The effect of COVID on Oral Reading Fluency during the 2020–2021 Academic Year

Benjamin W. Domingue^{1,†}, Madison Dell¹, David Lang¹, Rebecca Silverman¹, Jason
Yeatman¹, and Heather Hough¹

¹Graduate School of Education, Stanford University

[†]Correspondence about the paper should be sent to bdomingue@stanford.edu.

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Abstract

Education has faced unprecedented disruption during the COVID pandemic. Understanding how students have adapted as we have entered a different phase of the pandemic and some communities have returned to more typical schooling will inform a suite of policy interventions and subsequent research. We use data from an oral reading fluency assessment—a rapid assessment taking only a few minutes that measures a fundamental reading skill—to examine COVID’s effects on children’s reading ability during the pandemic. We find that students in the first 200 days of the 2020–2021 school year tended to experience slower growth in ORF relative to pre-pandemic years. We also observed slower growth in districts with a high percentage of English language learners (ELLs) and/or students eligible for free and reduced-price lunch (FRL).

1 Introduction

Beginning in March 2020, COVID disrupted virtually every aspect of life. The education of young children was particularly affected, with school being virtual for the remainder of the 2019–2020 academic year (AY) and a mixture of virtual and in-person the following year (with substantial variation between school districts). As we discuss below, evidence is accumulating about the lasting effects of the pandemic on students’ academic development [1]. However, this evidence tends to pertain to older children and to be based on assessments spanning a broad range of academic behaviors that may not have been amenable to at-home use.

We utilize a novel source of data on a critical reading skill—oral reading fluency (ORF; [2])—to study the effect of the pandemic on our youngest school-age students, a group that might be particularly vulnerable to the disruptive effect of the pandemic. Further, the measure we use has several appealing properties for understanding the effect of the pandemic. ORF can be rapidly measured, can be administered remotely to students learning via virtual instruction, and is an important predictor of subsequent reading ability. We briefly discuss the emerging research on the effects of COVID on learning before then turning to the specifics of our study.

1.1 Background

Given the unprecedented nature of the disruption, numerous studies have attempted to calibrate the pandemic’s effects on education. Evidence suggests that the pace of learning slowed after March 2020 and into the 2020–2021 school year relative to growth in pre-pandemic years [3, 4, 5, 6, 7]. These estimates vary based on the construct measured and the analytic strategy employed. Generally, existing work shows that students’ learning in math has been more negatively affected than their learning in reading [3, 6, 8, 9, 10]. Many

studies also find that younger students, particularly those in elementary school, have been more negatively affected than their older peers [7, 8, 9, 11], although some evidence suggests the opposite [6].

Perhaps the most concerning findings are related to heterogeneity by student and school characteristics. Existing literature indicates that low-income students [12, 13] and Black, Hispanic, and Native American students [3, 13] have less access to reliable internet and devices at home that facilitate high-quality remote learning experiences. Other learners—English language learners (ELLs), students with disabilities, homeless students, and students in foster care—may not be able to access remote instruction [13] or may not have received accommodations to which they are entitled or otherwise experienced increased instability, all of which may have affected opportunities to learn. There are also disparities in modality as Black and Hispanic students were more likely to be exposed to remote learning than their white peers: about 70% of Black and Hispanic students were learning remotely at the start of fall 2020 relative to 49% of white students [3]. Consistent with these facts, most studies find that the negative impact on student learning is indeed greater for students in majority-minority schools [3, 4], Black students [6, 7, 9, 14], Hispanic students [5, 6, 7, 14], American Indian and Alaska Native students [6, 7], low-income students [5, 6, 7, 9, 11, 14], students with lower prior achievement [5], students with disabilities [15], ELLs [5, 6, 11], and students in rural schools [6].

We emphasize a few notable limitations of existing research. One issue is that remote instruction induced missingness from the post-pandemic assessment data. Further, this missingness is often concentrated in the most vulnerable subgroups; Black students, Hispanic students, students with disabilities, low-income students, and students with lower prior achievement are more likely to be missing [5, 7, 10, 16]. This missingness may lead to bias in estimates of COVID’s impact on student learning; in particular, we may be underestimating the impact. A second issue is the modality of assessments during the pandemic, which were largely taken online and at home. Though some evidence [7] suggests that remote testing in fall 2020 had similar properties to in-person testing, other results have led to concerns about comparability over time. For example, one study found that at-home test-takers in grades 2 through 4 outperformed in-school test-takers [9], potentially suggesting that students may be receiving help from parents at home. Other evidence [5, 11] suggests surprising results (e.g., a learning acceleration in grades 8 through 10 relative to pre-pandemic years) that has led to speculation that either students could be cheating or there may be significant differences over time in which students are being assessed remotely (thus leading to questions about the comparability of the measures derived from different assessment modalities). A final issue is that the majority of research focuses on older students, specifically those in grades 3–8. Younger children may have been more impacted by the pandemic and yet relatively limited assessment data is collected for these students.

1.2 COVID’s effects on ORF

This project builds on earlier work focusing on ORF during the spring and fall of 2020 [17]. With those data, we identified distinctive patterns of growth during the early phase of the pandemic relative to pre-pandemic growth. Growth effectively stopped, especially for second and third graders, in spring 2020. However, that period was unique—schools were suddenly closed with effectively no time to prepare for virtual instruction and a host of other pressing problems (e.g., meal deliveries) that required substantial attention—and growth in fall 2020 was more robust.

Here, we focus on growth through the first 200 days of the 2020–2021 AY with emphasis on potential heterogeneity in growth across important student and/or environmental features. These data are unique in that they focus on a key skill of interest for younger learners, utilize a measure with high face validity, and allow for analysis of within-person growth given that students are observed at multiple time points. Further, as with the earlier study, we are able to probe dynamics of learning during COVID given that the assessments are administered continuously as opposed to only at a small number of fixed time points (cf. fall/spring testing).

2 Methods

2.1 Measuring ORF

We use measures of ORF to study the pandemic’s effect on reading skills. ORF is measured as the words correct per minute (WPM), or the number of words read correctly divided by the elapsed time. We use measures from Literably.¹ In this system, a child reads aloud from a passage displayed on an electronic device (e.g., tablet, laptop). The tablet records the reading and transmits the audio file, typically between 60 and 120 seconds long, to an offsite scoring system. Literably uses both human ratings and automated speech recognition to score these recordings. Previous work on the human rater component suggests that this approach can be used to generate scores that are appropriately predictive of downstream outcomes (e.g., standardized test scores) [18, 19]. These measures are ideal for examining the effects of the COVID pandemic given that they are easily/rapidly deployed and could be administered at home in a manner highly comparable to their administration in-school. Teachers in districts that contract with Literably are generally able to assess a student’s ORF at any point, and we also take advantage of the resulting fact that data are being continuously collected.

As an initial step, we consider yearly growth (from pre-COVID AYs) on the Literably ORF measure

¹<https://literably.com/>

to other established norms of ORF growth, see Table 1. We compare differences in fall to winter median scores using data from established benchmarks [20] to estimated growth over four months² from the basic specification discussed below in Equation 1. Growth in grade 2, especially in fall 2018, is similar in the Literably data to the reference norms. Comparisons in grade 1 are not possible, given the lack of grade 1 data in the reference norms. Differences are more pronounced in later grades, as Literably data tend to exhibit less growth. This could be due to differences in the measures (e.g., the specific text passages used), but it could also be due to other differences (e.g., students that are being assessed in the Literably system in those later grades may be those students exhibiting lower levels of growth). Such differences are one motivating reason for our utilization of models, described below, that focus on within-person growth.

Table 1: Estimated growth (in WPM) for first 4 months of AY.

Year	Grade			
	1	2	3	4
2018	23	20	14	12
2019	20	19	13	11
Ref Norms ^a		21	21	18

^a Taken from Table 1 in [20]. Fall results for Grade 1 are not reported. We report the difference between median winter and fall estimates for a grade.

2.2 Data

We emailed districts that used the Literably system describing the proposed research; districts were given an opportunity to opt-out. We use data from districts that did not opt out. We focus on data from grades 1–4 in the first 200 days (i.e., roughly September through early March) of the 2018–2019 through 2020–2021 AYs. Note that scores from the 2019–2020 AY should largely be unaffected by COVID given that 200 days from September 1, 2019 is March 19, 2020, roughly one week after the initiation of large-scale shutdowns across the US. Across those years, we have 376,489 ORF scores taken from 78,429 students. We primarily focus on data collected in the 2020–2021 AY. During that AY, we have 189,572 ORF measures collected from 52,280 students. Students take more ORF measures in younger grades. (In 2020–2021 for grades 1–4, we have an average of 4.2, 3.9, 3.5, and 3.0 measures per student, respectively.)

Data collection during the 2020–2021 AY is illustrated in Figure 1. The fact that data are being collected

²Note that we use an approximation of one month as 4 weeks.

continuously is apparent; data are being collected continuously across the year rather than at a few isolated points in time (as may be the case with, for example, benchmark testing systems [10]). Note that there is some increase in ORF scores across the year, but crucially, there may be systematic differences in which students are taking ORF measures at different points in the year, thus further motivating the within-person analytic approach we consider below.

Figure 1: Data collection through the 2020–2021 AY. Darker blue regions emphasize periods of heavier data collection (via `smoothScatter`). Red lines are LOESS lines showing changes in expected score as a function of when measure is taken.

Data are taken from a variety of districts; in particular, there was a large growth in districts represented in the data from the 2020–2021 AY. In 2020–2021, data came from 60 districts whereas in previous years no more than 35 districts were represented. The sample is unbalanced; in 2020–2021, some districts provide a few hundred ORF scores whereas others provide a few thousand (IQR: 354–3453). Table 2 shows information on the districts. Districts included here are higher-achieving and more affluent (e.g., over a half a SD above US districts on average) but are also more diverse and had higher levels of closure than US districts as a whole. As compared to districts in the Literably system in pre-COVID AYs, districts observed only in 2020–2021 were generally higher-achieving and higher socioeconomic status (SES) but also with higher levels of closure.

Table 2: Means (standardized relative to 11,328 schools in matched data) of district-level variables for analytic sample. Closure data from [21]; all other data from [22].

	All districts	Districts only observed in 2020–2021
Academic achievement	0.447	0.612
SES	0.672	0.830
FRL	-0.451	-0.618
Black	0.159	0.003
ELL	0.714	0.721
Closure ^a	0.846	0.950
N districts ^b	62	38

^a In January 2021

^b Not all districts could be matched ($N = 72$ districts in the full analytic sample).

2.3 Analysis

Our approach to analyzing growth is based on identifying expected changes in ORF score as a function of time after controlling for person and book (i.e., the specific text passage a student is asked to read aloud) fixed effects. Specialized approaches are needed to estimate models with large numbers of fixed effects. Here, we use the R package `lfe` [23]. To estimate growth in ORF for a given cohort, we first calculate the time since the start of the school year, which we assume is September 1 of a given AY. For student i , we denote the time of the j -th observation of that student as t_{ij} and the ORF score y_{ij} . In some cases, we treat time linearly and assume that

$$y_{ij} \sim \text{Normal}(\beta_t t_{ij} + \gamma_i + \lambda_b, \sigma^2). \quad (1)$$

We emphasize the inclusion of fixed effects for person, γ_i , and text, λ_b meant to exclude individual-specific performance differences and differences specific to texts. Thus, estimates of β_t tell us the expected growth in ORF per unit time for a student.

In other cases, we allow for nonlinear effects of time. To account for potential nonlinearities in student growth in ORF we use B-splines [24]. As used here, B-splines are a map from $\mathbb{R}^1$ to $\mathbb{R}^K$ where K is specified by the user. (We use $K = 5$ for Figure 2.) We then model score j for individual i when reading text b as

$$y_{ij} \sim \text{Normal}\left(\sum_k \beta_k B(t_{ij})_k + \gamma_i + \lambda_b, \sigma^2\right). \quad (2)$$

In such cases, we do not focus on estimates β_k but instead examine fitted trajectories of growth based on

$\sum_k \widehat{\beta}_k B(t)$ for some appropriate choice of t .

3 Results

3.1 Overall Growth during 2020–2021

We first examine growth in 2020–2021 relative to prior years using Equation 1; results are in Table 3. To ensure that results are not driven by a change in the kinds of districts using Literably in 2020–2021, we first analyze only those districts observed pre-COVID. We see generally reduced levels of growth in 2020 as compared to 2019. The biggest difference is in grade 2, wherein we expect students to grow over 0.5 WPM/month slower in 2020. Based on the pre-COVID growth rates, this translates to as many as 40 days of lost time; that is, students in 2020 would need as many as 40 additional days of skill development to make it up to the same point as students observed in the previous year.

As another means of quantifying the effect, note that during the first 200 days of the 2020–2021 AY, second graders were expected to grow by roughly 17.2 WPM as compared to nearly 21.6 WPM observed in prior years. To benchmark the magnitude of this difference, we conducted a randomization analysis where students from grade 2 were randomly assigned to the 2019–2020 or 2020–2021 AY. Across 250 iterations of this randomization we re-estimated growth; differences were never larger than 1.8 WPM, suggesting that the observed difference of 4.4 WPM is far greater than differences due to chance alone.

To examine potential temporal patterning of growth, we use Equation 2 to allow for nonlinearities in our growth models using splines (see Figure 2). We again see that, relative to growth in the prior AYs unaffected by COVID, growth in the 2020–2021 AY was affected. In particular, gaps seemed to emerge during the course of the AY with a larger departure from pre-COVID growth typically manifesting roughly 100 days into the AY.

One concern is that the picture of growth in 2020–2021 might be distorted due to changes in the composition of the sample of districts. Above, we attempt to control for the effect of new districts by focusing analysis on only those districts that are included pre-COVID. Estimates based on all data (i.e., 2020a) are generally somewhat larger than those based on consistently observed districts (resulting in a smaller gap in growth between 2020a and pre-pandemic years) but not universally so (see grade 4). The slightly larger estimates are potentially consistent with the introduction of even more high SES districts in 2020–2021, see Table 2. Figure 2 also suggests fairly comparable growth patterns between the consistently observed districts versus those observed only in 2020–2021. Given the interest in comparison to prior years, analyses below largely focus on all data from the 2020–2021 AY.

Table 3: Linear growth estimates (WPM/month) for first 200 days of each AY. Printed year represents first year in the AY. 2020a is based on analysis of all districts while all other lines represent analysis based on districts only observed pre-COVID.

Grade	AY	Estimate ^a	SE	N obs	N people	Days Lost ^b
1	2018	3.733	0.064	18222	4641	
1	2019	3.254	0.053	24586	5825	
1	2020	3.051	0.060	19049	4294	12
1	2020a	3.234	0.039	48559	11492	1
2	2018	3.036	0.054	21570	5291	
2	2019	3.024	0.045	28840	7151	
2	2020	2.411	0.060	19180	5142	40
2	2020a	2.621	0.037	51045	13102	26
3	2018	2.171	0.059	21518	6439	
3	2019	2.223	0.047	27405	7976	
3	2020	1.816	0.062	19819	6034	36
3	2020a	1.965	0.040	48103	13926	23
4	2018	1.819	0.063	18417	6228	
4	2019	1.915	0.053	23248	7954	
4	2020	1.742	0.067	16587	5910	18
4	2020a	1.649	0.044	41865	13783	27

^a We omit p-values for coefficient estimates given that all p-values are less than 1e-10.

^b Days of lost learning based on comparing difference between 2020 and 2019 growth rates for first 200 days and then using the 2019 growth rate to compute the number of days.

Figure 2: Growth in grades 1–4 across three AYs. Printed year represents first year in the AY (e.g., 2020–2021 is represented by 2020). 2020a is based on analysis of all districts while all other lines represent analysis based on districts only observed pre-COVID.

One assumption embedded in the results discussed thus far pertains to school starting on September 1 of a given academic year. We view this as a viable assumption given that we are interested in growth over the following 200 days (i.e., the difference between September 1 and the actual start date is likely to be relatively small given the length of time we focus on), but also explore the robustness of our results to this assumption. We obtained start dates for 2020–2021 for 53 school districts in our data. Most schools started within roughly one week of September 1 (IQR August 24 through September 8). Among these schools, growth estimates were quite similar whether we used the September 1 start date or the precise start date; the biggest difference was for grade 3 wherein an assumption of September 1 yielded a growth estimate of 1.777 versus 1.779 when we used the actual start date.

3.2 The role of missingness

We consider the sensitivity of results in Table 3 to different assumptions about missingness. In particular, if $\hat{\beta}_1$ is the estimate from Equation 1 based on observed data, we assume that the true estimate of growth is

$$\hat{\beta}_1(1 - p_{\text{missing}}) + \beta_{\text{missing}}p_{\text{missing}} \quad (3)$$

where p_{missing} is the proportion of missing respondents and β_{missing} is the rate at which the missing respondents are assumed to grow. Amongst the districts observed both before and after COVID, the average

district tested 73% as many students following COVID as before (excluding a small number of districts that tested fewer than 10% of the students in 2020–2021 as 2019–2020; such differences are, we assume, driven by non-COVID factors). However, we argue that this is likely due to structural changes in how the tests are administered as analysis of grade-to-grade cohorts present a different picture; 77% of grade 1 students observed in 2019–2020 are observed in 2020–2021 with similar proportions—75% and 84% respectively for grades 2 and 3—observed in other grades.

Based on these estimates, we assume $\beta_{\text{missing}} = 0$ and that $p_{\text{missing}} \in \{0.15, 0.3\}$. The assumption that missing students do not grow is, we argue, viable given the relatively flat levels of growth observed in spring 2020 in our previous work [17] and the 15% and 30% missing figures are meant to suggest slight under and overestimates of missingness given the above figures. In Figure 3, we compare estimates adjusted via Equation 3 to raw estimates for the 2020 cohort (gray bar) and the 2019 cohort (red line). While missingness clearly impacts the estimates, the estimated rate of growth would still be far above zero under the assumptions considered here. That said, the problem of missingness induced by COVID is a pronounced one [16, 25]. We view this sensitivity analysis as informative but not exhaustive and further comment on this matter in the discussion.

Figure 3: Linear growth estimates adjusted for missingness (estimates for 2020 cohort in Table 3). Gray bar represents grade-specific linear growth estimate for first 200 days of 2020–2021 AY (with 95% CI). Blue bars represent estimates adjusted for missingness (via mixture distribution shown in Equation 3) assuming different proportions of unobserved students with zero growth. Red bars represent 2019 growth estimates for the same grade.

3.3 Heterogeneity in growth as a function of early-year ability

One concern is that students with limited ORF skills at the start of the AY may be especially affected by the COVID pandemic. To analyze this possibility, we split data into quintiles as a function of a student’s mean ORF recorded in the first two months of a given AY and then re-estimate growth within quintile. Results based on linear growth estimates are shown in Figure 4. In grade 1, the lowest-ability students do seem to show the largest deviation from prior growth trajectories ($p = 2e - 6$). In grade 2, similar divergences are observable across quintile. In grades 3 and 4, the highest-ability students are those who show stunted growth relative to pre-COVID years. While we do not find consistent evidence that lower-ability students are especially impacted by COVID, there is evidence that the youngest lower-ability students may be those most at-risk.

Figure 4: Growth in grades 1–4 as a function of ORF quintile in the first two months of the AY. P-values are shown for significant differences in growth estimates. Lines start at the ORF average for measures observed in first two months of academic year.

3.4 Heterogeneity as a function of district characteristics

Districts with different level of material resources or pre-existing levels of student achievement may have been differentially affected by the pandemic. To test this, we examined variation in linear growth (i.e., a version of Equation 1 modified to include interactions³) during 2020–2021 as a function of the district’s SES, average

³We consider linear growth to simplify the resulting analyses. Linear growth does not seem to be an overly restrictive assumption, given the results in Figure 2.

academic achievement, and percentage of free and reduced-price lunch (FRL) students, Black students, and ELLs. Data are taken from the Stanford Education Data Archive (SEDA; [22]) and standardized for this analysis. Results are shown in Table 4.

Higher-SES districts tend to show slightly higher rates of growth in grades 1 and 2, but the magnitude of change varies. At its largest, a district two standard deviations (SDs) above the mean in SES in grade 1 would be expected to have a growth rate of 3.7 WPM/month as compared to an expected growth rate of 3.4 WPM/month. In grade 2, the rates would be 2.9 and 2.8 WPM/month, respectively. FRL results similarly suggest that districts with higher levels of FRL students are expected to show weaker growth, although the differences are fairly minor by grade 4.

Similarly, higher-achieving districts show somewhat stronger levels of growth. In general, the achievement-based gradient is bigger than the SES gradient. For example, a second grader in a district two SDs above the mean in achievement would be expected to grow at 3.4 WPM/month as compared to the expected 2.8 WPM/month at an average district.

Turning to demographics, districts with a higher percentage of Black students tend to show less growth in grades 1–2 but not grades 3–4. Differences are similar in magnitude to those previously discussed. Across all grades, districts with a larger share of ELLs tend to show lower levels of growth. Although speculative, we suspect that demographic heterogeneity is a function of unequal distribution of resources, both prior to and during the pandemic.

3.5 Heterogeneity as a function of school closure

We also examined heterogeneity as a function of school closure using data from [21]. These data exploit the geolocation functionality of cell phones to track changes in year-to-year visits to schools (i.e., schools with higher levels of closure had more substantial year-to-year declines in the level of visitorship). Overall during the 2020–2021 AY, the average district in our data had a closure level of 0.56 indicating that 56% of the schools in the geographic area had at least a 50% decline in visitors relative to the prior year. However, given the changing structure of closures during that AY, we allow for monthly variation in the level of district closure given the substantial variation in closure across the 2020–2021 AY. On average, districts were expected to have closure levels that drop 0.02 per month.

Results allowing for variation in ORF growth as a function of the level of closure in a district are in Table 5. In grade 1, no significant difference was observed. In grades 2–4, students in more closed districts grow at lower rates. However, all changes are quite small. These data are consistent with the hypothesis that while in-person learning may be the most effective in spurring ORF growth rates, districts were able to

Table 4: Heterogeneity in growth as a function of district characteristics. Time is denominated in months.

Grade	Coefficient	Est	SE	p
1	Time	3.352	0.029	0.000E+00
	Time:SES	0.161	0.022	2.180E-13
2	Time	2.823	0.026	0.000E+00
	Time:SES	0.052	0.021	1.174E-02
3	Time	2.049	0.028	0.000E+00
	Time:SES	-0.002	0.024	9.186E-01
4	Time	1.732	0.030	0.000E+00
	Time:SES	-0.077	0.025	2.363E-03
1	Time	3.343	0.029	0.000E+00
	Time:Achievement	0.228	0.022	1.395E-24
2	Time	2.823	0.026	0.000E+00
	Time:Achievement	0.275	0.021	1.550E-39
3	Time	2.059	0.028	0.000E+00
	Time:Achievement	0.157	0.024	4.918E-11
4	Time	1.745	0.030	0.000E+00
	Time:Achievement	0.039	0.025	1.288E-01
1	Time	3.339	0.029	0.000E+00
	Time:% FRL	-0.206	0.022	1.984E-21
2	Time	2.822	0.026	0.000E+00
	Time:% FRL	-0.198	0.020	7.515E-23
3	Time	2.057	0.028	0.000E+00
	Time:% FRL	-0.114	0.023	1.139E-06
4	Time	1.743	0.030	0.000E+00
	Time:% FRL	-0.013	0.025	6.103E-01
1	Time	3.324	0.029	0.000E+00
	Time:% Black	-0.160	0.026	1.335E-09
2	Time	2.806	0.026	0.000E+00
	Time:% Black	-0.185	0.024	8.055E-15
3	Time	2.054	0.028	0.000E+00
	Time:% Black	0.080	0.026	1.839E-03
4	Time	1.740	0.030	0.000E+00
	Time:% Black	0.102	0.026	1.069E-04
1	Time	3.319	0.030	0.000E+00
	Time:% ELL	-0.082	0.023	3.312E-04
2	Time	2.783	0.026	0.000E+00
	Time:% ELL	-0.280	0.021	1.865E-39
3	Time	2.035	0.028	0.000E+00
	Time:% ELL	-0.207	0.024	1.577E-18
4	Time	1.735	0.030	0.000E+00
	Time:% ELL	-0.120	0.025	1.860E-06

Table 5: Heterogeneity in growth as a function of district closure. Time is denominated in months. Closures are mean-centered in this analysis.

Grade	Coefficient	Est	SE	p
1	Time	3.331	0.009	0.000E+00
	Time:% Closed	0.006	0.005	2.142E-01
2	Time	2.817	0.008	0.000E+00
	Time:% Closed	-0.018	0.005	2.020E-04
3	Time	2.049	0.008	0.000E+00
	Time:% Closed	-0.011	0.005	3.121E-02
4	Time	1.742	0.008	0.000E+00
	Time:% Closed	-0.007	0.005	1.483E-01

adapt relatively efficaciously to virtual instruction.

4 Discussion

Student growth in oral reading fluency was lower during the 2020–2021 AY than in previous years. During the first 200 days of the 2020–2021 AY, second graders were expected to grow by roughly 17.2 WPM as compared to nearly 21.6 WPM observed in prior years. Differences in grades 3 and 4 were somewhat smaller. While there was evidence that the first graders who started with the lowest levels of ORF may have grown more slowly than their higher-ability peers, there was little additional evidence that lower-ability students in grades 2–4 grew less during COVID. Earlier work along these lines [17] suggested that there were substantial impacts of COVID on ORF growth in spring 2020 but that effects were more modest in fall 2020. Findings reported here continue to suggest this basic trend of growth that is closer to normal in the 2020–2021 AY. Even so, these lower levels of growth will put students behind, especially after accounting for potential effects of COVID on learning from the prior school year.

We find limited effects of school closure on ORF scores. Though we find evidence that second, third, and fourth graders in districts experiencing higher levels of closure grew at significantly lower rates than students in districts experiencing lower levels of closure, these differences do not, in our view, reflect qualitatively different levels of growth. We view these findings regarding closures as consistent with those of, for example, Figure 2 in that they suggest any differences in the efficacy of at-home versus in-person learning environments are relatively modest.

Further, we find evidence of heterogeneity as a function of district characteristics. On average, first and second graders in higher-SES districts grew at significantly faster rates than students in lower-SES districts, perhaps suggesting that students in higher-SES districts had greater access to resources that supported their virtual learning. Similarly, first through third graders in higher-achieving districts grew at significantly faster rates than students in lower-achieving districts. This achievement-based gradient is generally larger than the SES-based gradient. Districts with higher percentages of FRL students in first through third grade, Black students in first and second grade, and ELLs in first through fourth grade have significantly lower growth rates than districts with lower percentages of those student subgroups. These results are consistent with existing evidence [4, 5, 6, 15] suggesting that the educational impacts of COVID are not evenly distributed.

We acknowledge limitations. In particular, we discuss the role of missingness. Missingness may lead to bias in our results. In earlier work [17], we documented substantial missingness in spring 2020 but much less missingness in fall 2020. To the extent that students facing more challenging situations during COVID are those who are missing, we would expect some degree of downward bias in our growth estimates relative to historical trends. Here, we have attempted to benchmark the potential sensitivity of our estimates to different assumptions about missingness. Missingness is a serious problem [16] and missingness seems highly non-random (e.g., enrollment declines are larger in districts serving higher concentrations of economically disadvantaged students [25]). We view the approach taken here as one with high internal validity—i.e., we are assessing the learning happening for students that are observed in the assessment system—but emphasize that such results may not generalize to unobserved students.

A second limitation of our approach is that we focus on growth instead of, for example, differences in ability levels at the start of the academic year for the 2020–2021 cohort as compared to historical data. This limitation is due in part to our desire to remove the effects of idiosyncratic effects on ORF measures due to, for example, specific text passages that a student happens to read or non-random selection of students with certain ability profiles for assessment at certain times. We would additionally argue that the asynchronous data collection makes identification of ORF levels at a unique point in time challenging. We view the evidence provided here as robustly informative about growth rates during COVID (and as compared to years past); other studies are better situated to make claims about variation in levels at specific points in time.

Our findings complement the growing literature on COVID’s effect on student learning in three specific ways. First, we focus on children too young to be covered by many assessments (i.e., students in grades 1–4). Second, we use an assessment focused on an essential reading skill that was readily adapted for at-home use, given that it can be administered quickly and in the same format that a child was accustomed to at school. Third, our results are based on estimated within-student growth as opposed to between-cohort changes. We also note that assessment of specific, highly important skills may offer novel information vis-a-

vis the information gleaned from broader educational measures of the kind typically used in formative and summative assessment. These results suggest that children’s reading skills likely grew at a reduced pace in 2020–2021 and that such reductions were widely felt. While these reductions in the development of student skills are concerning, we think it noteworthy that students do seem to have made gains this year. Of course, other differences in the lives of children and their caregivers as compared to what they may have been absent COVID are massive; while we think it reassuring that students did not suffer greater loss in terms of developing reading skill we would still argue that in-person schooling is a policy priority for the future. In particular, we would encourage educators to focus on changes (e.g., high-dosage tutoring [26]) meant to ensure that these young learners have every opportunity to make up for the losses they experienced during COVID both in reading and more broadly.

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