemic. In this study, we produce a series of projections of COVID-19-related learning loss and its potential effect on test scores in the 2020-21 school year based on (a) estimates from prior literature and (b) analyses of typical summer learning patterns of five million students. Under these projections, students are likely to return in fall 2020 with approximately 63-68% of the learning gains in reading relative to a typical school year and with 37-50% of the learning gains in math. However, we estimate that losing ground during the COVID-19 school closures would not be universal, with the top third of students potentially making gains in reading. Thus, in preparing for fall 2020, educators will likely need to consider ways to support students who are academically behind and further differentiate instruction.

Introduction

Virtually all K-12 students in the United States had face-to-face instruction interrupted during the 2019-20 school year due to the SARS-CoV-2 (COVID-19) pandemic. The majority of school districts are providing some virtual instruction during the last months of the school year (Lake & Dusseault, 2020a). But it remains unclear how effective virtual learning will be, given that most K-12 students and teachers have little experience with online instruction and that large gaps in technology access exist in many parts of the country. Additionally, during the extended school closure, many working parents struggle to educate and care for their children. These unique educational challenges are accompanied by broader shocks to society, including a major economic downturn, job losses, and the tangible health threat that is COVID-19. In short, extended time out of school will almost certainly affect student achievement (likely in a negative way for many), and that impact is hard to estimate given all the unique aspects of COVID-19 on schooling and society.

While many aspects of the pandemic make anticipating its impact on achievement difficult, there are parallels between the current situation and other planned and unplanned reasons for which students miss school that can help us quantify the potential scale of the COVID-19 impact. Specifically, existing research on the effects on learning of (a) summer vacation, (b) weather-related school closures (e.g., Hurricane Katrina in New Orleans), and (c) out-of-school time due to absenteeism can provide a rough sense of how additional time out of school due to COVID-19 will affect achievement in the coming fall and longer term. The intent of our study is to better understand and project how COVID-19-based school closures might affect achievement and growth during the current school year (2019-20) and the next (2020-21). Given that our projections, while based on existing literature, are unable to account for the impact of virtual instruction, access to supplemental curriculum, or the availability of additional educational resources, among other important factors, we present these results as preliminary estimates of the potential negative impacts expected due to extended school closures.

Prior research on time students spend out of school is useful given the importance of forecasting the impact of COVID-19 on short- and long-term achievement. Teachers and schools can benefit from knowing not only how much lower achievement might be but also how much more variable it could be in the fall. If students begin school in the fall of 2020 (or whenever regular schooling resumes) with bigger gaps in content knowledge between low- and high-performing students, then strategies like expanding instructional differentiation may be warranted. Further, projections of how potential learning loss due to out-of-school time might affect growth in the coming school year may also help educators identify students who are not on track academically when school resumes and give them needed supports.

In this study,[1] we made projections about the effects of COVID-19 on student achievement trends from the spring of 2020, when schools were first shut down across the United States (U.S.), through to the start of the 2020-21 school year. To provide preliminary estimates of the potential impacts of the extended pause on face-to-face academic instruction during the pandemic, we used a national sample of five million students in Grades 3-8 who took MAP® Growth™ assessments in the 2017-18 and 2018-19 school years (e.g., about 22% of the approximately 22 million U.S. public school students in Grades 3-8 according to NCES [2018]). Specifically, we compared typical growth trajectories across a standard-length school year to

[1] This paper has its origins in a NWEA brief (Kuhfeld & Tarasawa, 2020), which presents some preliminary learning projections. The current paper is distinct from the brief in terms of the volume of analyses and theoretical grounding.

learning projections that assume students are out of school for the last three months of the 2019-20 school year. In so doing, we investigated three research questions:

(1) What are possible scenarios (based on prior literature and recent MAP Growth data) for student learning patterns during the 2019-20 school year as a result of the school closures?

(2) How much variability do we expect in (a) students' learning rates during the extended school closure period and (b) students' fall 2020 scores assuming a normal 2019-20 school year versus one disrupted by COVID-19?

(3) What is the association between out-of-school time due to COVID-19 and projected subsequent learning rates over the course of the 2020-21 school year?

Background

While the COVID-19 school closures are unprecedented in the U.S., there are multiple bodies of research on which we can draw to anticipate the impacts[2] of extended closures on student learning. These include (a) seasonal learning studies that compare learning that occurs during the school year to learning that occurs during summer breaks, (b) studies on weather-related school closures, and (c) studies on student absenteeism. Table 1 provides a summary of the effect sizes (reported in standard deviation [SD] units for each day out of school) from key studies in each body of literature that are discussed below (further details on the studies are provided in Appendix A of the supplemental materials). We then discuss the degrees to which

[2] Studies from these three lines of research provide descriptive as well as credibly causal evidence. For the purpose of this study, we consider the research evidence collectively without distinguishing causal estimates from associations and refer to all estimated relations between out-of-school time and achievement as effects or impacts.

each of these bodies of work is likely to reflect the conditions observed during the COVID-19 school closures.

Seasonal Learning Studies

Seasonal learning research (including studies to understand the effects of summer learning loss) makes comparisons of student learning patterns when school is in versus out of session. Thus, one way to think about COVID-19 school closures is to consider them extensions of summer break for most students. Research has consistently shown that achievement typically slows or declines over the summer months (on average) and that the declines tend to be steeper for math than for reading (Quinn & Polikoff, 2017). However, there is much debate about the magnitude of summer loss and the degree to which summer vacation contributes to socioeconomic achievement gaps (von Hippel, 2019).

Prominent early work on summer learning loss found that students lost about a month of learning over the summer, with lower-income students falling behind middle- and high-income students in reading (Cooper, Nye, Charlton, Lindsay, & Greathouse, 1996; Alexander, Entwisle, & Olson 2001). Recent summer loss research using the Early Childhood Longitudinal Study, Kindergarten Cohort (ECLS-K) has indicated minimal loss on average during the summer, while studies using NWEA's MAP Growth assessment showed fairly sizable drops (Atteberry & McEachin; 2020; Kuhfeld, Condron, & Downey, 2019). This variability in estimates can be seen in Table 1, where summer drop estimates range from 0.001 to 0.010 SDs per day of school missed across grades/subjects. However, research using both recent data sources agree that summer does not appear to be a time in which socioeconomic and racial/ethnic inequalities widen (e.g., von Hippel & Hamrock, 2019; Kuhfeld, 2019; von Hippel, 2019).

School Closures due to Inclement Weather and Natural Disasters

The literature on school closures also provides some insight into the potential effect of COVID-19 school closures, especially given such closures occur unexpectedly and disrupt scheduled instruction. Although they occur over a shorter duration, school closures resulting from inclement weather or natural disasters provide an analog to school closures due to COVID-19. Absent the weather event or natural disaster, schools would be in session and learning for most students would occur as normal. Hansen (2011) found that each day of school cancellation due to snow in Colorado reduced 8th grade math achievement by magnitudes ranging from 0.013 to 0.039 SDs, and the impact effects of snow days in Maryland ranged from 0.013 to 0.016 SDs. Goodman (2014) studied snow day closures in Massachusetts and found that each day of school closure had null effects on math and reading achievement overall, but that students attending poor schools experienced a decline of 0.014 SDs in math and 0.016 SDs in reading for every day of school closure. A related line of research found that the displacement effect of Hurricane Katrina led to drops in achievement at a magnitude of approximately 0.10 SDs in the year after, though these studies did not investigate effect heterogeneity by student demographics or school poverty (e.g., Sacerdote, 2012). However, these estimates are not comparable to those provided by the snow day literature due to differences in research design and recorded units of time.

Absenteeism

In contrast to the seasonal learning and school closure studies discussed above, an emerging literature on school absenteeism focuses on the impact of instructional time loss due to absences while schools are in session. Unlike the school closure due to the COVID-19 that forces every student to be out of school, not all students are absent during a normal school year. There are numerous reasons for which a student might miss school, including lack of access to reliable transportation and need to care for family members. Minority and low-income students tend to have more absences and are more likely to be chronically absent (i.e., missing at least 10% of school days), compared with their more affluent peers (Whitney & Liu, 2016).

Research consistently found that absences had negative effects on end-of-year test scores. Several studies that used a value-added model found similar effect sizes in both elementary and secondary schools. Specifically, missing ten school days can decrease student math test scores by 0.06 to 0.08 SDs; the effect sizes for ELA scores were slightly smaller (Aucejo & Romano, 2016; Gershenson, Jacknowitz, & Brannegan, 2017; Liu, Lee, & Gershenson, 2019). Studies that used either flu or snow days as an instrumental variable for absences tended to yield much larger estimates (Aucejo & Romano, 2016; Goodman, 2014) largely due to the specific variation used in estimating the impact of absences. For example, Goodman (2014) found that one moderate snow day-induced absence reduced student math scores by 0.05 SDs. Another takeaway from the absenteeism literature is that the negative effects of absences were linear, meaning that each additional absence caused similar learning loss no matter how many absences a student had already accrued (Gershenson et al., 2017; Liu et al., 2019).

Similarities/Differences Between Out-of-School Time Studies and COVID-19 School Closures

The literatures on summer vacation, school closures due to weather and natural disasters, and absenteeism indicate that student learning is likely to be negatively impacted by being out of school. While there is a fair amount of variability in the effect size estimates by grade and study (Table 1), some clear trends emerge. Students showed bigger losses in math than reading while out of school. Being absent from school is generally associated with larger impacts on learning than being out of school due to summer vacation, particularly in middle school. Finally, our review suggests that studies on summer loss and absenteeism may provide better (if imperfect) models for the impact of COVID-19 than the literature on weather-related school closures, which was sparse (only two studies with effect size estimates), generated inconsistent findings, and tended to rely on small sample sizes from specific geographical settings. Accordingly, we draw on the absenteeism effect sizes reported in Table 1, as well as new summer loss analyses, to produce the projections reported in this study.

Before describing our approach, we consider how current and past school closures and their impact on achievement may differ. First, relying on past precedent may overstate the effect of COVID-19 school closures. Specifically, the biggest difference between school closures examined by previous studies and those of COVID-19 is that most school districts are now providing online instruction. Many districts have offered remote learning plans, which may include formal curriculum, assignments, and/or progress-monitoring as well as access to general educational resources. By April 3rd - 4th, 83 percent of parents in a Gallup poll indicated their child was involved in an online learning program from their school (Brenan, 2020). Further, one could imagine that parents of high socioeconomic status (SES) might leverage their cultural capital such that their children actually make larger academic gains than in typical school days, and these gains could further contribute to educational disparities.

Second, there is also evidence suggesting that measures taken by schools may not be as effective as hoped. There are concerning signs that many teachers have had no contact at all with a significant portion of students (Lieberman, 2020). According to national survey of teachers conducted by EdWeek (Kurtz, 2020), as of April 8th only 39% of teachers reported interacting with their students at least once a day, and most teacher-student communication occurred over email. There is also evidence that, even when teachers are making themselves and their instructional materials available virtually, many students lack the means to access online materials from home. Nearly 50% of low-income families and 42% of families of color lack sufficient devices at home to access distance learning, according to an Education Trust (2020b) poll. Moreover, few school systems provide plans to support students who need accommodations or other special populations (Lake & Dusseault, 2020b). Thus, despite many administrative leaders' and educators' best efforts, students and their families may bear the brunt of the responsibility for ensuring learning continues during the closures.

There is also uncertainty about whether virtual instruction, even when well-implemented, is likely to be as effective as traditional face-to-face instruction. Prior comparisons of online and traditional public schools show that students in online schools lose between 0.1 and 0.4 SDs on standardized tests compared to students in traditional schools (Gill et al. 2015; CREDO, 2015; Ahn & McEachin, 2017). The COVID-19 virtual instruction is somewhat different because students already know their teachers and are potentially doing review rather than being taught new material. However, many public teachers have not been trained on how to provide effective virtual instruction.

Finally, past precedent on out-of-school time may understate the impact of COVID-19 on student learning, especially compared to summer break, which is a wholly anticipated event. The same Education Trust (2020b) poll of California and New York parents found that elevated stress levels for families (parents and children) continue due to economic uncertainty and job loss, fears about catching a life-threatening virus, and the psychological impact of social isolation and disruptions to everyday life. The (almost certainly adverse) effect of these economic and psychological factors on the learning occurring in homes is difficult to anticipate. However, extended school closures due to natural disasters such as Hurricane Katrina and the Christchurch, New Zealand earthquakes may provide some clues. Research suggests the impact of school disruptions following natural disasters on student development was long lasting, with some students continuing to show psychological distress and trouble concentrating for several years afterwards (Picou & Marshall, 2007; Duncan, 2016).

Given unique elements of the current situation, we are not positioned in this study to speculate about whether current research and historical trends in achievement will likely understate or overstate the effects of COVID-19 school closures on achievement. However, given the scale of our data and what we know from past research, we can make forecasts about potential impacts of COVID-19 based on multiple scenarios and assumptions about how learning might have changed this past school year (2019-20) and will change over the next (2020-21). Even if forecasts can only provide a range of potential impacts based on different assumptions made about the current situation, forecasts are nonetheless invaluable in helping educators and policymakers understand what to expect when students return in the fall, including how learning might progress differently over the course of the 2020-21 school year.

To that end, our study includes several analyses that can prepare educators and policymakers for what they may face next year. First, we produce two sets of possible scenarios for COVID-19 learning loss while students would have otherwise been in school in 2019-20. One set of projections is based on empirical analyses examining summer loss using MAP Growth data. We then compare those projections to a second set of projections for learning loss based on the absenteeism literature, obtained by multiplying the daily learning loss rate from that literature by the days of school missed during the pandemic. Second, we provide estimates of (a) predicted variability in learning rates and (b) predicted variability in student scores at the beginning of the 2020-21 school year that account for the extended time out of school. Third, we go beyond prior school closure research to look not only at the potential effect of school closure on current achievement, but also the relationship between out-of-school time achievement declines and growth during the following year (i.e., how strongly associated is the magnitude of learning loss with the gains made in the next year?).

Methods

Analytic Sample

The data for this study are from NWEA's anonymized longitudinal student achievement database. School districts use NWEA's MAP Growth assessments to monitor elementary and secondary students' reading and math growth throughout the school year, with assessments typically administered in the fall, winter, and spring. We use the test scores of approximately five million third- to seventh-grade students[3] in 18,958 schools across the United States. In this study, we follow students across two school years (2017-18 and 2018-19) and one summer break (summer of 2018). The NWEA data also include demographic information, including student race/ethnicity, gender, and age at assessment, though student-level SES is not available. Table 2 provides descriptive statistics for the sample by subject and grade. Overall, the sample is 51% male, 47% White, 17% Black, 4% Asian, and 18% Hispanic. School-level free or reduced priced lunch (FRPL) eligibility was obtained from the 2017-18 Common Core of Data (CCD) file from the National Center of Education Statistics (NCES). The average student in our sample attends a school that is 51% FRPL-eligible. A comparison of the 18,972 schools in our sample relative to U.S. population of public elementary and middle schools (72,075 schools serving Grades 3-8) is provided in Appendix B of the supplemental materials. Overall, the sample closely aligns to the

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[3] Due to limited MAP Growth testing in high schools, we did not follow the cohort of 8th graders in 2017-18 into 9th grade in 2018-19.

characteristics of U.S. public schools, with a slight overrepresentation of Black students and underrepresentation of Hispanic students.

Measures of Achievement

Student test scores from NWEA's MAP Growth reading and math assessments are used in this study. MAP Growth is a computer adaptive test that precisely measures achievement even for students above or below grade level and is vertically scaled to allow for the estimation of gains across time. The MAP Growth assessments are typically administered three times a year (fall, winter, and spring) and are aligned to state content standards. Test scores are reported on the RIT (Rasch unIT) scale, which is a linear transformation of the logit scale units from the Rasch item response theory model.

Projecting COVID-19 School Closure Impacts on Learning Trajectories

In this study, we present two sets of estimates of the potential impacts of COVID-19 school closures on student learning: (a) empirical estimates calculated using MAP Growth data based on summer loss patterns during the summer of 2018, and (b) estimates calculated based on prior absenteeism literature. We begin by describing our empirical approach to estimating students' academic growth during the school year and learning loss during summer break under normal (pre-COVID-19) conditions. Subsequently, we discuss how we use the absenteeism and summer loss estimates to produce COVID-19 projections.

We first estimated typical growth rates across two school years (2017-18 and 2018-19) and the summer break in between using a series of multilevel growth models (longitudinal test scores nested within students within schools). Following other seasonal learning research studies (e.g., von Hippel et al., 2018; Kuhfeld et al., 2019), we estimated student learning rates as a function of the months that elapsed during the two school years and the summer between. Given that prior research using MAP Growth data found evidence of non-linearity in students' within-school growth trajectories (Kuhfeld & Soland, 2020), particularly in reading, we modeled student learning rates across the school year using a quadratic function (though a set of models assuming linear growth are also reported in Appendix Tables C3 and C4). Under this model, the test score y_{tij} for student *i* in school *j* at timepoint *t* was modeled as a quadratic function of the months that a student had been exposed to the 2017-18 school year (MonY1_{ij}), the summer of 2018 (Sum_{ij}), and the 2018-19 school year (MonY2_{ij}). At level 1, the growth model can be expressed as:

$$\begin{aligned} y_{tij} = {} & \pi_{0ij} + \pi_{1ij}\text{MonY1}_{tij} + \pi_{2ij}\text{MonY1}_{tij}^2 + \pi_{3ij}\text{Sum}_{tij} \\ & + \pi_{4ij}\text{MonY2}_{tij} + \pi_{5ij}\text{MonY2}_{tij}^2 + e_{tij}. \end{aligned} \quad (1)$$

The intercept (π_{0ij}) is the predicted score for student *i* in school *j* tested on the first day of the 2017-18 school year, π_{1ij} is the average instantaneous rate of change at the start of the 2017-18 school year, and π_{2ij} is the average rate of change of the linear growth term in 2017-18 for a one-month change in time (e.g., the acceleration or deceleration in growth), π_{3ij} is the monthly summer linear loss rate, and π_{4ij} and π_{5ij} are the linear and quadratic terms in the 2018-19 school year, respectively. At level 2 and 3 of the model, the intercept and growth parameters were allowed to vary among students within schools and between schools:

Level-2 Model (student (i) within school (j)): (2)

$$\begin{aligned} \pi_{0ij} &= \beta_{00j} + r_{0ij} \\ \pi_{1ij} &= \beta_{10j} + r_{1ij} \\ \pi_{2ij} &= \beta_{20j} \\ \pi_{3ij} &= \beta_{30j} + r_{3ij} \\ \pi_{4ij} &= \beta_{40j} + r_{4ij} \\ \pi_{5ij} &= \beta_{50j} \end{aligned}$$

Level-3 Model (school (j)):

$$\beta_{00j} = \gamma_{000} + u_{00j}$$

$$\beta_{10j} = \gamma_{100} + u_{10j}$$

$$\beta_{20j} = \gamma_{200}$$

$$\beta_{30j} = \gamma_{300} + u_{30j}$$

$$\beta_{40j} = \gamma_{400} + u_{40j}$$

$$\beta_{50j} = \gamma_{500}$$

Variance component specification:

$$e_{tis} \sim \mathrm{N}(0, \sigma_{tis}^2),\ \boldsymbol{r_{is}} \sim \mathrm{MVN}(\boldsymbol{0}, \boldsymbol{T}_{St}),\ \boldsymbol{u_s} \sim \mathrm{MVN}(\boldsymbol{0}, \boldsymbol{T}_{Sch}).$$

This model was estimated separately by subject (math and reading) and grade (3-7) using HLM Version 7 (Raudenbush, Bryk, & Congdon, 2013). Estimated parameters from these models are reported in Appendix Tables C1 and C2.

We began by calculating "typical" growth rates across a standard 9.5-month school year (assuming students start school on September 1st and end on June 15th). To estimate typical growth, we used the estimated parameter estimates from the 2017-18 school year for each grade *g* and subject separately:

$$\widehat{\mathrm{RIT}}_{tg} = \hat{\gamma}_{000} + (\hat{\gamma}_{100}) * \mathrm{Mon_t} + (\hat{\gamma}_{200}) * \mathrm{Mon_t^2}, \tag{3}$$

where $\mathrm{Mon_t}$ takes values from 0 to 9.5. We then calculated "typical" summer loss across a 2.5-month summer:

$$\widehat{\mathrm{SumLoss}}_{tg} = (\hat{\gamma}_{300}) * \mathrm{SumMon_t}, \tag{4}$$

where $\mathrm{SumMon_t}$ takes values from 0 to 2.5 months. Under the standard-length school year, students end the year at their 9.5-month achievement level ($\widehat{\mathrm{RIT}}_{9.5g}$) and then were assumed to lose ground linearly across a 2.5-month summer. We provided the "typical" school year growth rates and summer loss as a reference for the COVID-19 projections described below.

The first scenario, which we refer to as "COVID Loss Summer Slide", assumes that assumes that typical summer loss patterns would extend through the prolonged school closure. Linear projections were made based on the same $\widehat{\mathrm{SumLoss}}_{tg}$ calculation described above, but starting from the projected achievement level at 6.5 months ($\widehat{\mathrm{RIT}}_{6.5g}$) and extending to the presumed start of the next school year (12 months, September 1st). During the "normal" summer period (9.5 to 12 months), the typical summer loss and COVID Loss Summer Slide rates were the same, and so these lines were parallel during the summer months (June 15^{th} to September 1^{st}).

The second scenario for our COVID-19 projections, which we refer to as "COVID Loss Absenteeism", draws on existing absenteeism literature. We first calculated an average effect size (in SD units) for each day missed of school by subject based on the effect sizes reported in Table 1 (e.g., an average -0.007 SDs per day in math and -0.004 SDs per day in reading). Next we converted these estimates into monthly losses on the RIT scale using NWEA's subject- and grade-specific achievement norms (Thum & Kuhfeld, 2020), assuming there are approximately 20 potential instructional days in a typical month and that students are absent during the entire school closure period. Given the majority of schools in the U.S. shut down around the week of March 15^{th} (6.5 months into the school year), we used students' projected achievement level at 6.5 months ($\widehat{\mathrm{RIT}}_{6.5g}$) as the starting point for the projection and then assumed students lose ground from that point at that monthly rate calculated for each subject/grade. Given that students can only be absent while schools are still in session, we produced absenteeism projections only to the end of the school year (9.5 months).

RQ1. Possible Scenarios for Learning Gains during the 2019-20 School Year

To display the possible scenarios for learning as a result of the school closures during the 2019-20 school year, we produced a set of plots to compare these empirical- and literature-based projections to typical learning rates. The plots display students' estimated learning rates across the 2019-20 school year and summer of 2020 based on the absenteeism and summer loss projections. In addition to the plots, we also reported the impact of school closures as a percentage of learning gains that students were expected to make relative to a typical school year. These percentages were calculated by estimating the total gains during the school year (subtracting the initial score on September 1st, 2019 from the projected score on June 15th, 2020) under the two different COVID Loss assumptions and dividing those estimates by the total gains expected under typical growth.

RQ2. Quantifying Variability in COVID-19 Impacts

We do not expect that all students will be impacted by COVID-19 school closures equally. Prior summer learning loss research indicated that there is a considerable variability in students' learning patterns over the summer (e.g., Atteberry & McEachin, 2019; Kuhfeld et al., 2019), most of which cannot be explained by observed student and family characteristics (von Hippel et al., 2019; Kuhfeld, 2019; Borman, Benson, Overman, 2005). In addition to producing average estimates of learning rates during time out of school, we estimated variation in these learning rates across students. Specifically, we used the variance term of the within-school summer loss random effect (r_{3ij}) to examine the potential variability in COVID-19 impacts based on learning patterns during the summer of 2018. Based on the average monthly summer loss rate ($\hat{\gamma}_{300}$) and the standard deviation of the learning loss across students within the same school ($T_{St(3,3)}$), we calculated the monthly learning rates for students at the 25th, 50th, and 75th percentiles of the summer learning distribution. These estimates were then plotted to allow for an examination of the potential spread in fall 2020 RIT scores by grade/subject assuming students maintained the same rate of growth from school closure (March 15th) to the start of the 2020-21 school year.

There are two potential limitations to this approach. First, while this approach allowed us to quantify variability in potential growth rates while students are out of school, it did not provide a direct estimate of the possible variability in test scores when students return to school following the COVID-19 school closures. Second, it ignored the correlation between gains made while in school and losses that occur out of school. Prior research has indicated school-year and summer learning are negatively correlated, with students who made the largest gains during the school year showing the biggest drops in the summer (e.g., Kuhfeld, 2019; von Hippel et al., 2018).

Therefore, we also used the empirical Bayes (EB) estimates of students' learning rates from our models to project students' achievement in fall 2020 under two scenarios. Under the first scenario, we used the EB estimates from the 2017-18 school year and the summer of 2018 to produce projected scores at the start of the 2018-19 school year. These projected fall scores were treated as what would be expected in fall 2020 under "business as usual", had students completed the full 2019-20 school year and a typical summer break. The fall RIT scores are predicted using the following equation, in which $\hat{\gamma}$ are parameter estimates from the model and $\hat{r}$ are EB estimates of the random intercepts and slopes:

$$\widehat{\text{RIT}}_{Typical_{Fall},gij} = \hat{\gamma}_{000} + \hat{r}_{0ij} + \left(\hat{\gamma}_{100} + \hat{r}_{1ij}\right) * 9.5 + (\hat{\gamma}_{200}) * 9.5^2 + \left(\hat{\gamma}_{300} + \hat{r}_{3ij}\right) * 2.5. \tag{5}$$

In the second scenario, we assumed that COVID-19 increased the effects of summer loss by extending out of school time. In this case, projected fall scores were calculated for each student assuming a 6.5-month school year followed by a 5.5-month summer break, using the following equation:

$$\widehat{\mathrm{RIT}}_{COVID_{Fall},gij} = \hat{\gamma}_{000} + \hat{r}_{0ij} + \left(\hat{\gamma}_{100} + \hat{r}_{1ij}\right) * 6.5 + (\hat{\gamma}_{200}) * 6.5^2 + \left(\hat{\gamma}_{300} + \hat{r}_{3ij}\right) * 5.5 \tag{6}$$

Further details on the calculation of the projected scores under each scenario are provided in Appendix D. We then compared the distribution of scores under each condition to understand how much more variable the fall scores were under the COVID-19 Summer Slide assumption relative to a normal fall.

RQ3. Estimating the Relationship Between Summer Loss and Next School Year's Growth

To guide planning to support student learning during this pandemic and school closures, it is important to understand not only the possible impact of school closures on student learning, but also whether students with large losses recover at similar or different rates than other students. To investigate this question, we examined the correlation among the learning rates during the summer of 2018 and in the 2018-19 school year. Specifically, we examined the level-2 random effect correlation matrix to understand the association between out of school learning rates and growth in the following school year. Though the empirical data are from a typical school year and summer, the results from this analysis can inform decision-making by serving as a proxy for student learning recovery post-COVID-19.

Results

RQ1. Possible Scenarios for Learning Gains during the 2019-20 School Year

Projected COVID-19 impacts on average academic growth trajectories are presented in Figure 1 for mathematics (Panel A) and reading (Panel B). In a typical year (shown as solid lines), average academic growth is not constant across the academic year (shown as the curved lines seen in some grades) and generally declines from the last day of school through the summer, with steeper declines in mathematics than in reading. The dashed line shows projected trajectories based on prior absenteeism literature (from COVID-19 school closure to the end of the 2019-20 school year), and dotted lines show projected trajectories under summer learning loss patterns (from COVID-19 school closure to start of the 2020-21 school year). Since the absenteeism estimates pertain to missing school while schools are still open, we did not extend the COVID Loss Absenteeism projections past June 15th.

Under both sets of projections, students' learning gains are projected to be substantially lower at the end of the school year than under typical conditions. The COVID Loss Absenteeism projections for losses in learning are more dire than the COVID Loss Summer Slide projections, implying steeper drops while students are out of school across all grades and subjects. We also calculated the percentage of learning gains that students would be expected to have made relative to a normal year under each condition. Our results suggest that under the COVID Loss Summer Slide projections, students end the abbreviated 2019-20 school year with roughly 63-68% of the learning gains in reading relative to a typical school year (see Table D1 in the supplemental materials). However, in mathematics, students are likely to show much smaller gains, ending the school year with 37-50% of the average gains in a normal school year. For students moving from fifth to sixth grade, we expect under COVID Loss Summer Slide projections that students end the school year with only 19% of total mathematics gains. Under the COVID Loss Absenteeism projections, the story is even more dire, with students in sixth and seventh grade projected to end the school year with less than 30% of their typical learning gains in both math and reading.

RQ2. Quantifying Variability in COVID-19 Impacts

Beyond average achievement, educators may be equally concerned about whether COVID-19 will result in greater variability in the academic skills that students bring with them when school resumes. In Figure 2, we display the variability in learning expected under the COVID Loss Summer Slide model from March 15th (when schools shut down) to September 1st (when schools are expected to reopen). These estimates are based on variability seen during a typical summer, but with the duration of that summer extended. For parsimony, we only display Grades 4 and 6, but the model-based variability estimates for all grades/subjects are presented in Table D3 of the supplemental materials. The shaded areas display the spread in potential outcomes between students who were in the 25th percentile of summer learning loss (who showed steep declines) and those in the 75th percentile (who showed flat scores or even small gains during the summer). In mathematics, we see a fair amount of variability in learning rates, though the majority of students show losses over the extended closure and summer period. However, in reading, there is an even wider spread of potential outcomes, with students who are in the 75th percentile and above showing sizable learning gains during the summer. As seen in Table D3, approximately the upper half of the distribution (39-46% of students) are projected to show monthly gains in reading during the summer. Altogether, these plots show that extended time out of school may lead to more variability in achievement when students return in the fall.

One limitation of the plots in Figure 2 is that they do not provide concrete evidence on the variability in fall achievement under COVID-19 *relative* to variability under a typical school year. Thus, in Figure 3 we display the spread of the projected fall 2020 test scores under "typical" conditions as well as the COVID Loss Summer Slide projections. The box plot shows the interquartile range (e.g., the 25th, 50th, and 75th percentiles) and the vertical lines extending above and below the box stretch one and half times the interquartile range, with scores outside that range displayed as outliers (circles in the figure). The estimated means, SDs, and percentiles scores for each condition and grade/subject are reported in Table D3 in the supplemental materials. Across the board, students are projected to return in the fall with lower scores and more variability relative to a typical fall. In reading, the SDs of expected scores are expected to be up to 1.2 times the SDs expected in a typical fall. Thus, students will likely return not only with lower achievement (on average), but with a wider range of academic skills that may require teachers to further differentiate instruction.

RQ3. Estimating the Relationship Between Summer Loss and Next School Year's Growth

Finally, to project whether larger COVID-19 learning losses would be associated with faster growth rates during the 2020-21 school year, we examined whether students who lost more ground during a typical summer showed slower rates of recovery during the subsequent typical school year. Correlations between students' summer loss and linear growth during the 2018-19 school year are presented in Tables C1 and C2 in the supplemental materials. In mathematics, student-level correlations ranged from -0.41 to -0.43, and in reading the correlations ranged from -0.45 to -0.46. These correlations imply that students who lost more ground during the summer of 2018 showed steeper growth during the following school year (2018-19) than students with less summer loss. Accordingly, this suggests that a student who lost ground during the summer does not necessarily continue to lose ground during the next school year; rather, they are likely to gain ground.

Discussion

Educators, policymakers, families, and students find themselves in uncharted territory during the COVID-19 crisis. School districts in particular are on the front lines to help ensure all students have access to academic materials, instruction, and digital resources, among other basic needs such as food for students from low income backgrounds and support for students with disabilities, English learners, and students in temporary housing (Education Trust, 2020a). Despite these efforts, a majority of parents with children in K-12 schools are concerned that their children will fall behind academically due to the disruptions of COVID-19 school closures (Horowitz, 2020). In this study, we produced a set of possible scenarios for learning loss rates during the extended period when schools are physically closed and students are not receiving normal face-to-face instruction. These projections can help prepare educators and parents for the degree of variability in student achievement to expect when school resumes, including over the course of the upcoming school year.

First, we show that students will likely (a) not have grown as much during the truncated 2019-2020 academic year and (b) will likely lose more of those gains due to extended time out of school. Based on our projections, students will return in fall 2020 with approximately 63-68% of the learning gains in reading relative to a typical school year and with 37-50% of the learning gains in math. In some grades, students may come back close to a full year behind in math. While such projections may reinforce the worst fears of educators and parents, we should note that they do not factor in the home schooling and online instruction that students may currently be receiving. Therefore, they should be viewed as a likely upper bound for the potential negative effects on students' learning.

Second, we also examined variability in possible learning outcomes during the school closures and in the fall of 2020. We found that losing ground over the summer was not universal, with the top third of students in reading making gains during a typical summer. As a result of this variability, we project that the range of students' academic achievement will be more spread out in the fall of 2020 relative to a normal fall term, particularly in reading. In presenting these projections, we assume that the variability in typical summer loss can act as a proxy for the large variability in learning that is expected due to the widely differing home and school district conditions impacti learning during the school closure period. In all likelihood, differential access to parent and teacher supports for learning during the school closure months will produce variation larger than what typical summer break variability would imply.

Finally, we show that, although our projections are dire, our models also suggest that students who lose the most while out of school tend to gain the most the following year (at least under typical summer loss conditions). Thus, there is hope that students most impacted by the additional average achievement losses under COVID-19 may also be the ones who rebound the most by the end of the 2020-21 academic school year. At the same time, one cannot be sure how financial uncertainty, health issues related to the virus, and psychological stresses may affect the association between summer loss and subsequent academic growth.

Limitations of Our Projections

While we provide two sets of projections in this study—one based on growth rates calculated from MAP Growth data and the other based on prior literature on student absenteeism—we acknowledge that it is impossible to accurately weigh the complex range of supports and challenges that students are facing during this period. The school closures caused by COVID-19 have additional aspects of trauma to students, loss of resources, and loss of opportunity to learn that go well beyond a traditional summer break for many families. In other words, families with financial resources, stable employment, and flexible work-from-home and childcare arrangements will likely weather this storm more easily than families who are renting their housing, working in low-paying fields that are hardest hit by the economic impacts, and experiencing higher rates of food insecurity, family instability, and other shocks from this disruption.

Given the uncertain impact of COVID-19, we have chosen not to make projections specific to inequalities by race/ethnicity, biological sex, and SES. Recent analyses of both ECLS-K and MAP Growth data have found little evidence that achievement gaps by race/ethnicity and SES widen during summer months (von Hippel & Hamrock, 2019; Kuhfeld, 2019). This is likely due to the fact that families of all income levels typically treat summer break as a vacation from math and reading, a time when "kids can be kids" (von Hippel, 2020). Were we to base estimates of COVID-19 impacts on racial/ethnic disparities in achievement and growth on these historical summer learning loss patterns, we would likely conclude that the COVID-19 pandemic is going to minimally impact long-standing inequalities in this country.

However, there are many reasons to believe the COVID-19 impacts might be larger for children in poverty and children of color. There are higher rates of COVID-19 infections and deaths in the African American community (Bouie, 2020), and the economic downturn has been particularly damaging for African American and Hispanic parents, who are less likely to be able to work from home during the pandemic (Krogstad, Gonzalez-Barrera, & Noe-Bustamente 2020; Cerullo, 2020). Furthermore, the so-called "digital divide" in technology and internet access by race/ethnicity and socioeconomic status (Musu, 2018) likely contributes to greater inequalities during the COVID-19 pandemic than a typical summer. Given this evidence that the impacts of the COVID-19 school closures will have disproportionate impacts on our country's most underserved communities in ways that historic summer data fails to capture, we chose not to produce projections based on pre-COVID-19 MAP Growth summer learning data for individual subgroups. However, we believe it will be of great importance to study how existing inequalities have widened or been reshaped once schools have reopened.

Furthermore, in calculating the projected impact of out-of-school time on learning in this study, we assumed that it is appropriate to linearly extrapolate learning loss from research on absenteeism and summer loss across the three months of school closure. Liu and colleagues (2019) found that additional absences had an approximately linear impact on student learning, though the number of absences assumed in this study (approximately 60 school days) far exceeds the average number of absences observed in their study. Furthermore, we have very little data about whether the summer months have a linear impact on students' reading and mathematics skills. Campbell and Frey (1970) hypothesize that forgetting learned material may occur non-linearly, with rapid initial deceleration of knowledge followed by slower drop offs as time passes. However, we are unaware of any studies that have examined this phenomenon in the context of summer break. If the true effect of being out of school accelerates the longer students are out of school, we could be underestimating the impact on learning. But if summer loss simply reflects a process of forgetting and re-remembering that is not directly linked to the amount of time out of school, we could be greatly over-estimating the potential impacts on learning.

Where Do We Go From Here?

While we are not well-positioned to make recommendations for ways to remedy the learning loss that is likely occurring due to COVID-19, our results do provide takeaways that can inform how educators and leaders can prepare to support students upon return. First, we show that students may be substantially behind, especially in mathematics. Thus, teachers of different grade levels may wish to coordinate in order to determine where to start instruction. Educators will also need to find ways to assess students early, either formally or informally, to understand exactly where students are academically.

Second, students are likely to enter school with more variability in their academic skills than under normal circumstances. Prior research suggests greater heterogeneity in student achievement affects a classroom teacher's ability to adapt instruction to meet the instructional needs of all students (Connor, Piasta, Fishman, Glasney, Schatschneider, Crowe, & Morrison, 2009; Evertson, Sanford, & Emmer, 1981).Therefore, educators may need to consider ways to further differentiate instruction or provide opportunities for individualized learning. For a summary of related literature, one could turn to Peters, Rambo-Hernandez, Makel, Matthews, and Plucker (2017).

Third, under typical schooling conditions, the students who lose the most during the summer tend to gain the most when back in school. Nonetheless, the ground that students have to make up during the 2020-21 academic year will probably be greater due to COVID-19. Therefore, educators may want to work with students to determine growth rates needed to catch up and set learning goals for the year that are ambitious but obtainable. These strategies might include establishing out-of-school learning supports during the 2020-21 school year for the students most affected by school closures.

Finally, the effects of COVID-19 to which our study cannot speak may be ones most worthy of addressing. Districts are rushing to support educators who are attempting to teach academic content remotely while also caring for their students' social emotional well-being. Prior research on students displaced by Hurricane Katrina indicated that students had difficulty concentrating and often manifested symptoms of depression in the months following the hurricane (Picou & Marshall, 2007). Understanding these impacts and how to best support students' social and emotional needs after this huge disruption of COVID-19 will be essential. Many students may face greater food insecurity, loss of family income, loss of family members to the coronavirus, and fear of catching the virus themselves (NAACP, 2020). While the scale of the COVID-19 school closures is novel, the inequalities in our school systems are unfortunately anything but new. Our models cannot account for the reality that the crisis is having an unequal impact on our most underserved communities. Nonetheless, we hope these analyses, which synthesize what we know from existing bodies of research, will inform tomorrow's decision making.

Conclusions

These preliminary forecasts parallel many education leaders' fears: missing school for a prolonged period will likely have major impacts on student achievement. Further, students will likely return in the fall of 2020 with greater variability in their academic skills. While we are unable to account for students' exposure to virtual instruction while schools are closed, our learning loss projections imply that educators and policymakers will need to prepare for many students to be substantially behind academically when they return.

Similar to the research that found students took nearly two full years to make up lost ground for the loss in instructional time due to Hurricane Katrina (Harris & Larsen, 2019), our COVID Loss projections provide new evidence on the scope of the long-term educational recovery efforts that will be required. We believe this study is one in a growing body of important work that leverages prior research to empower school leaders, policy makers, and researchers to make urgent evidence-informed post-COVID-19 recovery decisions.

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Table 1

Estimates of the Impact of Out-of-School Days on Standardized Test Scores Across Summer Loss, School Closure, and Absenteeism Literature

Citation	Location	Grade level	Math Effect	ELA Effect
		Summer Loss		
Atteberry & McEachin (2019)	National (NWEA)	1st grade	-0.009	-0.010
		2nd grade	-0.006	-0.006
		3rd grade	-0.006	-0.005
		4th grade	-0.005	-0.003
		5th grade	-0.005	-0.003
		6th grade	-0.003	-0.002
		7th grade	-0.002	-0.001
von Hippel, Workman, & Downey (2018)	National (ECLS-K:2011)	Kindergarten	0.002	-0.001
		1st grade	-0.001	-0.001
Kuhfeld, Condron, & Downey (2019)	National (NWEA)	Kindergarten	-0.005	-0.004
		1st grade	-0.007	-0.004
		3rd grade	-0.006	-0.004
		4th grade	-0.005	-0.003
		6th grade	-0.004	-0.002
		7th grade	-0.002	-0.001
		Absenteeism		
Liu, Lee, & Gershenson (2020)	large urban CA school district	6th-8th grade	-0.008	-0.006
Gershenson, Jacknowitz, & Brannegan (2017)	ECLS-K + NC	K-1st grade	−0.002	−0.002
	NC public schools	3rd-5th grade	-0.007	-0.004
Aucejo & Romano (2016)	NC public schools	3rd-5th grade	-0.006	-0.003
		School Closures due to Inclement Weather		
Hansen (2011)	CO and MD public schools	8th grade (CO)	-0.013 to -0.039	N/A
		3rd grade (MD)	-0.003 to -0.011 (NS)	
		5th grade (MD)	-0.015 to -0.016	
		8th grade (MD)	-0.009 to -0.013	
Goodman (2014)	MA public schools	3rd-8th + 10th grade	-0.000 (NS)	0.003 (NS)

Note. ECLS-K=Early Childhood Longitudinal Study, Kindergarten Cohort, CA=California, NC=North Carolina, CO=Colorado, MD=Maryland, MA=Massachusetts, NS=Not significant. All coefficients are reported as drops in standard deviation units on math and reading/English Language Arts assessments for each day of school missed. More details on each study are presented in Appendix Table A1.

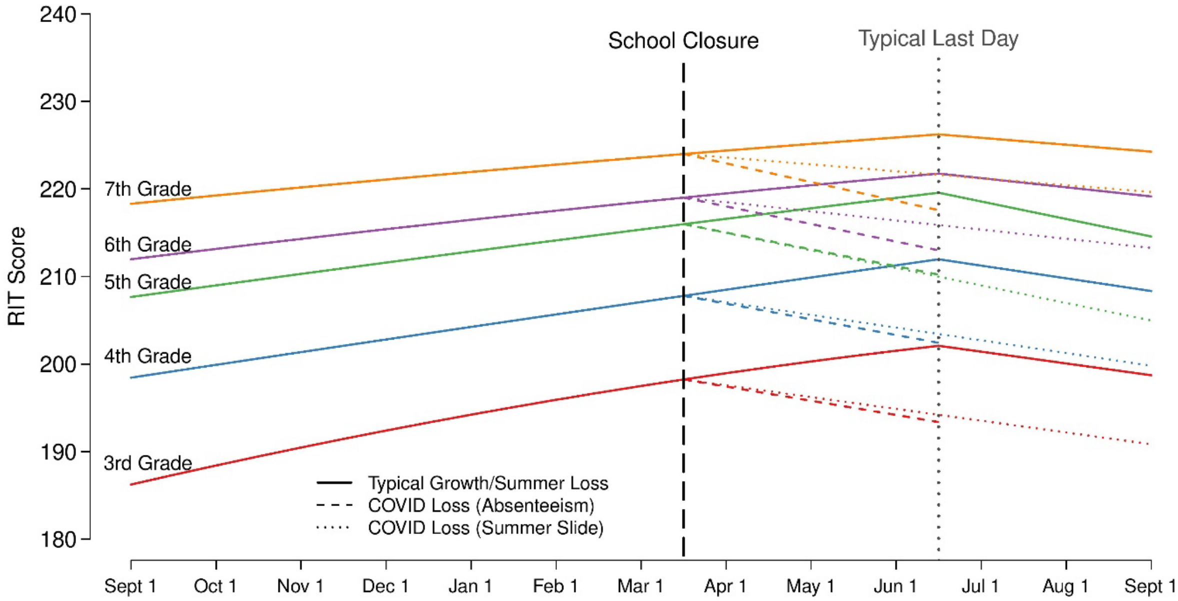
Table 2

Descriptive Statistics for the Sample

Grade	N. Schools	N. Students	Race/ethnicity					Male	% FRPL
			White	Black	Asian	Hispanic	Other race		
Mathematics									
3	12,816	986,862	0.45	0.18	0.04	0.18	0.14	0.51	0.51
4	13,071	999,788	0.46	0.17	0.04	0.18	0.14	0.51	0.50
5	14,146	1,029,363	0.47	0.17	0.05	0.18	0.13	0.51	0.50
6	8,952	976,105	0.47	0.17	0.04	0.18	0.14	0.51	0.50
7	7,040	937,054	0.47	0.16	0.04	0.18	0.13	0.51	0.50
Full Sample	18,972	4,929,172	0.47	0.17	0.04	0.18	0.14	0.51	0.50
Reading									
3	12,874	988,644	0.45	0.18	0.04	0.18	0.14	0.51	0.51
4	13,066	997,088	0.47	0.18	0.04	0.18	0.14	0.51	0.51
5	14,129	1,026,057	0.47	0.17	0.04	0.18	0.13	0.51	0.50
6	8,943	970,524	0.47	0.17	0.04	0.18	0.14	0.51	0.50
7	6,995	934,960	0.48	0.17	0.04	0.18	0.13	0.51	0.50
Full Sample	18,958	4,917,273	0.47	0.17	0.04	0.18	0.14	0.51	0.50

Note. N=Number, %FRPL=percentage of free or reduced priced lunch. Grade is the grade level students were in during the 2017-18 school year.

(A) Mathematics Projections



(B) Reading Projections

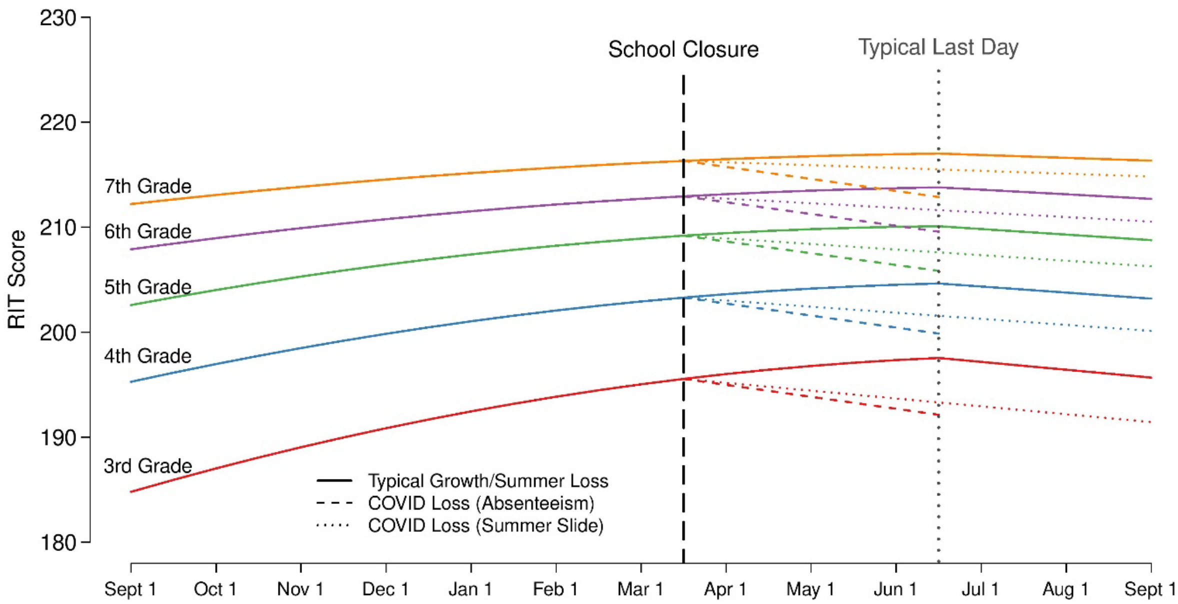
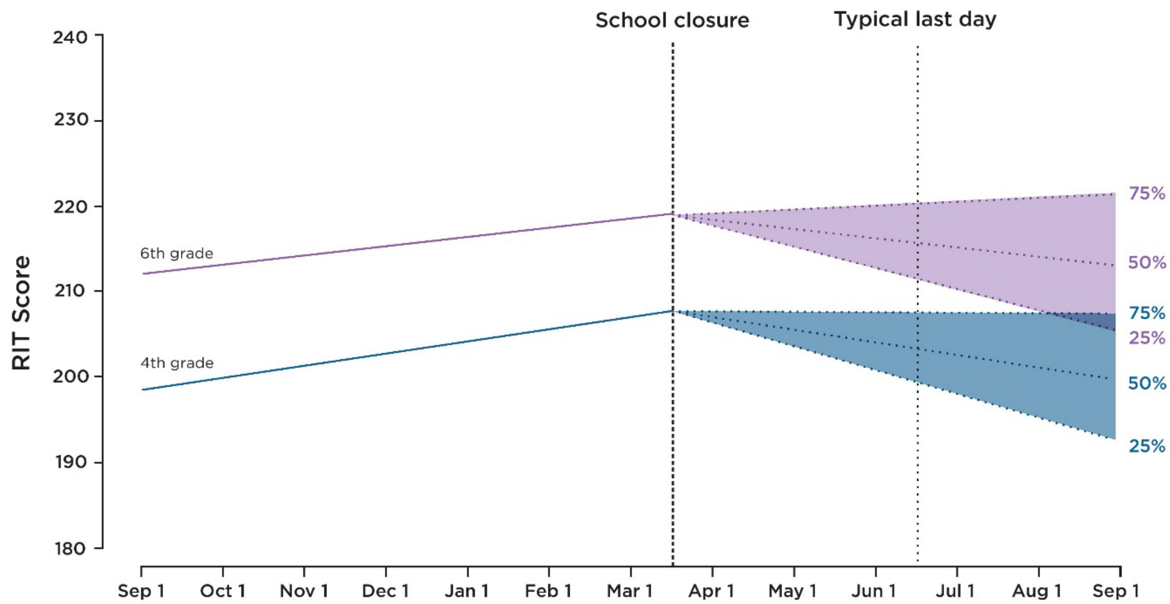


Figure 1. Mathematics and reading forecasts based on summer loss estimates and absenteeism literature.

(A) Mathematics Projections



(B) Reading Projections

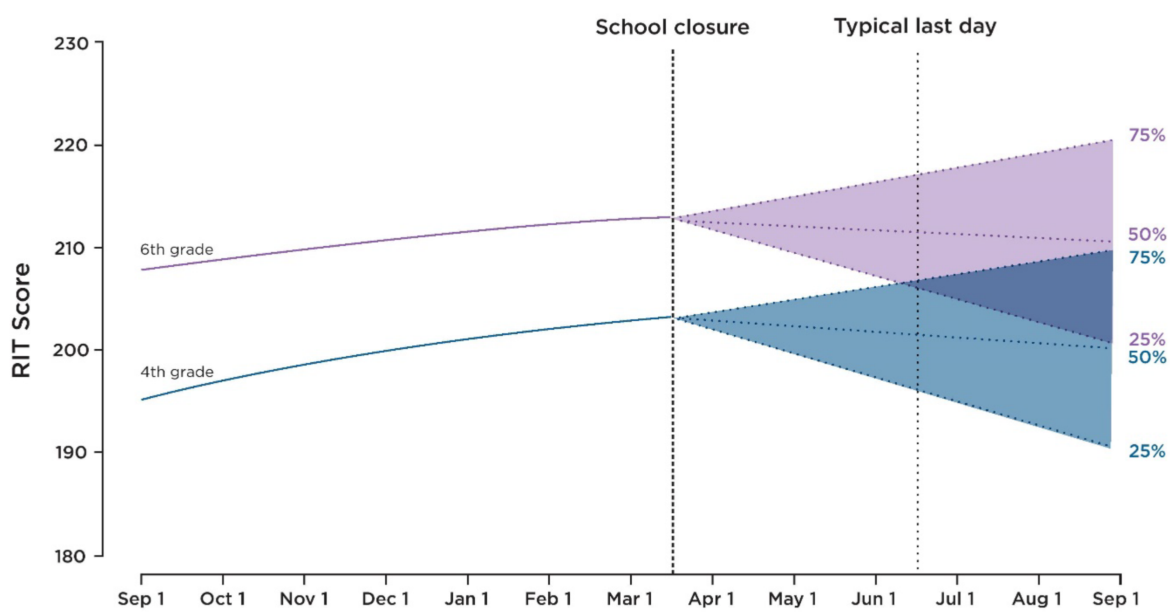


Figure 2. Mathematics and reading forecasts for the 2019-20 school year accounting for the variability observed in typical summer loss patterns.

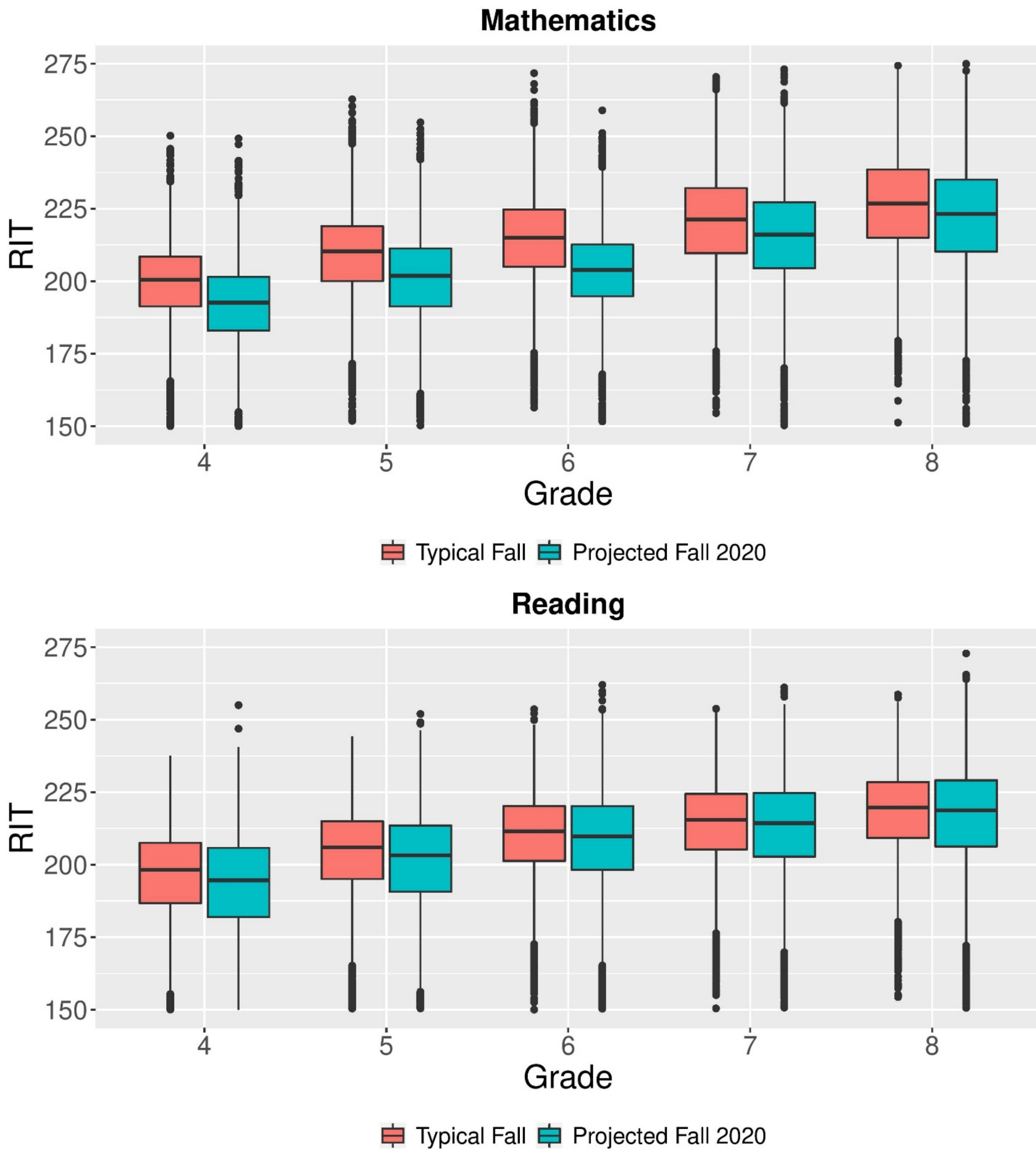


Figure 3. Projected fall 2020 score distributions under a typical fall (fall 2018) and COVID Loss Summer Slide conditions

Appendix A. Literature Review on Out-of-School Time Impacts

In Tables A1-A3, we describe the studies included and excluded from our effect size table (Table 1 in the main paper) as well as the approach taken to convert the reported estimates into a single metric (SD loss per day of school missed). These articles were identified through a combination of database searches (e.g., Google Scholar), review of cited literature within recent studies, and inquiries of experts in each area. While we tried to capture key studies in each area, this review should not be considered a full representation of the work on each topic. In selecting studies for inclusion in Table 1, we prioritized recent studies where (a) the outcome was a math or reading test score and (b) the paper had estimates that could be converted into standard deviation (SD) units. For all studies that were included in Table 1, we present both the reported estimate (in the unit of the original reported coefficient) as well as the "Calculated" estimate (units of SD loss per day of school missed), which is consistent across all included studies.

Table A1

Review of Key Summer Learning Loss Studies

Citation	Location	Research Design	Grade Level	Calc. Math Effect	Calc. ELA Effect	Reported Math Effect	Report ELA Effect	Description of Units
Included in Literature Review Table 1								
Atteberry & McEachin (2020)	National (NWEA - 1st to 8th grade)	Seasonal growth model	Summer after 1st	-0.009	-0.010	-0.19	-0.19	**Scale of original estimate:** total RIT point drop across entire summer (reported in Tables 2 and 3) **Conversion:** Divided estimate by 2020 spring SDs (by grade/subject) and then converted into instructional days (assuming approx. 50 weekdays during the summer)
			Summer after 2nd	-0.006	-0.006	-0.14	-0.10	
			Summer after 3rd	-0.006	-0.005	-0.13	-0.08	
			Summer after 4th	-0.005	-0.003	-0.11	-0.06	
			Summer after 5th	-0.005	-0.003	-0.10	-0.06	
			Summer after 6th	-0.003	-0.002	-0.06	-0.04	
			Summer after 7th	-0.002	-0.001	-0.04	-0.02	
von Hippel, Workman & Downey (2018)	National (ECLS-K:2011)	Seasonal growth model	Summer after K	0.002	-0.001	0.03	-0.01	**Scale of original estimate**: Monthly SD units (reported in Table 4) **Conversion:** Divided by 20 weekdays per month to get SD per day
			Summer after 1st	-0.001	-0.001	-0.02	-0.02	
Kuhfeld, Condron, & Downey (2019)	National (NWEA, K-8)	Seasonal growth model	Summer after K	-0.005	-0.004	-1.19	-1.00	**Scale of original estimate:** RIT point drop per summer month (reported in Table 2) **Conversion:** Divided estimate by 2020 spring SDs (by grade/subject) and then divided by 20 weekdays per month to get SD per day
			Summer after 1st	-0.007	-0.004	-1.89	-1.06	
			Summer after 3rd	-0.006	-0.004	-1.72	-1.14	
			Summer after 4th	-0.005	-0.003	-1.58	-0.88	
			Summer after 6th	-0.004	-0.002	-1.44	-0.75	
			Summer after 7th	-0.002	-0.001	-0.85	-0.41	
Excluded from Literature Review Table 1								
Cooper, Nye, Charlton, Lindsay, & Greathouse (1996)	13 different studies	Meta-analysis	1st-9th	N/A	N/A	-0.14	-0.05	Reported estimates are in SD units across the whole summer (pg. 253). This study was excluded due to measurement issues (described by von Hippel & Hamrock, 2019) in the studies reviewed.
Quinn, Cooc, McIntyre, & Gomez, (2016)	National (ECLS-K:2011)	Seasonal growth model	K-2nd	N/A	N/A	N/A	N/A	This study only compares race/SES differences in summer loss and does not provide overall summer drop estimates, so we did not include the results from this study in Table 1.
Kuhfeld (2019)	National (NWEA)	Projected test scores	K-7th	N/A	N/A	70-78% lost ground	62% to 73%	This paper reports the percentage of students who lost ground during the summer, which can not be translated into SD units.
von Hippel & Hamrock (2019)	National (ECLS-K:2011 + NWEA) and Baltimore schools	Seasonal growth model	K-8th	N/A	N/A	N/A	N/A	This study only compares race/SES differences in summer loss and does not provide overall summer drop estimates, so we did not include the results from this study in Table 1.

Table A2

Review of Key School Closures Studies

Citation	Location	Research Design	Grade Level	Calc. Math Effect	Calc. ELA Effect	Reported Math Effect	Reported ELA Effect	Notes
Included in Literature Review Table 1								
Hansen (2011)	CO; MD	Two-sample least squares	8th grade (CO)	-0.013 to -0.039	N/A	.013-.039 (NS)	N/A	**Scale of original estimate**: SD units for every absence (reported in Table 6 on pg 36) **Conversion**: None necessary
			3rd grade (MD)	-0.003 to -0.011 (NS)		.003-.011 (NS)		
			5th grade (MD)	-0.015 to -0.016		.015-.016		
			8th grade (MD)	-0.009 to -0.013		.009- .013		
Goodman (2014)	MA	Instrumental variables	3rd-8th + 10th grade	-0.000 (NS)	0.003 (NS)	-0.000 (NS)	0.003 (NS)	**Scale of original estimate**: SD units for every day closed (reported as maximum plausible effect size), Column (IV) Table 6 on pg 35 **Conversion:** None necessary
Excluded from Literature Review Table 1								
Sacerdote (2012)	LA/TX	Difference-in-Difference	students impacted by Hurricane Katrina	N/A	N/A	initial decline of 0.1 SD, but gained back within 3 years	initial decline of 0.1 SD, then gained back	The comparison reported in this study is by "evacuee" status. The reported estimate is drop one year later on standardized test scores, which we could not convert into the SD/day metric of the other studies so it was excluded from Table 1.
			students impacted by Hurricane Rita	N/A	N/A	Initial decline of 0.08 SD, then gained slightly	initial decline of 0.06 SD, and not gained back by 2009	The comparison reported in this study is by "evacuee" status. The reported estimate is drop one year later on standardized test scores, which we could not convert into the SD/day metric of the other studies so it was excluded from Table 1.
Ward, Shelley, Kaase, & Pane (2008)	MS	Means of scale scores	3rd to 8th grade	N/A	N/A	5-7 points	4-7 points	The comparison reported in this study was students who were and were not "displaced" by Hurricane Katrina. We are unable to covert the mean scale score differences into SD units so it was excluded from Table 1.

Marcotte (2007)	MD	Regression	3rd grade	N/A	N/A	-1.20%	-0.78%	The reported metric was change in % of students getting 'satisfactory' per SD increase in snow accumulation. We are unable to covert the mean scale score differences into SD units so it was excluded from Table 1.
			5th grade	N/A	N/A	-0.93%	not sig	
			8th grade	N/A	N/A	-0.94%	not sig	
Marcotte & Hemelt (2007)	MD	Regression	3rd grade	N/A	N/A	-0.53%	-0.51%	The reported metric was change in % of students getting 'satisfactory' per day lost. We are unable to covert the mean scale score differences into SD units so it was excluded from Table 1.
			5th grade	N/A	N/A	smaller than 3rd grade	smaller than 3rd grade	
			8th grade	N/A	N/A	smaller than 3rd grade	half 3rd grade	

Table A3

Review of Key Absenteeism Studies

Citation	Location	Research Design	Grade Level	Calc. Math Effect	Calc. ELA Effect	Reported Math Effect	Report ELA Effect	Notes
Included in Literature Review Table								
Liu, Lee, & Gershenson (2020)	large urban CA school district	Lagged-score VAM and between-subject differences	middle school	-0.008	-0.006	-0.077	-0.057	**Scale of original estimate**: SD units for every 10 spring absences. Math results are taken from column (5) of Table 4 and ELA results are results are taken from column (5) of Table A2. **Conversion:** Divided by 10 to get SD units per day
			high school	-0.009	-0.008	-0.085	-0.075	
Gershenson, Jacknowitz, & Brannegan (2017)	ECLS-K	Value-added models	K-1st	−0.002	−0.002	−0.002	−0.002	**Scale of original estimate**: SD units for every absence. Results are taken from Table 4. **Conversion:** None necessary
	NC public schools		3rd-5th	-0.007	-0.004	-0.007	-0.004	
Aucejo & Romano (2016)	NC public schools	Student/School fixed effects model + Instrumental variables	3rd – 5th	-0.006	-0.003	-0.0055	-0.0029	**Scale of original estimate**: SD units for every absence. Results taken from columns (5) from Table 3. **Conversion:** None necessary.
Excluded from Lit Review Table								
Gottfried & Kirskey (2017)	small urban CA district	School and classroom fixed effects.	3rd-5th	N/A	N/A	-0.07	-0.03	The reported metric is change in SD for one spring absence (pg. 124).
Gottfried (2011)	Philadelphia school district	Family-FE estimates	2nd-4th grade	N/A	N/A	-0.10	-0.08	We are reporting the effect sizes from pg. 172 from the family fixed effects models. These results are from comparing siblings in the same family.
Gottfried (2009)	Philadelphia school district	Lagged test score VAM	2nd-4th grade	N/A	N/A	-0.099	-0.054	We are reporting the VAM estimates (Column 8) from Table 4 and 7.

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Gottfried, M. & Kirskey, J.J. (2017). “When” students miss school: The role of timing of absenteeism on students’ test performance. *Educational Researcher, 46*(3), 119–130.

Gottfried, MA. (2011). The detrimental effects of missing school: evidence from urban siblings. *American Journal of Education, 117*(2), 147-182.

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Appendix B. Comparison of NWEA and US Public Schools

NWEA schools. We defined a NWEA school as one that tests at least 10 students in Grades 3-8 in math or reading in either 2017-18 or 2018-19. The final sample included 18,958 NWEA schools.

Population of Public Schools. We downloaded the 2017-18 Public Elementary/Secondary School Universe Survey data file from https://nces.ed.gov/ccd/pubschuniv.asp. We define the population of interest as the set of US operational (e.g., school status variable SY_STATUS does not indicate the school is closed or yet to be opened) public schools in the 50 states and District of Columbia serving students in grades 3-8 (based on the minimum (GSLO) and maximum (GSHI) grades offered at the school). In 2017-18, the population of interest consists of 72,075 schools. The NCES school characteristics included in our comparison include enrollment by grade, percentage of students receiving free or reduced-price lunch (TOTFRL divided by school enrollment), and percentages of the students in the school who were Hispanic, Black, and White, and Asian (HI, BL, WH and AS) divided by total enrollment, and urbanicity (NCES' LOCALE codes, collapsed into City, Suburb, Town, and Rural).

Comparison of Sample and Population. Table B1 presents the comparison between the NWEA schools and population of US public schools serving students in Grades 3-8 based on 2017-18 CCD information. The NWEA and population of schools match closely on Percent FRPL and urbanicity, but there were small differences in the percentage of students enrolled of different racial/ethnic groups. Specifically, the NWEA sample of schools has a slightly higher percentage of Black students on average (17% vs. 15% overall) and lower percentage of Hispanic students (20% vs. 24% overall).

Table B1

Characteristics of the NWEA Sample of Schools Relative to the US Population of Public Schools

	NWEA Sample of Schools			Population of US Public Schools Serving Grades 3-8		
	N	M	SD	N	M	SD
3rd grade	13,699	71.51	42.55	53,430	70.87	44.72
4th grade	13,621	73.03	45.54	53,180	72.54	47.21
5th grade	13,220	75.83	54.75	51,881	74.69	55.75
6th grade	9,006	104.08	107.37	37,688	101.47	110.08
7th grade	7,452	123.14	122.29	31,995	117.88	129.00
8th grade	7,344	124.27	124.38	31,770	118.47	130.32
Percent FRPL	18,479	0.50	0.30	72,062	0.51	0.31
Percent Hispanic	18,480	0.20	0.24	72,063	0.24	0.27
Percent Black	18,480	0.17	0.25	72,063	0.15	0.23
Percent White	18,480	0.53	0.33	72,063	0.51	0.33
Percent Asian	18,480	0.04	0.07	72,063	0.04	0.09
City	18,483	0.29	0.45	72,075	0.28	0.45
Suburb	18,483	0.33	0.47	72,075	0.33	0.47
Town	18,483	0.11	0.32	72,075	0.11	0.32
Rural	18,483	0.26	0.44	72,075	0.28	0.45

Appendix C. Parameter Estimates from Multilevel Growth Models

Tables C1 and C2 display the random and fixed effects from the quadratic growth models for mathematics and reading, respectively. The right half of the tables show the school- and student-level correlations among the random effects. Tables C3 and C4 display the random and fixed effects from the linear growth models for mathematics and reading, respectively. These models were estimated to confirm the findings that were observed with the quadratic growth models.

Table C1

Multilevel Quadratic Growth Model Parameter Estimates for Mathematics

				Random Effects			School-level Correlation				Student-level Correlation			
Subject	Grade	Growth Term	Fixed Effect	School SD	Student SD	ICC	Int.	Lin. - Y1	Sum.	Lin. - Y2	Int.	Lin. - Y1	Sum.	Lin. - Y2
Math	3	Intercept	186.24 (0.06)***	6.24	12.01	0.21	1.00				1.00			
Math	3	Linear Growth - Year 1	2.23 (0.01)***	0.33	0.78	0.15	0.00	1.00			-0.20	1.00		
Math	3	Quadratic Growth - Year 1	-0.06 (0.00)***											
Math	3	Summer Drop	-1.35 (0.01)***	0.90	1.98	0.17	0.08	-0.71	1.00		0.11	-0.57	1.00	
Math	3	Linear Growth - Year 2	1.49 (0.01)***	0.32	0.76	0.15	0.17	0.26	-0.31	1.00	0.08	0.06	-0.42	1.00
Math	3	Quadratic Growth - Year 2	-0.01 (0.00)***											
Math	4	Intercept	198.45 (0.06)***	6.72	12.40	0.23	1.00				1.00			
Math	4	Linear Growth - Year 1	1.47 (0.01)***	0.34	0.77	0.16	0.20	1.00			-0.06	1.00		
Math	4	Quadratic Growth - Year 1	0.00 (0.00)***											
Math	4	Summer Drop	-1.45 (0.01)***	0.90	2.01	0.17	-0.01	-0.68	1.00		0.07	-0.57	1.00	
Math	4	Linear Growth - Year 2	1.28 (0.01)***	0.34	0.79	0.16	0.23	0.32	-0.35	1.00	0.14	0.08	-0.41	1.00
Math	4	Quadratic Growth - Year 2	-0.01 (0.00)***											
Math	5	Intercept	207.66 (0.07)***	7.66	13.62	0.24	1.00				1.00			
Math	5	Linear Growth - Year 1	1.34 (0.01)***	0.36	0.81	0.17	0.25	1.00			0.00	1.00		
Math	5	Quadratic Growth - Year 1	-0.01 (0.00)***											
Math	5	Summer Drop	-2.51 (0.01)***	1.12	2.30	0.19	-0.26	-0.72	1.00		-0.19	-0.65	1.00	
Math	5	Linear Growth - Year 2	1.11 (0.01)***	0.32	0.76	0.15	0.19	0.22	-0.29	1.00	0.15	0.08	-0.41	1.00
Math	5	Quadratic Growth - Year 2	-0.01 (0.00)***											
Math	6	Intercept	211.97 (0.09)***	8.20	14.07	0.25	1.00				1.00			
Math	6	Linear Growth - Year 1	1.20 (0.01)***	0.36	0.80	0.17	0.17	1.00			-0.02	1.00		
Math	6	Quadratic Growth - Year 1	-0.02 (0.00)***											
Math	6	Summer Drop	-1.04 (0.01)***	0.91	2.17	0.15	-0.05	-0.77	1.00		0.02	-0.58	1.00	
Math	6	Linear Growth - Year 2	0.87 (0.01)***	0.31	0.80	0.13	0.18	0.34	-0.36	1.00	0.11	0.07	-0.42	1.00
Math	6	Quadratic Growth - Year 2	-0.01 (0.00)***											
Math	7	Intercept	218.30 (0.11)***	8.97	15.64	0.25	1.00				1.00			
Math	7	Linear Growth - Year 1	0.96 (0.01)***	0.35	0.83	0.15	0.13	1.00			-0.06	1.00		
Math	7	Quadratic Growth - Year 1	-0.01 (0.00)***											
Math	7	Summer Drop	-0.79 (0.02)***	0.97	2.29	0.15	-0.04	-0.75	1.00		0.00	-0.60	1.00	
Math	7	Linear Growth - Year 2	0.90 (0.01)***	0.34	0.85	0.14	0.14	0.47	-0.55	1.00	0.13	0.07	-0.43	1.00
Math	7	Quadratic Growth - Year 2	-0.02 (0.00)***											

Table C2

Multilevel Quadratic Growth Model Parameter Estimates for Reading

				Random Effects			School-level Correlation				Student-level Correlation			
Subject	Grade	Growth Term	Fixed Effect	School SD	Student SD	ICC	Int.	Lin. - Y1	Sum.	Lin. - Y2	Int.	Lin. - Y1	Sum.	Lin. - Y2
Reading	3	Intercept	184.80 (0.07)***	7.33	15.56	0.18	1.00				1.00			
Reading	3	Linear Growth - Year 1	2.33 (0.01)***	0.32	1.03	0.09	-0.21	1.00			-0.39	1.00		
Reading	3	Quadratic Growth - Year 1	-0.10 (0.00)***											
Reading	3	Summer Drop	-0.75 (0.01)***	0.92	2.72	0.10	0.08	-0.73	1.00		0.15	-0.58	1.00	
Reading	3	Linear Growth - Year 2	1.71 (0.01)***	0.28	0.95	0.08	-0.19	0.25	-0.38	1.00	-0.17	0.05	-0.45	1.00
Reading	3	Quadratic Growth - Year 2	-0.08 (0.00)***											
Reading	4	Intercept	195.28 (0.07)***	7.35	15.18	0.19	1.00				1.00			
Reading	4	Linear Growth - Year 1	1.77 (0.01)***	0.29	0.96	0.08	-0.23	1.00			-0.38	1.00		
Reading	4	Quadratic Growth - Year 1	-0.08 (0.00)***											
Reading	4	Summer Drop	-0.58 (0.01)***	0.85	2.61	0.10	0.05	-0.71	1.00		0.15	-0.59	1.00	
Reading	4	Linear Growth - Year 2	1.44 (0.01)***	0.27	0.90	0.08	-0.21	0.27	-0.40	1.00	-0.15	0.04	-0.46	1.00
Reading	4	Quadratic Growth - Year 2	-0.07 (0.00)***											
Reading	5	Intercept	202.58 (0.07)***	7.44	14.87	0.20	1.00				1.00			
Reading	5	Linear Growth - Year 1	1.51 (0.01)***	0.27	0.93	0.08	-0.27	1.00			-0.37	1.00		
Reading	5	Quadratic Growth - Year 1	-0.08 (0.00)***											
Reading	5	Summer Drop	-0.53 (0.01)***	0.87	2.63	0.10	0.07	-0.67	1.00		0.14	-0.57	1.00	
Reading	5	Linear Growth - Year 2	1.02 (0.01)***	0.27	0.93	0.08	-0.18	0.20	-0.31	1.00	-0.11	0.02	-0.46	1.00
Reading	5	Quadratic Growth - Year 2	-0.05 (0.00)***											
Reading	6	Intercept	207.89 (0.09)***	7.66	14.90	0.21	1.00				1.00			
Reading	6	Linear Growth - Year 1	1.11 (0.01)***	0.30	0.96	0.09	-0.22	1.00			-0.34	1.00		
Reading	6	Quadratic Growth - Year 1	-0.05 (0.00)***											
Reading	6	Summer Drop	-0.44 (0.01)***	0.88	2.71	0.10	0.06	-0.73	1.00		0.12	-0.58	1.00	
Reading	6	Linear Growth - Year 2	0.83 (0.01)***	0.27	0.95	0.08	-0.15	0.30	-0.41	1.00	-0.08	0.02	-0.46	1.00
Reading	6	Quadratic Growth - Year 2	-0.04 (0.00)***											
Reading	7	Intercept	212.20 (0.10)***	7.67	15.04	0.21	1.00				1.00			
Reading	7	Linear Growth - Year 1	0.90 (0.01)***	0.31	0.99	0.09	-0.22	1.00			-0.32	1.00		
Reading	7	Quadratic Growth - Year 1	-0.04 (0.00)***											
Reading	7	Summer Drop	-0.27 (0.02)***	0.93	2.78	0.10	0.03	-0.73	1.00		0.09	-0.59	1.00	
Reading	7	Linear Growth - Year 2	0.86 (0.01)***	0.29	0.97	0.08	-0.14	0.38	-0.54	1.00	-0.07	0.01	-0.46	1.00
Reading	7	Quadratic Growth - Year 2	-0.05 (0.00)***											

Table C3

Multilevel Linear Growth Model Parameter Estimates for Mathematics

				Random Effects			School-level Correlation				Student-level Correlation			
Subject	Grade	Growth Term	Fixed Effect	School SD	Student SD	ICC	Int.	Lin. - Y1	Sum.	Lin. - Y2	Int.	Lin. - Y1	Sum.	Lin. - Y
Math	3	Intercept	186.91 (0.06)***	6.21	12.01	0.21	1.00				1.00			
Math	3	Linear Growth - Year 1	1.69 (0.00)***	0.33	0.78	0.15	0.02	1.00			-0.20	1.00		
Math	3	Summer Drop	-1.62 (0.01)***	0.93	1.99	0.18	0.07	-0.68	1.00		0.11	-0.57	1.00	
Math	3	Linear Growth - Year 2	1.42 (0.00)***	0.32	0.76	0.15	0.18	0.26	-0.30	1.00	0.08	0.06	-0.42	1.00
Math	4	Intercept	198.50 (0.06)***	6.71	12.40	0.23	1.00				1.00			
Math	4	Linear Growth - Year 1	1.42 (0.00)***	0.34	0.77	0.16	0.20	1.00			-0.06	1.00		
Math	4	Summer Drop	-1.45 (0.01)***	0.90	2.01	0.17	-0.01	-0.67	1.00		0.07	-0.57	1.00	
Math	4	Linear Growth - Year 2	1.23 (0.00)***	0.34	0.79	0.16	0.23	0.32	-0.35	1.00	0.14	0.08	-0.41	1.00
Math	5	Intercept	207.75 (0.07)***	7.66	13.62	0.24	1.00				1.00			
Math	5	Linear Growth - Year 1	1.26 (0.00)***	0.36	0.81	0.17	0.25	1.00			0.00	1.00		
Math	5	Summer Drop	-2.51 (0.01)***	1.12	2.30	0.19	-0.27	-0.72	1.00		-0.19	-0.65	1.00	
Math	5	Linear Growth - Year 2	0.99 (0.00)***	0.32	0.76	0.15	0.20	0.22	-0.29	1.00	0.15	0.08	-0.41	1.00
Math	6	Intercept	212.16 (0.09)***	8.19	14.07	0.25	1.00				1.00			
Math	6	Linear Growth - Year 1	1.04 (0.00)***	0.36	0.80	0.17	0.18	1.00			-0.02	1.00		
Math	6	Summer Drop	-1.10 (0.01)***	0.91	2.17	0.15	-0.06	-0.76	1.00		0.02	-0.58	1.00	
Math	6	Linear Growth - Year 2	0.79 (0.00)***	0.31	0.80	0.13	0.18	0.34	-0.35	1.00	0.11	0.07	-0.42	1.00
Math	7	Intercept	218.46 (0.11)***	8.97	15.64	0.25	1.00				1.00			
Math	7	Linear Growth - Year 1	0.84 (0.00)***	0.34	0.83	0.15	0.13	1.00			-0.06	1.00		
Math	7	Summer Drop	-0.77 (0.01)***	0.95	2.29	0.15	-0.05	-0.74	1.00		0.00	-0.60	1.00	
Math	7	Linear Growth - Year 2	0.69 (0.00)***	0.34	0.85	0.14	0.14	0.45	-0.54	1.00	0.13	0.07	-0.43	1.00

Table C4

Multilevel Linear Growth Model Parameter Estimates for Reading

				Random Effects			School-level Correlation				Student-level Correlation			
Subject	Grade	Growth Term	Fixed Effect	School SD	Student SD	ICC	Int.	Lin. - Y1	Sum.	Lin. - Y2	Int.	Lin. - Y1	Sum.	Lin. - Y2
Reading	3	Intercept	185.95 (0.07)***	7.31	15.55	0.18	1.00				1.00			
Reading	3	Linear Growth - Year 1	1.39 (0.00)***	0.35	1.03	0.10	-0.19	1.00			-0.39	1.00		
Reading	3	Summer Drop	-0.99 (0.01)***	1.00	2.72	0.12	0.06	-0.73	1.00		0.15	-0.58	1.00	
Reading	3	Linear Growth - Year 2	0.99 (0.00)***	0.29	0.95	0.09	-0.16	0.28	-0.41	1.00	-0.16	0.05	-0.45	1.00
Reading	4	Intercept	196.18 (0.07)***	7.34	15.17	0.19	1.00				1.00			
Reading	4	Linear Growth - Year 1	1.02 (0.00)***	0.31	0.97	0.09	-0.22	1.00			-0.38	1.00		
Reading	4	Summer Drop	-0.74 (0.01)***	0.91	2.61	0.11	0.05	-0.72	1.00		0.15	-0.59	1.00	
Reading	4	Linear Growth - Year 2	0.79 (0.00)***	0.28	0.91	0.09	-0.18	0.30	-0.42	1.00	-0.15	0.04	-0.46	1.00
Reading	5	Intercept	203.39 (0.07)***	7.43	14.86	0.20	1.00				1.00			
Reading	5	Linear Growth - Year 1	0.83 (0.00)***	0.29	0.93	0.09	-0.26	1.00			-0.37	1.00		
Reading	5	Summer Drop	-0.76 (0.01)***	0.93	2.63	0.11	0.06	-0.69	1.00		0.14	-0.57	1.00	
Reading	5	Linear Growth - Year 2	0.59 (0.00)***	0.28	0.93	0.08	-0.16	0.20	-0.33	1.00	-0.11	0.02	-0.46	1.00
Reading	6	Intercept	208.44 (0.09)***	7.64	14.90	0.21	1.00				1.00			
Reading	6	Linear Growth - Year 1	0.65 (0.00)***	0.31	0.96	0.10	-0.22	1.00			-0.34	1.00		
Reading	6	Summer Drop	-0.56 (0.01)***	0.91	2.71	0.10	0.05	-0.73	1.00		0.12	-0.58	1.00	
Reading	6	Linear Growth - Year 2	0.48 (0.00)***	0.27	0.95	0.08	-0.13	0.28	-0.40	1.00	-0.08	0.02	-0.46	1.00
Reading	7	Intercept	212.66 (0.10)***	7.66	15.03	0.21	1.00				1.00			
Reading	7	Linear Growth - Year 1	0.53 (0.00)***	0.31	0.99	0.09	-0.22	1.00			-0.31	1.00		
Reading	7	Summer Drop	-0.30 (0.01)***	0.94	2.78	0.10	0.02	-0.72	1.00		0.09	-0.59	1.00	
Reading	7	Linear Growth - Year 2	0.41 (0.00)***	0.29	0.97	0.08	-0.12	0.36	-0.53	1.00	-0.06	0.01	-0.46	1.00

Appendix D. Supplemental Results

Table D1 contains (a) the predicted monthly drop in RIT scores from the absenteeism literature, (b) estimates of typical fall-spring growth across 9.5 months (based on the linear $\hat{\gamma}_{100}$ and quadratic $\hat{\gamma}_{200}$growth parameters) and summer loss ($\hat{\gamma}_{300}$) based on parameters from quadratic growth model, (c) projected gains by the end of the school year under COVID Loss Absenteeism and COVID Loss Summer Slide (assuming students were in school for 6.5 months followed by three months of out of school time), and (d) percentage of learning gains made relative to a typical school year under the two projections. The COVID Loss Absenteeism rate was calculated by averaging the effect size estimates from the absenteeism studies in Table 1 of the paper (separately for mathematics and Reading/ELA) and converting those SD drops into RIT units using the spring RIT SDs per/grade subject in NWEA's 2020 Norms (see Thum & Kuhfeld, 2020). With the exception of 5th grade mathematics, the COVID Loss Absenteeism estimates implied larger RIT drops per month than the COVID Loss Summer Slide projections.

Projected gains by the end of the school year under typical growth, COVID Loss Absenteeism, and COVID Loss Summer Slide assumptions were calculated as follows. Assuming that students were learning at a typical rate 6.5 months out of a standard 9.5-month followed by three months of learning lost at each projected rate, the estimate gain would be

$$\widehat{\text{Gain}}_{Typical,g} = (\hat{\gamma}_{100}) * 9.5 + (\hat{\gamma}_{200}) * 9.5^2$$

$$\widehat{\text{Gain}}_{Abstent,g} = (\hat{\gamma}_{100}) * 6.5 + (\hat{\gamma}_{200}) * 6.5^2 + (Absent) * 3$$

$$\widehat{\text{Gain}}_{Summer,g} = (\hat{\gamma}_{100}) * 6.5 + (\hat{\gamma}_{200}) * 6.5^2 + (\hat{\gamma}_{300}) * 3,$$

where the $Absent$ is the monthly absenteeism rate reported in Table D1 and the parameters estimates are presented in Tables C1 and C2. The percentage of learning gains made relative to a typical year is calculated by dividing the projected gains under each scenario ($\widehat{\text{Gain}}_{Abstent,g}$ and $\widehat{\text{Gain}}_{Summer,g}$) by the typical gains ($\widehat{\text{Gain}}_{Typical,g}$) estimated in each grade/subject. The percentages of learning gains made under the two scenarios (final columns of Table D1) reveal that students may be expected to show large losses, particularly in math, due to the COVID school closures.

Table D2 presents the summer loss parameter estimates (e.g., the parameter estimate $\hat{\gamma}_{300}$ and random effect SD $\sqrt{T_{St(3,3)}}$) from the multilevel growth models as well as the monthly learning rates for students at the 25th, 50th, and 75th percentiles of the summer learning distribution across grades/subjects. Additionally, we report the percentile in the summer learning distribution at which students show monthly gains rather than losses. In both mathematics and reading, there is a large amount of variability in summer learning rates. In mathematics, students in the top 20-30% of the distribution (depending on the grade) actually show monthly gains rather than losses. In reading, approximately the upper half of the distribution (39-46% of students) show gains during the summer. Based on these findings, it is clear that summer loss is common but far from universal, and provide some evidence that we could expect that the COVID-19 extended school closures may not be associated with academic loss for all students.

As a second part of Research Question 2, we compared projected fall scores under two different scenarios based on the empirical Bayes (EB) estimates from the models fit to the 2017-18 and 2018-19 MAP Growth data. The first scenario assumes "typical" fall scores assuming student *i* in grade *g* within school *j* completed the prior school year and had a standard summer break:

$$\widehat{\mathrm{RIT}}_{Typical\_Fall,gij} = \hat{\gamma}_{000} + \hat{r}_{0ij} + \left(\hat{\gamma}_{100} + \hat{r}_{1ij}\right) * 9.5 + (\hat{\gamma}_{200}) * 9.5^2 + \left(\hat{\gamma}_{300} + \hat{r}_{3ij}\right) * 2.5.$$

In the second scenario, we produce COVID-19 projected fall assuming students were out of school during the last three months of the 2019-20 school year:

$$\widehat{\mathrm{RIT}}_{COVID\_Fall,gij} = \hat{\gamma}_{000} + \hat{r}_{0ij} + \left(\hat{\gamma}_{100} + \hat{r}_{1ij}\right) * 6.5 + (\hat{\gamma}_{200}) * 6.5^2 + \left(\hat{\gamma}_{300} + \hat{r}_{3ij}\right) * 5.5.$$

For each grade/subject, we calculated projected fall scores under each scenario for all of the students in the analysis. Table D3 displays the predicted means, SDs, and percentile scores (based on NWEA's 2020 Norms) under two scenarios. We observed that the test scores under the COVID-19 projections are more variable, with SDs that are slightly larger in mathematics and close to 16-20% larger in reading as compared with SDs in a typical fall. Also, while under normal conditions this sample of students' projected scores is close to the national norms on average (e.g., near 50th percentile in their fall scores), under the COVID-19 Summer Slide projections these students would be considered well-below average in the fall based on NWEA's grade/subject-specific norms.

Table D1

Projected Gains Retained at the End of the 2019-20 School Year

Grade	Subject	Absenteeism Drops per Month	2017-18 Results (based on Quadratic Growth Model): Fall Score	Fall-Spring Growth	Summer Drop Per Month	Projected Gains by the End of School Year: COVID Loss Absenteeism	COVID Loss Summer Slide	Percentage of Learning Gains Made Relative to a Typical School Year: COVID Loss Absenteeism	COVID Loss Summer Slide
3	Mathematics	-1.62	186.24	15.77	-1.35	7.09	7.91	45%	50%
4	Mathematics	-1.79	198.45	13.97	-1.45	4.19	5.21	30%	37%
5	Mathematics	-1.92	207.66	11.83	-2.01	2.53	2.26	21%	19%
6	Mathematics	-2.01	211.97	9.60	-1.04	0.93	3.84	10%	40%
7	Mathematics	-2.14	218.30	8.22	-0.79	0.12	3.45	1%	42%
3	Reading	-1.14	184.80	13.11	-0.75	7.50	8.67	57%	66%
4	Reading	-1.14	195.28	9.60	-0.58	4.70	6.39	49%	67%
5	Reading	-1.12	202.58	7.13	-0.53	3.08	4.85	43%	68%
6	Reading	-1.12	207.89	6.03	-0.44	1.74	3.78	29%	63%
7	Reading	-1.15	212.20	4.94	-0.27	0.72	3.35	15%	68%

Note. The absenteeism rate (reported in RIT points per month) is a transformation of the SD results seen in existing literature whereas the 2017-18 results presented are model-based estimates based on the quadratic model results displayed in Tables C1 and C2.

Table D2

Variability in Summer Learning Loss Estimates During Summer of 2018

Grade	Subject	Summer Drop Fixed Effect	Summer Drop SD	Perc. at Which Students Show Gains	Monthly Learning Loss at Different Points in the Distribution 25th Perc.	50th Perc.	75th Perc.
3	Mathematics	-1.35	1.98	75%	-2.68	-1.35	-0.01
4	Mathematics	-1.45	2.01	76%	-2.81	-1.45	-0.09
5	Mathematics	-2.01	2.30	81%	-3.55	-2.01	-0.45
6	Mathematics	-1.04	2.17	68%	-2.51	-1.04	0.42
7	Mathematics	-0.79	2.29	64%	-2.33	-0.79	0.75
3	Reading	-0.75	2.72	61%	-2.58	-0.75	1.09
4	Reading	-0.58	2.61	59%	-2.34	-0.58	1.18
5	Reading	-0.53	2.63	58%	-2.30	-0.53	1.24
6	Reading	-0.44	2.71	56%	-2.26	-0.44	1.39
7	Reading	-0.27	2.78	54%	-2.15	-0.27	1.60

Note. Perc=Percentile. Reported estimates are monthly gains/losses in RIT points during the summer months. The reported percentile is the estimated percentile in which students are showing positive monthly growth rates in either reading or mathematics during the summer.

Table D3

Fall 2020 Score Projections Under "Typical" and COVID-19 Conditions

		"Typical" Fall Scores			COVID-19 (Summer Slide) Projected Fall Scores		
Grade	Subject	M	SD	Perc.	M	SD	Perc.
4	Mathematics	199.20	13.90	0.49	191.32	15.24	0.28
5	Mathematics	209.12	15.30	0.50	200.53	16.08	0.29
6	Mathematics	214.41	15.59	0.49	203.04	15.40	0.23
7	Mathematics	220.69	17.27	0.51	215.10	17.65	0.38
8	Mathematics	226.21	18.46	0.50	221.76	18.89	0.43
4	Reading	196.13	15.98	0.49	191.98	19.06	0.39
5	Reading	203.81	15.63	0.49	200.82	18.52	0.41
6	Reading	209.70	15.41	0.49	207.29	18.37	0.43
7	Reading	213.82	15.58	0.49	211.96	18.36	0.45
8	Reading	217.64	15.68	0.49	216.40	18.27	0.46

Note. M=Mean, SD=Standard deviation, and Perc. = Percentile score under NWEA's 2020 Norms (Thum & Kuhfeld, 2020). Scores are reported for Grades 4-8 because we are tracking cohorts of students who are in Grades 3-7 in 2017-18 into the fall of 2018, so results are only reported for the subsequent grade levels (e.g., Grades 4-8).