

## **Projecting the potential impact of COVID-19 school closures on academic achievement**

### **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 mathematics. 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 are struggling to educate and care for their children (Harris, 2020). 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,<sup>1</sup> 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 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:

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<sup>1</sup> 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.

- (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<sup>2</sup> 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 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

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<sup>2</sup> 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.

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 mathematics 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 summers following kindergarten and first grade, while studies using NWEA's MAP Growth assessment showed fairly sizable drops across grade levels (Atteberry & McEachin; 2020; Kuhfeld, Condrón, & 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 has not replicated the finding of widening socioeconomic inequalities during the summer (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 eighth grade mathematics 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 mathematics and reading achievement overall, but that students attending poor schools experienced a decline of 0.014 SDs in mathematics 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 mathematics 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 mathematics 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 mathematics 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 early April, 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 the first week of April 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 mathematics 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<sup>3</sup> 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 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 mathematics 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.

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

## 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 ( $\text{MonY1}_{ij}$ ), the summer of 2018 ( $\text{Sum}_{ij}$ ), and the 2018-19 school year ( $\text{MonY2}_{ij}$ ). At level 1, the growth model can be expressed as:

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

The intercept ( $\pi_{0ij}$ ) is the predicted score for student  $i$  in school  $j$  tested on the first day of the 2017-18 school year,  $\pi_{1ij}$  is the average instantaneous rate of change at the start of the 2017-18 school year, and  $\pi_{2ij}$  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),  $\pi_{3ij}$  is the monthly summer linear loss rate, and  $\pi_{4ij}$  and  $\pi_{5ij}$  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)):*

$$\begin{aligned}\beta_{00j} &= \gamma_{000} + u_{00j} \\ \beta_{10j} &= \gamma_{100} + u_{10j} \\ \beta_{20j} &= \gamma_{200} \\ \beta_{30j} &= \gamma_{300} + u_{30j} \\ \beta_{40j} &= \gamma_{400} + u_{40j} \\ \beta_{50j} &= \gamma_{500}\end{aligned}$$

*Variance component specification:*

$$e_{tis} \sim N(0, \sigma_{tis}^2), \mathbf{r}_{is} \sim \text{MVN}(\mathbf{0}, \mathbf{T}_{St}), \mathbf{u}_s \sim \text{MVN}(\mathbf{0}, \mathbf{T}_{Sch}).$$

This model was estimated separately by subject (mathematics 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 1<sup>st</sup> and end on June 15<sup>th</sup>). To estimate typical

growth, we used the estimated parameter estimates from the 2017-18 school year for each grade  $g$  and subject separately:

$$\widehat{RIT}_{tg} = \hat{\gamma}_{000} + (\hat{\gamma}_{100}) * \text{Mon}_t + (\hat{\gamma}_{200}) * \text{Mon}_t^2, \quad (3)$$

where  $\text{Mon}_t$  takes values from 0 to 9.5. We then calculated “typical” summer loss across a 2.5-month summer:

$$\widehat{\text{SumLoss}}_{tg} = (\hat{\gamma}_{300}) * \text{SumMon}_t, \quad (4)$$

where  $\text{SumMon}_t$  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 ( $\widehat{RIT}_{9.5g}$ ) 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  $\widehat{\text{SumLoss}}_{tg}$  calculation described above, but starting from the projected achievement level at 6.5 months ( $\widehat{RIT}_{6.5g}$ ) 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<sup>th</sup> to September 1<sup>st</sup>).

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 mathematics 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<sup>th</sup> (6.5 months into the school year), we used students' projected achievement level at 6.5 months ( $\widehat{RIT}_{6.5g}$ ) 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 1<sup>st</sup>, 2019 from the projected score on June 15<sup>th</sup>, 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, 2020; 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 25<sup>th</sup>, 50<sup>th</sup>, and 75<sup>th</sup> 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 15<sup>th</sup>) 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:

$$\begin{aligned} \widehat{RIT}_{Typical_{Fall},gij} = & \hat{\gamma}_{000} + \hat{r}_{0ij} + (\hat{\gamma}_{100} + \hat{r}_{1ij}) * 9.5 + (\hat{\gamma}_{200}) * 9.5^2 \\ & + (\hat{\gamma}_{300} + \hat{r}_{3ij}) * 2.5. \end{aligned} \quad (5)$$

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:

$$\begin{aligned} \widehat{RIT}_{COVID_{Fall},gij} = & \hat{\gamma}_{000} + \hat{r}_{0ij} + (\hat{\gamma}_{100} + \hat{r}_{1ij}) * 6.5 + (\hat{\gamma}_{200}) * 6.5^2 \\ & + (\hat{\gamma}_{300} + \hat{r}_{3ij}) * 5.5 \end{aligned} \quad (6)$$

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 15<sup>th</sup>.

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 mathematics 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 15<sup>th</sup> (when schools shut down) to September 1<sup>st</sup> (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 25<sup>th</sup> percentile of summer learning loss (who showed steep declines) and those in the 75<sup>th</sup> 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 75<sup>th</sup> 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 25<sup>th</sup>, 50<sup>th</sup>, and 75<sup>th</sup> 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 mathematics. In some grades, students may come back close to a full year behind in mathematics. 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 impact 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 mathematics 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. Additionally, 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*

School Closure, and Absenteeism Literature				
Citation	Location	Grade level	Math Effect	ELA Effect
Summer Loss				
Atteberry & McEachin (2020)	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 mathematics 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*

Descriptive Statistics for the Sample			Race/ethnicity					Male	% FRPL
Grade	N. Schools	N. Students	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.

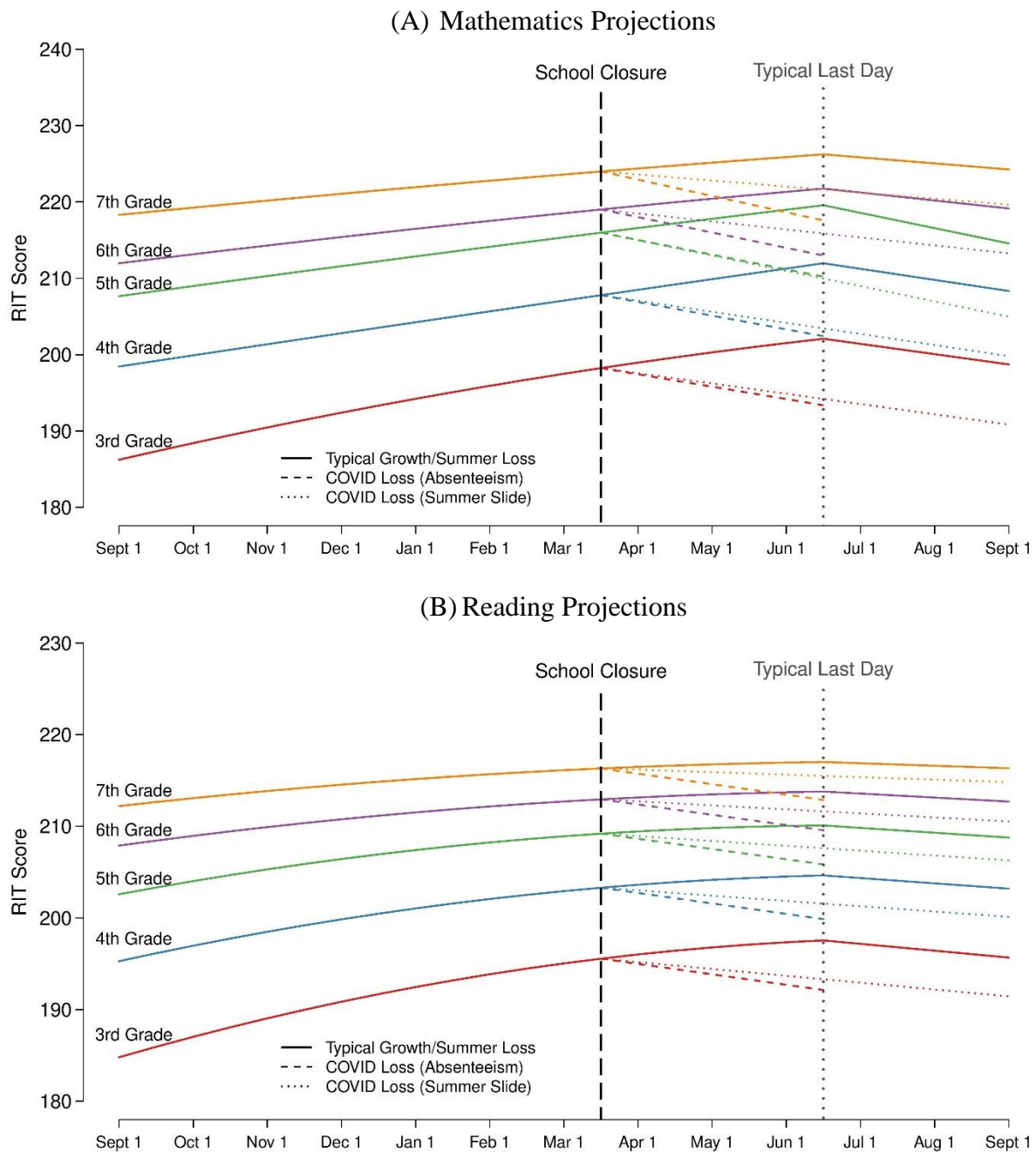
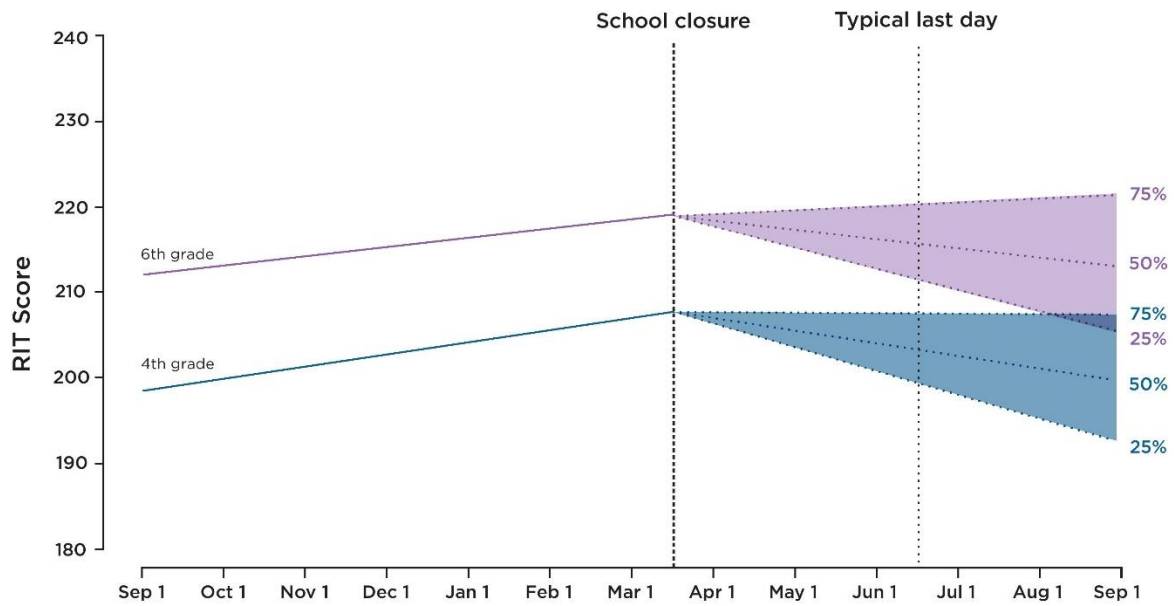


Figure 1. Mathematics and reading forecasts based on summer loss estimates and absenteeism literature.

### (A) Mathematics Projections



### (B) Reading Projections

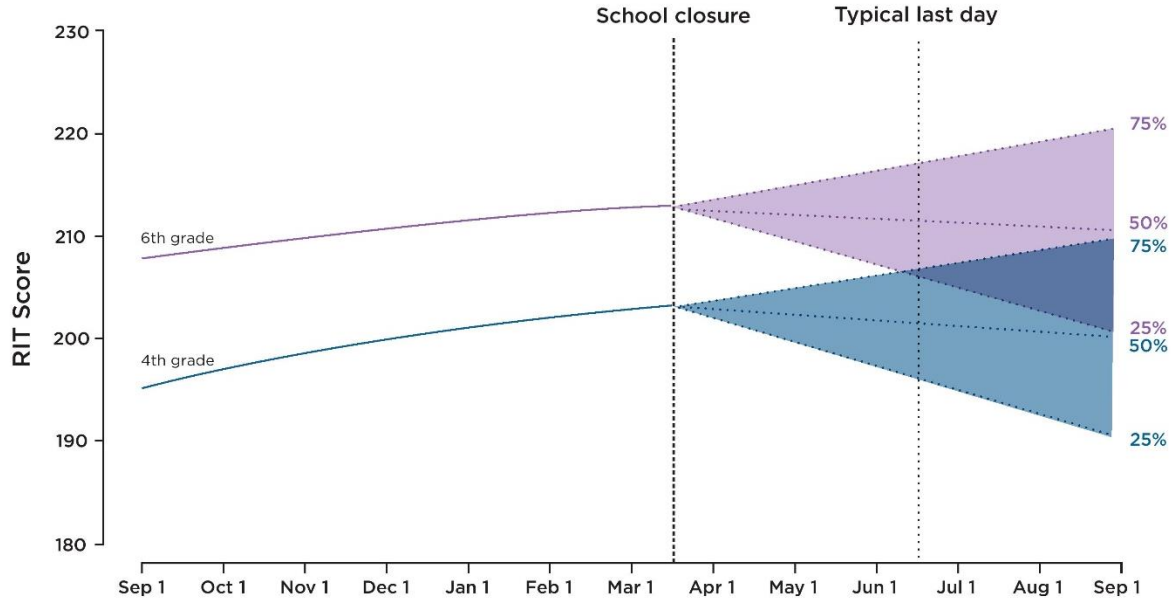


Figure 2. Mathematics and reading forecasts for the 2019-20 school year accounting for the variability observed in typical summer loss patterns.

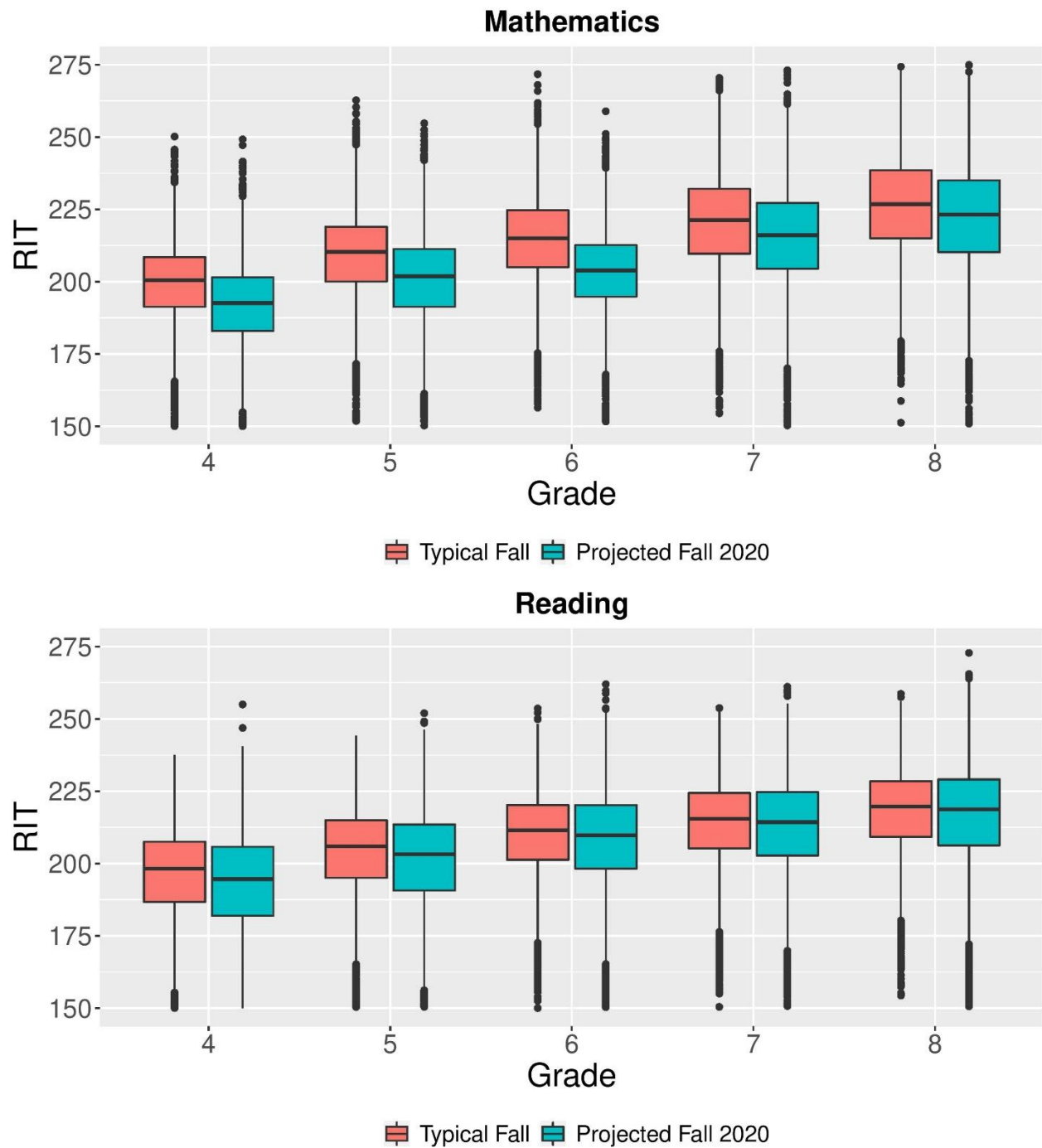


Figure 3. Projected fall 2020 score distributions under a typical fall (fall 2018) and COVID Loss Summer Slide conditions.