COVID-19 Impacts on Student Learning

Evidence from Interim Assessments in California

Libby Pier
Michael Christian
Hayley Tymeson
Robert H. Meyer

June 2021

PACE
Policy Analysis for California Education
CORE-PACE RESEARCH PARTNERSHIP

COVID-19 Impacts on Student Learning

Evidence from Interim Assessments in California

Libby Pier, Michael Christian, Hayley Tymeson, & Robert H. Meyer
Education Analytics

Acknowledgements

This paper was produced as part of the CORE-PACE Research Partnership, which is focused on producing research that informs continuous improvement in the CORE districts as well as policy and practice in California and beyond; we thank the participating districts in the CORE Data Collaborative for partnering with us in this research, providing the data for this study, and giving feedback on earlier drafts of the report. We also thank the Education Analytics staff members who contributed their efforts to this research, including Nineveh O'Connell, Taylor Garcia, Britt Wilkenfeld, Makenzie Peake, Brianna Pollari, Jeff Dominitz, and the Data Engineering Team. We would also like to thank the two PACE reviewers for their comments and feedback. This report, like all PACE publications, has been thoroughly reviewed for factual accuracy and research integrity. The authors assume full responsibility for the accuracy of the report contents.

Suggested Citation

Pier, L., Christian, M., Tymeson, H., & Meyer, R. H. (2021 , June). *COVID-19 impacts on student learning: Evidence from interim assessments in California* [Report]. Policy Analysis for California Education. https://edpolicyinca.org/publications/covid-19-impacts-student-learning

PACE
Policy Analysis for California Education
CORE-PACE RESEARCH PARTNERSHIP

Contents

Executive Summary

At the first anniversary of school closures due to COVID-19, nearly half of the K–12 students in the U.S. were attending schools that were either fully remote or offering hybrid instruction, with more than 70 percent of California students attending schools remotely. For this reason, continued efforts to unpack the effects of COVID-19 on student outcomes are especially important for California students, who may be experiencing larger-than-average effects of continued school closures relative to the nation overall.

In this report, we used data from multiple interim assessments to examine how the rate of student learning from fall 2019 through winter 2020–21 differs from that of student learning before COVID-19. Specifically, we assessed the degree to which approximately 100,000 students across 19 local education agencies (LEAs) in California experienced slower academic growth compared to previous school years (i.e., a *learning lag*) by the time they completed winter 2021 interim assessments (NWEA MAP Growth, Renaissance Learning Star, and Curriculum Associates i-Ready) in Grades 4–8. To understand equity gaps in the degree to which students have experienced lost instructional opportunities, we disaggregated these results for students who were economically disadvantaged, students who were English learners, students with disabilities, students of different racial/ethnic backgrounds, students with low prior achievement, and students who were experiencing homelessness.

We opted to use the term *learning lag* rather than *learning loss* in order to underscore that a lag in learning can occur relative to expected progress, even as students continue to learn and gain new knowledge and skills, and also that learning that has been delayed during the pandemic can be recouped through deliberate intervention. Our results show that by the time students completed winter interim assessments in the 2020–21 school year, they had experienced a learning lag of approximately 2.6 months in English language arts (ELA) and 2.5 months in math. We further found that students who were economically disadvantaged, English learners, and Latinx experienced greater learning lag than students who were not in these groups. We position these findings in the context of other recent studies that have estimated COVID-19 impacts on student learning, discuss caveats of using interim assessments (including those administered remotely), and highlight the importance of examining differences in the effects for students in different groups. These findings can be useful for guiding decision-making and resource allocation at the state and local levels.

COVID-19 Impacts on Student Learning: Evidence from Interim Assessments in California

More than one year has passed since schools across the U.S. closed their doors in response to the global COVID-19 pandemic. As of March 22, 2021, roughly half of students in the U.S. were still attending schools that were either fully remote or offering hybrid instruction, with more than 70 percent of California students attending virtual-only schools at that time (Burbio School and Community Events Data Platform, 2021). Studies have also established concerning differences regarding in-person learning opportunities that continue to disproportionately affect students who are economically disadvantaged and students of color. Last spring, 22 percent of surveyed parents in California reported that their children had no live contact with their teachers (via phone or internet), with an even higher share of parents of low-income (28 percent), Latinx (26 percent), and Black (37 percent) students reporting no live contact (Gao et al., 2020). And, as of April 30, 2021, the percentage of students attending school in person and full time was three times higher for schools serving the least number of low-income families than those serving the most low-income families (Willis & Fensterwald, 2021).

Since the start of school closures, multiple studies have emerged that predicted the potential impact of COVID-related school closures on students' academic performance (e.g., Kuhfeld, Soland, et al., 2020; The Center for Research on Student Outcomes, 2020) and that assessed the magnitude of the impact on student learning given available data (e.g., Curriculum Associates, 2020, 2021; Domingue et al., 2021; Dorn et al., 2020; Kogan & Lavertu, 2021; Kuhfeld, Tarasawa, et al., 2020; Renaissance Learning, 2020). Though differing in the assessments and methodology used, these studies converged on a similar conclusion: students showed slower academic progress in the 2019–20 school year than would have been expected in the absence of COVID-related school closures. These studies also generally found more severe impacts on math achievement than on ELA or reading.

Given the absence of statewide summative assessments in spring 2020, these studies have relied on the use of interim assessments to examine differences in learning patterns between pre-COVID-19 school years and COVID-affected school years. It is important to note that interim assessments are not equivalent to statewide summative assessments, which are designed to measure student proficiency and growth for informing high-stakes education policy decisions at local and state levels, among other purposes (O'Keefe & Lewis, 2019). Interim assessments are often shorter than statewide summative assessments, and therefore do not reflect all the learning standards that are expected to be taught in a given school year. Additional work is needed to systematically evaluate differences in various interim assessments, as well as differences between statewide summative and interim assessments (Dadey & Gong, 2017). Nevertheless, interim assessments are the best source of large-scale data about student learning available during the pandemic. They are by no means the only source of information about how students are progressing. Indeed, other recent research aims to leverage alternative sources of data, such as student well-being survey responses, to gain a complete picture of the impact of COVID-19 on students (e.g., Wang et al., 2021).

In addition, interim assessments in California have been administered almost exclusively at home as students continued distance learning either entirely or partially. Recent analyses from NWEA and Renaissance found that assessments administered remotely versus in person in fall 2020 showed similar levels of reliability (Kuhfeld, Lewis, et al., 2020; Renaissance Learning, 2021); however, the Renaissance report did find that, in the winter, scores for early grades were higher for remote testers than for in-school testers. Our results from learning lag analyses in South Carolina, where we had a student-level indicator of where most students completed the assessment, indicate that the students who completed winter interim assessments remotely experienced greater learning lag than those who completed the assessments in person (Meyer et al., 2021). Because we do not have any data at the student or school level in California about whether students were tested remotely or in person, we cannot tease apart whether and how learning lag estimates might differ for students in different testing or learning environments. One encouraging finding is that the correlations between students' fall 2019 and winter 2021 interim assessment scores, while lower than similar fall-to-winter correlations in previous years (not unexpected given the influence of COVID-19), were not lower by a dramatic degree. A representative example is the case of eighth graders' ELA scores in our MAP sample: although the correlation between fall 2018 and winter 2020 scores was 0.85, it was 0.79 between fall 2019 and winter 2021.

Among the studies leveraging interim assessments to compare student learning pre-COVID-19 to during the pandemic, few studies to date have used assessments that are more recent than the beginning of the 2020–21 school year (Curriculum Associates, 2021; Renaissance Learning, 2021). In addition, one challenge that has emerged from the many studies measuring COVID-19 impacts on student learning is the difficulty of drawing direct comparisons across multiple assessments because each study has used a unique methodology and has focused on one assessment.

To address these gaps, we are reporting our recent research results to contribute to what we know about how much students' learning is lagging (or accelerating) relative to the rate we would expect, based on students' growth in pre-COVID-19 school years and on interim assessment data from winter 2021.[1] We include results from three different interim assessments—the NWEA MAP Growth, Renaissance Learning Star, and Curriculum Associates i-Ready—administered across 19 local education agencies (LEAs) in California that are part of the CORE Data Collaborative.[2] In doing so, we aim to contribute to and expand upon the existing research documenting the magnitude of COVID-19 impacts on learning across assessment types,

[1] We also include results from fall 2020 interim assessment data, reported in the Appendix.
[2] The CORE Data Collaborative is a consortium of more than 200 LEAs across California that focuses on school and student improvement through highly productive and meaningful partnerships between member school districts.

grades, subjects, and student characteristics. We disaggregated our results by multiple student characteristics in order to answer questions about differential impacts on particular student groups.

We opted to use the terms *learning change, learning lag,* and *learning acceleration* rather than the more commonly referenced *learning loss*. We used *learning change* to describe our overall measures, *learning lag* to describe when those measures indicate students' growth was slower during the COVID-affected years than pre-COVID-19 years, and *learning acceleration* to describe when those measures indicated students' growth was faster during the COVID-affected years than the pre-COVID-19 years. We selected these terms in order to emphasize that a lag in learning can occur relative to expected progress—even as students continue to learn and gain new knowledge and skills—and that learning that has been delayed during the pandemic can be recouped through deliberate intervention. Although the results in this report are not causal estimates of schools' (or educators') impacts on student learning, they nevertheless can be considered empirical estimates of students' academic progress during the pandemic, as influenced by school systems, educators, families, and communities. These estimates can therefore help identify which grades and which student subgroups were most affected by the COVID-19 disruption to schooling so that LEAs and state education agencies can provide the necessary resources to help students and educators emerge from this crisis.

In the following sections, we outline our methods, including how we defined the sample of students and LEAs in these analyses, as well as the models we used to estimate learning change as of the winter of the 2020–21 school year. We then summarize the results for overall learning change and different student subgroups. We conclude with a discussion of the results, an acknowledgement of the limitations of our analysis, and a brief preview of future work in this area.

Methods

In this report, we summarize the results of "fall-to-winter" models that examined student growth from fall 2019 to winter 2021 and how that growth compared to average fall-to-next-winter growth in the last two years. This approach enabled us to capture the full impact of the pandemic to date. In the Appendix, we also report results that examined student growth from fall 2019 to fall 2020, as reported in a recent PACE commentary. We do not discuss the fall-to-fall results in detail in this report, but we do provide the results in the Appendix for interested readers.

Sample

In our analysis, we included approximately 100,000 unique students within the 19 California LEAs who are members of the CORE Data Collaborative. Almost all of these LEAs were offering distance-only learning, with a few smaller districts offering hybrid instruction as an option at some point between fall 2020 and winter 2021. In order to be included in the sample used to produce the learning change measures, an LEA needed to provide sufficient interim assessment data to measure academic growth for a given grade, subject, and assessment type in the most recent growth year (i.e., fall 2019 pretest and winter 2021 posttest) and in at least one of the two prior growth years (i.e., fall 2017 pretest and winter 2019 posttest, and/or fall 2018 pretest and winter 2020 posttest). Figure 1 provides a visual of these data requirements for LEAs to be included in each model.

Figure 1. Local Education Agency Data Requirements for Learning Change Model

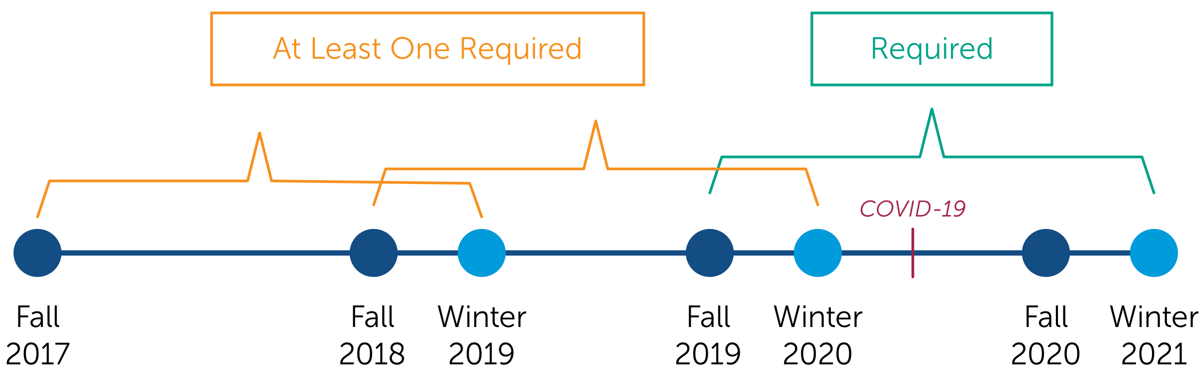


Table 1 displays the number of students included in our sample in each posttest grade[3] and for each assessment type and growth year. We did not measure learning lag in math using the i-Ready assessment due to data only being available for a small number of districts. In addition, we only had one historic growth year (fall 2018–winter 2020) of i-Ready assessment data in ELA.

[3] In prior work examining fall-to-fall growth (Pier et al., 2021), we also reported results for high school grades. In this report, we restricted our analysis to Grades 3–8 due to smaller sample sizes in high school. These smaller sample sizes led to less precise learning lag estimates and more uncertainty around appropriate interpretation of results.

Table 1. Number of Students in Each Posttest Grade by Assessment, Subject (English Language Arts—ELA—and Math), and Growth Year

Panel A: MAP

	Fall 2017 to Winter 2019		Fall 2018 to Winter 2020		Fall 2019 to Winter 2021	
	ELA	Math	ELA	Math	ELA	Math
Grade 4	6,690	6,704	6,676	6,711	4,957	4,981
Grade 5	7,160	7,217	6,677	6,740	5,214	5,198
Grade 6	6,705	6,501	5,342	5,007	4,133	3,925
Grade 7	7,250	7,393	4,998	5,340	4,666	4,711
Grade 8	6,295	6,390	5,146	5,135	4,081	4,206
Total *n*	34,100	34,205	28,839	28,933	23,051	23,021

Panel B: Star

	Fall 2017 to Winter 2019		Fall 2018 to Winter 2020		Fall 2019 to Winter 2021	
	ELA	Math	ELA	Math	ELA	Math
Grade 4	4,131	915	4,117	980	3,521	946
Grade 5	4,114	939	3,897	941	3,364	983
Grade 6	2,966	478	3,687	394	3,248	828
Grade 7	2,414	357	2,878	172	3,100	457
Grade 8	2,661	274	2,929	406	3,121	337
Total *n*	16,286	2,963	17,508	2,893	16,354	3,551

Panel C: i-Ready

	Fall 2018 to Winter 2020		Fall 2019 to Winter 2021	
	ELA	Math	ELA	Math
Grade 4	1,318	n/a	2,015	n/a
Grade 5	1,986	n/a	2,149	n/a
Grade 6	2,147	n/a	2,209	n/a
Grade 7	2,915	n/a	2,523	n/a
Grade 8	3,512	n/a	2,761	n/a
Total *n*	11,878	0	11,657	0

Table 2 reports our sample across growth years by student subgroup, combined across assessments to aid interpretability, though our models were all run separately by assessment type (see Table A1 in the Appendix for these sample numbers separated by assessment type). Note that we defined students who were economically disadvantaged and English learners to match the way the California Department of Education defines these groups (California Department of Education, 2019, p. 39). Comparing the sample across growth years allowed us to gain a sense of whether students in a particular subgroup disproportionately dropped out of our sample during COVID-19 compared to before COVID-19.

Table 2. Percent (and Number) of Students in Each Student Subgroup by Year versus California State Student Population

	2019–20 California State Population	Fall 2017 to Winter 2019		Fall 2018 to Winter 2020		Fall 2019 to Winter 2021	
		ELA	Math	ELA	Math	ELA	Math
Native American and Pacific Islander	< 1 (30,282)	< 1 (166)	< 1 (116)	< 1 (243)	< 1 (142)	< 1 (229)	< 1 (128)
Asian American	9 (575,067)	4 (1,766)	2 (762)	5 (2,723)	2 (600)	5 (2,620)	2 (588)
Black	5 (324,496)	6 (2,897)	5 (1,684)	5 (2,954)	4 (1,199)	4 (2,231)	3 (782)
Latinx	55 (3,381,198)	73 (36,955)	78 (28,900)	67 (38,935)	79 (25,014)	64 (32,800)	75 (20,043)
White	22 (1,381,737)	13 (6,525)	12 (4,579)	18 (10,524)	12 (3,899)	19 (9,829)	13 (3,564)
English Learners	19 (1,148,024)	27 (13,381)	27 (10,162)	22 (12,841)	24 (7,743)	22 (11,232)	25 (6,557)
Students with Disabilities	12 (721,198)	13 (6,788)	14 (5,382)	14 (7,983)	15 (4,714)	9 (4,777)	11 (2,834)
Economically Disadvantaged	61 (3,741,755)	79 (39,743)	81 (30,232)	70 (40,472)	80 (25,542)	68 (34,580)	78 (20,858)

Table 2 indicates that when comparing the pre-COVID-19 and COVID-year samples combined across assessments, there are proportionally fewer Black and Latinx students and more White students (in ELA only), though the decreases appear to be gradual across the years rather than dropping off in the COVID-year sample (i.e., fall 2019–winter 2021). The proportion of English learners and economically disadvantaged students is smaller in both the fall 2018–winter 2020 (pre-COVID-19) sample and the fall 2019–winter 2021 (COVID-affected) sample compared to the fall 2017–winter 2019 (pre-COVID-19) sample. Together, these changes imply that, although the demographics of our sample did shift slightly over time, this does not appear to be due to a dramatic change in the students who have been assessed in the COVID-affected years relative to the pre-COVID-19 years. The exception is students with disabilities, who are underrepresented in the COVID-affected growth year relative to the pre-COVID-19 growth years.

In addition, Table 2 includes the percent (and number) of students in each demographic group in the 2019–20 California state student population[4] in order to show how representative our sample is of the state population. Our sample has a lower proportion of Asian American students across all years, a lower proportion of Black students (in math only) that becomes lower over time, and a lower proportion of White students (which becomes more similar to the state population in ELA over time). Our sample has a higher proportion of Latinx students, English learners, and economically disadvantaged students than the state population. Our sample of students with disabilities is similar to the state population in pre-COVID-19 years but lower than the state population in COVID-affected years. In summary, our sample generally has an overrepresentation of Latinx, English learner, and economically disadvantaged students compared to the state population as well as an underrepresentation of Asian American, Black, and White students compared to the state population; we further observed fewer students with disabilities assessed in the COVID-affected years compared to the state population.

Overall Approach

We used four years of fall and winter interim assessment data (from fall 2017–18 through winter 2020–21) to compute three years of academic growth from fall to the following winter (fall 2017–winter 2019, fall 2018–winter 2020, fall 2019–winter 2021). For a given period (e.g., fall 2017–winter 2019), students needed to have assessment data for both the pretest (e.g., fall 2017) and the posttest (e.g., winter 2019). **For simplicity, we labeled each winter with the latter number of the school year (e.g., winter 2018–19 is referred to as winter 2019).**

In most cases, we defined a fall assessment as one attempted between August 1 and November 25 and a winter assessment as one attempted between November 26[5] and the last day of February. We made an exception to this for the i-Ready assessment because using these dates for the fall i-Ready assessment led to intervals of time between posttest and pretest assessments that were substantially different in the COVID-affected and pre-COVID-19 years. This difference does not reflect a problem in the assessment or its administration; it was a timing phenomenon that happened to confound this particular analysis. For the i-Ready, we defined a fall assessment as one attempted between August 1 and October 31. We kept the winter assessment defined as one attempted from November 26 to the last day of February.

[4] For race/ethnicity data, see https://dq.cde.ca.gov/dataquest/dqcensus/EnrEthGrd.aspx?cds=00&agglevel=state&year=2019-20. For English learner, students with disabilities, and economically disadvantaged data, see https://dq.cde.ca.gov/dataquest/dqcensus/EnrCharterSub.aspx?cds=00&agglevel=state&year=2019-20.

[5] We chose November 26 as the cutoff date by identifying the earliest date for the first Monday after Thanksgiving between 2017 and 2020, as winter testing typically begins after the Thanksgiving break.

We first computed growth models separately for each grade (Grades 4–8, where the grade corresponds to the posttest grade but represents growth from the prior fall until the following winter), subject (ELA and math), and assessment type (MAP, Star, and i-Ready) using data pooled over all available years. The growth models calculated a predicted score for a student's posttest based on that student's pretest score and demographic information (English learner, disability, economic disadvantage, and homelessness status). We then measured growth as the difference between the student's predicted posttest score and the student's actual posttest score. Those growth measures were averaged across students in the same year, grade, subject, assessment type, and LEA to produce an overall estimate of growth. The sample over which this growth model was estimated included LEAs for which we had assessment data in any growth year—pre-COVID-19 or COVID-affected. This was a larger sample than that described above and included some LEAs that were not included in the learning change measures themselves due to not having growth measures *both* in a pre-COVID-19 growth year and in the COVID-affected growth year.

We then calculated the learning change, which is the difference between growth in the most recent year and the average growth in the two prior years. Specifically, learning change compares (i) growth from fall 2019 to winter 2021 and (ii) the average growth from fall 2017 to winter 2019 and fall 2018 to winter 2020. Note that learning change can only be measured in LEAs where growth is measured in both a pre-COVID-19 growth year and in the COVID-affected growth year; these LEAs make up the sample described in the previous section.

Learning change is always calculated by comparing growth from year to year for students in the same grade, subject, assessment, and LEA; as a result, these measures compare different cohorts of students. In other words, the learning change measure compares fall-to-winter growth between the current cohort of students in a grade and subject to that of previous cohorts of students in that same grade and subject. Thus, our model is structurally similar to a quasi-evaluation model in which the students in the COVID-affected period represent a treatment group and the students in the pre-COVID-19 period represent a control group. To control for potential differences across the treatment and control groups caused by changes in the demographic composition of the samples and differences in test participation, we used a multilevel growth model that controls for prior achievement, student demographic characteristics, and district of enrollment. We averaged learning change measures across LEAs to compute learning change across our sample in California.

In order to visualize and summarize results across different assessments and to help make the magnitude of learning change observed more intuitive for readers, we converted our results from scale scores to a *months of learning* metric. To do this, we used a transformation based either on a typical amount of growth from one year to the next or on the amount of variation in attainment within a given year.[6] Although we appreciate the interpretability that this metric provides, we also caution readers that this conversion is an approximation.

Model Specification

The fall-to-winter growth and learning change model is given by the following formula:

$$y_{ijt} = y_{ijt-1}\lambda + X_{ijt-1}\beta + \alpha_{jt} + \varepsilon_{ijt} \tag{1}$$

where:

- student *i* is in LEA *j* in year *t*;
- y_{ijt} yis student *i's* score in the winter of year *t*;
- y_{ijt-1} is student *i's* score in the fall of year *t*-1;
- X_{ijt-1} is a vector of student-level variables (disability, English learner, economic disadvantage, homelessness status, and number of days between assessments); and
- α_{jt} are LEA-year fixed effects.

We estimated Equation 1 over a multi-LEA and multiyear sample of students for a single grade, subject, and assessment type. This sample pools observations over three years so that some observations measured growth from fall 2019 to winter 2021, others measured growth from fall 2018 to winter 2020, and yet others measured growth from fall 2017 to winter 2019. Note that observations for different years will be for different cohorts of students. For example, the sample for the MAP assessment for Grade 4 will pool growth for three cohorts of students progressing from third to fourth grade:[7] those students progressing from Grade 3 to Grade 4 between the 2019–20 and 2020–21 school years; those progressing from Grade 3 to Grade 4 between the 2018–19 and 2019–20 school years; and those making the same progression between the 2017–18 and 2018–19 school years.

---

[6] For the MAP, we measured a month of growth by dividing fall-to-spring growth norms by 7.5 for a given grade. For the i-Ready, we measured a month of growth by computing the difference between the 50th percentile achievement norms for fall and spring and dividing the result by 7.5. For the Star, we used one of two approaches. In some subjects and grades (reading Grades 4–7, math Grades 4–5), we measured a month of growth by computing the difference between the achievement norm at the beginning of the year and the achievement norm in the ninth month of the year, and by dividing that difference by 9. In other subjects and grades (reading Grade 8, math Grades 6–8), we measured a month of growth by computing the difference between the achievement norms at the 31st and 69th percentiles (corresponding to a difference of one standard deviation around the median, assuming a normal distribution), multiplying that difference by a 10-month longitudinal standardized growth norm presented in Table 1 of Lee et al. (2011), and dividing the result by 10. We chose one approach over the other by whichever one led to the greater number of scale score points per month of learning. (Applying a similar rule to the MAP or the i-Ready always led to using an approach similar to the first approach, based on average growth rather than standard deviation of attainment.) In all cases, the conversions were based on growth or achievement norms for the year of the pretest (e.g., Grade 3 when measuring growth from Grade 3 to Grade 4).

[7] In practice, the sample also included a very small number of students who repeated a grade or skipped a grade. We defined these samples according to the grade of the outcome assessment. We allowed into the sample the small number of students who were in a grade different than the previous one in the previous fall. For example, a student who was in Grade 4 in fall 2019 and Grade 6 in winter 2021 would have been included in the Grade 6 analytic sample.

The model in Equation 1 was estimated using errors-in-variables regression (Fuller, 1987) to account for measurement error in the pretest $\boldsymbol{y_{ijt-1}}$. Estimating this regression yields slope-coefficient estimates $\hat{\boldsymbol{\lambda}}$ and $\hat{\boldsymbol{\beta}}$ and LEA-year fixed-effects estimates $\hat{\boldsymbol{\alpha}}_{\boldsymbol{jt}}$. We estimated learning change for an individual LEA *j* by taking the LEA's fixed-effect estimate for the COVID-affected year (2020) and subtracting from it a weighted average of the same LEA's fixed-effect estimates for the non-COVID-19 years (2018 and 2019):

$$\hat{\ell}_j = \hat{\alpha}_{j20} - \left(\frac{n_{j19}}{n_{j18}+n_{j19}}\hat{\alpha}_{j19} + \frac{n_{j18}}{n_{j18}+n_{j19}}\hat{\alpha}_{j18}\right) \tag{2}$$

where $\boldsymbol{n_{jt}}$ is the number of students in the sample associated with LEA *j* in year *t*.

We produced a precision-weighted aggregate learning change measure $\hat{\boldsymbol{\ell}}$ for a given combination of assessment type, subject, and grade by averaging across LEA-level learning change measures $\hat{\boldsymbol{\ell}}_{\boldsymbol{j}}$, using the inverse of the squared standard error of $\hat{\boldsymbol{\ell}}_{\boldsymbol{j}}$ as a weight. We expressed this mathematically in Equation 3:

$$\hat{\ell} = \left(\sum_j \frac{1}{\hat{\sigma}^2_{\ell(j)}}\hat{\ell}_j\right)\Big/\left(\sum_j \frac{1}{\hat{\sigma}^2_{\ell(j)}}\right) \tag{3}$$

where $\hat{\boldsymbol{\sigma}}_{\boldsymbol{\ell(j)}}$ is the estimated standard error of $\hat{\boldsymbol{\ell}}_{\boldsymbol{j}}$. This approach to weighting effectively applies more weight to the LEAs with more students, for whom estimates of learning change are more precise.

By estimating learning change one LEA at a time and then averaging learning change across LEAs to produce an overall learning change measure, we avoided problems from changes in the composition of students by LEA in our sample. In addition, controlling for $\boldsymbol{y_{ijt-1}}$ and $\boldsymbol{X_{ijt-1}}$ should help control for differences across years in student prior attainment and student demographics in our sample.

It is useful to note that the set of control variables $\boldsymbol{X_{ijt-1}}$ includes the number of days between the fall and winter assessments used to measure growth. This is especially relevant on the MAP assessment, where the number of days between assessments was often one month longer in 2020–21 than in the pre-COVID-19 comparison years. It is also relevant to note that, in the MAP sample, there were substantial differences between 2020–21 and the pre-COVID-19 years in the proportion of students taking the assessment before and after the winter break. For the MAP, about four fifths of students in pre-COVID-19 years took the winter assessment before the break, while nearly all students in 2020–21 took the winter assessment after the break. To check the extent to which this could affect the results, we re-estimated the model using an alternative specification in which we included the number of days between assessments and an indicator variable for whether the winter assessments were administered in January or later. The finding of learning lag was robust to this alternative specification, although we did find that learning lag was on average about one MAP scale score point smaller in math, corresponding to about three quarters of a month of learning. The Star and i-Ready assessments were more balanced, and results were largely unaffected by this alternative specification; in both the pre-COVID-19 years and in 2020–21, most students took the winter assessment after the break using the Star, while about two thirds of students took the winter assessment before the break using the i-Ready.

Measuring Learning Change by Student Subgroup. We were interested in the extent of learning change overall and the extent of learning change for specific student subgroups. For example, we may be interested in learning change among English learners. To produce subgroup-specific learning change measures, we began by producing a student growth measure equal to

$$\hat{q}_{ijt} = y_{ijt} - y_{ijt-1}\hat{\lambda} - X_{ijt-1}\hat{\beta} \tag{4}$$

The measure $\hat{q}_{ijt}$ is an estimate of student growth from fall to winter that takes into account the extent to which students with higher or lower fall achievement y_{ijt-1} or different characteristics X_{ijt-1} tend to grow more or less in general. To obtain estimates of subgroup-specific growth and learning change, we computed the means of student growth for each subgroup for each LEA in each year. This calculation produced estimates of growth for each subgroup similar to the fixed effect estimates $\hat{\alpha}_{jt}$. As above, we produced LEA-and-subgroup-specific learning change $\hat{\ell}_j$ and overall subgroup-specific learning change $\hat{\ell}$ using Equations 2 and 3.

These subgroup-specific learning change measures compared the growth of students in that subgroup in the year affected by COVID-19 to the growth of students in that subgroup in years unaffected by COVID-19. For example, a learning change measure produced for English learners in the way described above measures the difference between the growth of English learners in the COVID-disrupted year and the growth of English learners in pre-COVID-19 years. It does not measure whether student growth is lower for a specific subgroup relative to other subgroups. Rather, it measures whether student growth for that subgroup is lower than what it had been for the same subgroup in the past.

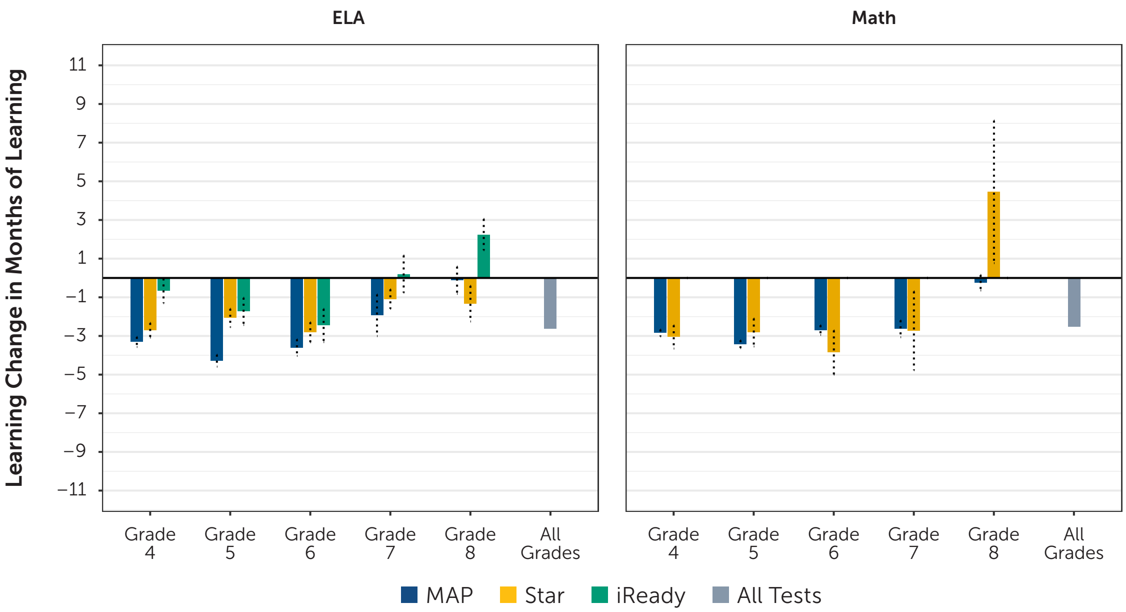
Results

Our fall-to-winter models answered the following question: How did students progress academically from fall 2019 to winter 2021, compared to how they progressed over the same time frame in prior school years? In other words, the models measured the degree to which students grew faster or slower in 2019–20 and into the 2020–21 school year, a period in which COVID-19 emerged and schools provided instruction either entirely or partially via distance learning, compared to an equivalent time period in pre-COVID-19 years. In the results below, we identify students by their posttest grade. However, it is important to note that the learning change estimates describe the growth that occurred during the entire school year in the *pretest* grade and at the beginning of the school year in the *posttest* grade; in other words, the learning change results for fourth graders describe their growth from the beginning of third grade until the winter of fourth grade.

Figure 2 displays results across subjects, grades, and assessment types in units of months of learning (on the vertical axis). The horizontal axis displays the students' grades during the 2020–21 school year (i.e., the posttest grade). The vertical dotted black lines depict 95 percent confidence intervals. Dotted lines that cross zero indicate that the estimate is not statistically significantly different from zero, indicating we cannot conclusively determine if students' academic growth from 2019–20 was faster or slower than growth in prior years. For example, in ELA, fourth-grade students experienced 3.3 months of learning lag on the MAP, 2.7 months of learning lag on the Star, and 0.7 months of learning lag on the i-Ready. All three ELA estimates for fourth graders are significantly different from zero, as indicated by the vertical dotted lines that are not crossing the horizontal axis.

The results in Figure 2 show that we find evidence of learning lag across all three assessments in nearly all cases. We averaged the results across grades and assessments using an inverse-variance weighted mean that weights more heavily the results for grade-assessment combinations that are estimated more precisely. Using this average, we find that, compared to growth in prior years, students are experiencing a learning lag of approximately 2.6 months of learning in ELA and 2.5 months of learning in math; these are presented in the grey bars in Figure 2 labeled "All Grades." However, it is important to note that there are substantial differences in the learning change results across subjects, assessment types, and grades. Specifically, learning change is *not* statistically significantly different from zero in either ELA or math among eighth graders when measured using the MAP. It is also not statistically significantly different from zero in ELA for seventh graders when measured using the i-Ready. In addition, results from the Star in math and results from the i-Ready in both math and ELA suggest that eighth-grade students experienced learning *acceleration* rather than lag.

Figure 2. Overall Learning Change



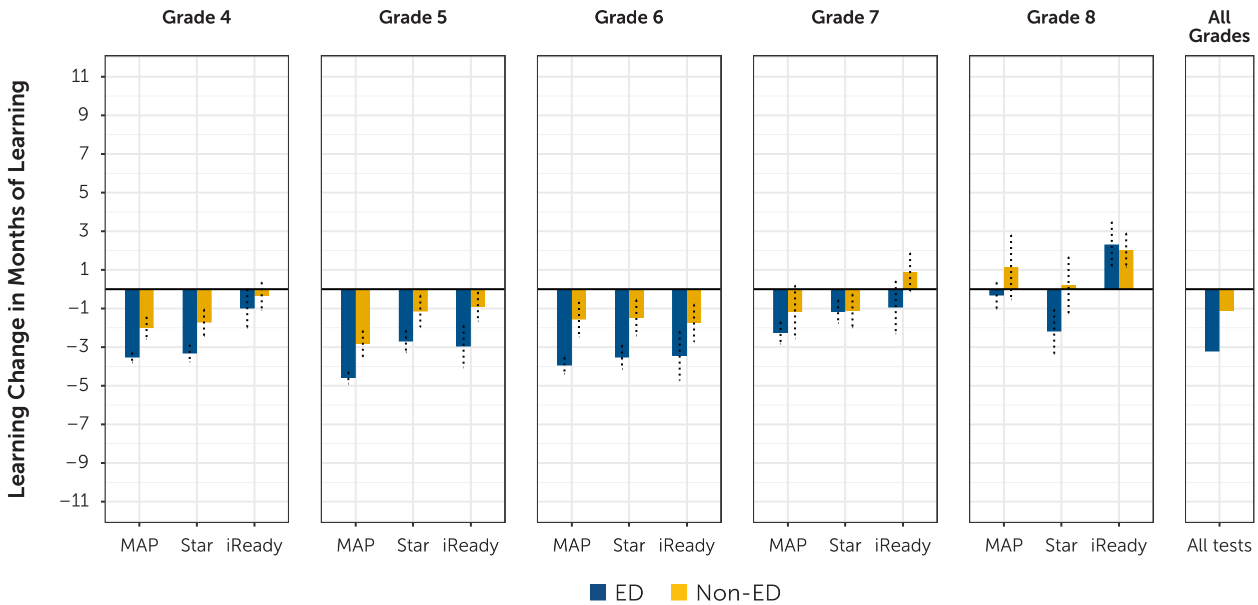
Results for Student Subgroups. We extended the above analysis to examine how learning change differs for different student subgroups. We did this by examining whether a particular subgroup experienced significantly more or less learning change from fall to winter this year (relative to prior years) than their peers who were not in the subgroup. We included results for students who were economically disadvantaged, students who were English learners, students with disabilities, students of different racial/ethnic backgrounds, students with low prior achievement, and students experiencing homelessness.

Figure 3 depicts the fall-to-winter results for students who were economically disadvantaged. On average, across grades and assessments, students who were economically disadvantaged experienced 3.2 months of learning lag in ELA and 2.8 months of learning lag in math, while students who were not economically disadvantaged experienced 1.1 months of learning lag in ELA and 1.7 months of learning lag in math. These averages are presented in Figure 3 in the panel on the far right, labeled "All Grades." At a more granular level, students who were economically disadvantaged experienced greater learning lag in ELA than their non-disadvantaged peers in Grade 4 (except on the i-Ready), Grade 5, and Grade 6. In higher grades, the results were more mixed: Students who were economically disadvantaged experienced greater learning lag in ELA only in Grade 7 on the i-Ready and Grade 8 on the Star. In math, these students experienced significantly greater learning lag in Grades 4 and 5 on the MAP,[8] Grades 5 and 7 on the Star, and Grade 7 on the i-Ready.

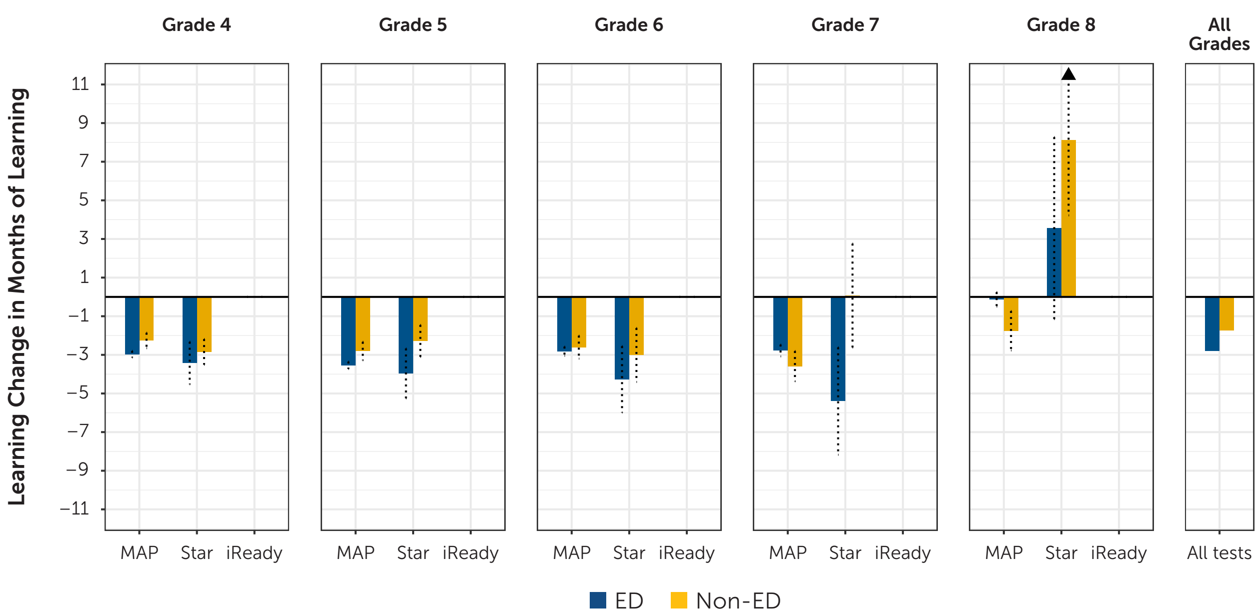
[8] Note that in math for eighth graders on the MAP, students who were economically disadvantaged experienced significantly *less* learning lag than students who were non-economically disadvantaged.

Figure 3. Fall-to-Winter Results: Economic Disadvantage

Panel A: English Language Arts: Economically Disadvantaged versus Non-Economically Disadvantaged



Panel B: Math: Economically Disadvantaged versus Non-Economically Disadvantaged



Figures A1–A5 in the Appendix display these results for English learners, students with disabilities, students of different racial/ethnic backgrounds, students at different levels of prior achievement, and students experiencing homelessness. Figure 4 summarizes learning loss by subgroup by depicting the average learning lag experienced by students in each subgroup across grades and assessment type. However, results vary by grade and assessment type (in terms of direction [i.e., learning loss or gain], magnitude, and precision); therefore, we further called out which results were statistically significant in the paragraphs that follow.

English learners (versus non-English learners) experienced, on average, 3.8 (versus 2.3) months of learning lag in ELA and 3.1 (versus 2.4) months of learning lag in math. Specifically, both the MAP and Star assessments indicated greater learning lag for English learners across grades.

Students with disabilities (versus students without disabilities) experienced, on average, 3.0 (versus 2.7) months of learning lag in ELA and 2.8 (versus 2.6) months of learning lag in math. However, the results by grade and assessment were mixed: the only statistically significant result was a greater learning lag for students with disabilities in eighth-grade math, as measured by the MAP.

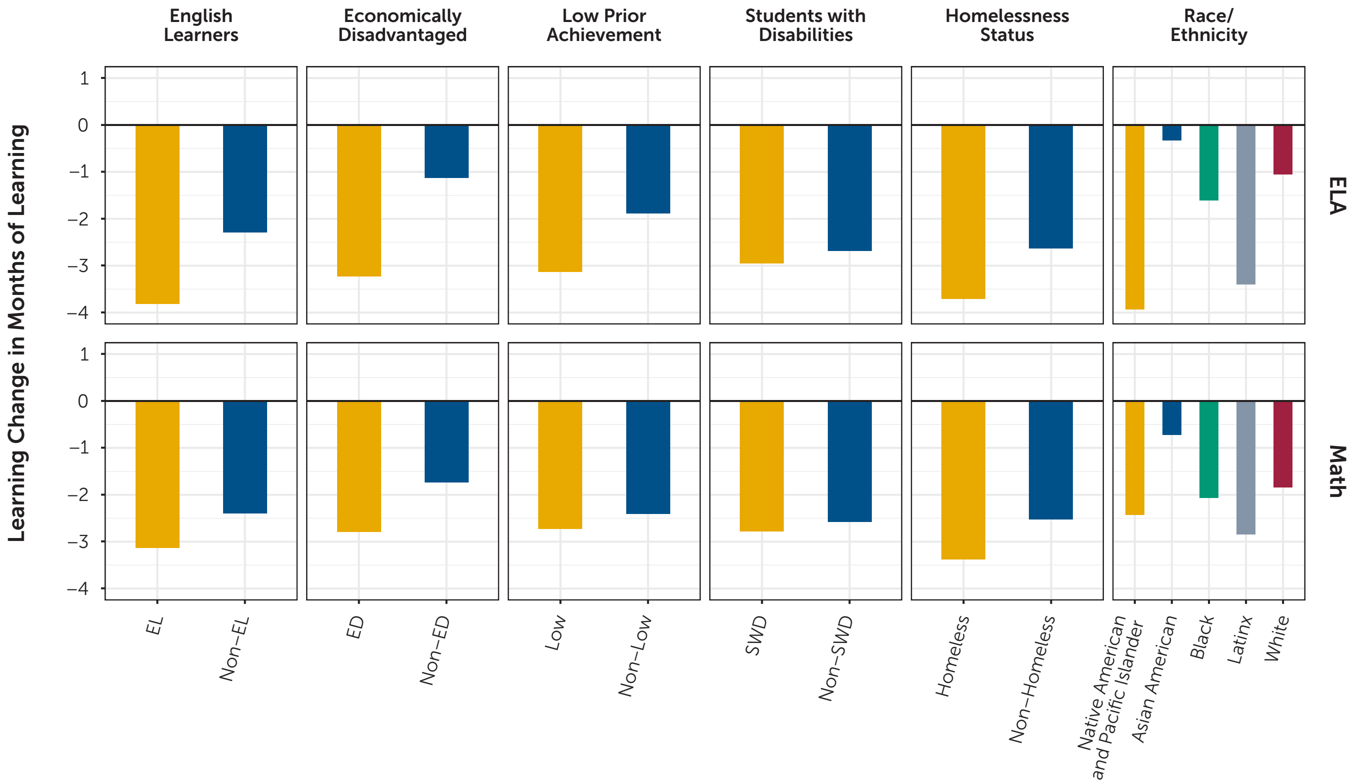
Latinx students experienced, on average, 3.4 months of learning lag in ELA and 2.8 months of learning lag in math—the largest magnitude of learning lag for any racial/ethnic subgroup in our sample—except Native American and Pacific Islander students in ELA (for which we have a small sample that is therefore imprecisely estimated). Specifically, we found greater learning lag for Latinx students in comparison to White students in ELA and math on all three assessments, with larger gaps in earlier grades.

Students with low prior achievement (versus students who did not have low prior achievement) experienced, on average, 3.1 (versus 1.9) months of learning lag in ELA and 2.7 (versus 2.4) months of learning lag in math. Most notably, we found more learning lag among low-achieving students in ELA on the MAP across grades.[9]

Finally, students experiencing homelessness (versus students not experiencing homelessness) experienced, on average, 3.7 (versus 2.6) months of learning lag in ELA and 3.4 (versus 2.5) months of learning lag in math. However, results are usually not statistically significant, likely due to the small number of students in our sample who were experiencing homelessness.

[9] We define low prior achievement as students scoring in the bottom two performance categories on each assessment. The MAP performance categories are based on quintiles, such that students in the bottom two categories correspond to students in the 40th percentile or lower. The two bottom performance categories on the Star include “Did not meet standard” and “Nearly met standard,” and on the i-Ready include “Three or more grade levels below” and “Two grade levels below.”

Figure 4. Average Learning Lag (in Months of Learning) Across Grades and Assessments by Subgroup



To summarize, we observed more learning lag for students who are economically disadvantaged (except in upper grades in math, as measured by the MAP), English learners, and Latinx. We further observed evidence of learning lag across all assessments for students who were previously low achieving (except in ELA, as measured by Star, where results were more mixed). We found mixed results for students with disabilities, as they experienced more learning lag on the MAP (relative to students without disabilities) but less learning lag on the Star in ELA. Note that because we observed fewer students with disabilities in the COVID-affected years, it is possible we were less reliably estimating the learning lag for these students. These mixed results may be due to differences in the various assessments, differences in the LEAs that administer different assessments, or differences in how students actually experienced instruction between math and ELA.

When examining the results of the fall-to-fall learning lag models provided in the Appendix, we find evidence that is suggestive of continued learning lag during the 2020–21 school year compared to the learning lag sustained by fall 2020. However, additional research is needed to quantify precisely how much additional learning lag was sustained. Nevertheless, our results here show the accumulated effect of school closures since the onset of the pandemic through winter 2021.

Discussion

When assessing how much faster or slower students' achievement has progressed during the prior school year and so far this school year (through winter 2020–21), we found evidence across assessment types, grades, and subjects that student learning is progressing more slowly than we would have expected in the absence of COVID-19, affecting the delivery of instruction. Our analyses indicate that students experienced 2.6 months of learning lag in ELA and 2.5 months of learning lag in math as of this winter, compared to expectations in a typical school year.

However, eighth graders showed either comparable gains in achievement to prior years or showed evidence of some learning acceleration in math and ELA. Therefore, it is important to attend to the differences in results by grade and assessment type, even though we provide average effects for interpretability.

When we disaggregated the results based on student characteristics, we observed that students who were economically disadvantaged, English learners, and Latinx experienced greater learning lag than did students who were not in those groups. In addition, we found that students who were previously low achieving experienced greater learning lag than students who were not previously low achieving.

We wish to emphasize that we observed differences in the effects by grade, subject, and assessment type with all these results. For instance, as noted above, we did not observe learning lag consistently for eighth graders in math or ELA. We found mixed results for students with disabilities over both periods—with the MAP assessment suggesting a greater learning lag and the other assessments suggesting less learning lag in some grades and subjects. Seeing as we observed fewer students with disabilities assessed in 2019–20 and 2020–21 compared to in the pre-COVID-19 years, it is possible our results estimated learning lag for these students less reliably. For all the student subgroup results, there are assessment/grade/subject combinations where gaps are statistically significant and others where they are not, and there are some combinations that show the opposite result from the overall pattern. Our goal with this report is to highlight overall patterns that appear consistently across assessments and grades. We believe that, together, all of these findings provide stronger evidence of real patterns than if a pattern were consistently true for one assessment but not another.

However, because we did not have a sample where students completed more than one assessment, it is impossible to disentangle whether differences in the pattern of results between assessments are due to differences in the assessments themselves (e.g., the degree of curriculum sensitivity), due to differences in the administration of the assessment (e.g., how remote assessments were conducted), or due to differences in the schools or LEAs where that particular assessment was used.

Related to this, the lack of available data at the student (or even school) level about whether students were tested or if they were learning fully remotely or in a hybrid environment made it impossible to sufficiently control for or differentiate by testing environment or learning environment. In addition, results may differ depending on whether students completed the winter interim assessment in a school building versus at home (which is correlated with but not equivalent to whether students received any in-person instruction). Although NWEA found that the MAP assessments administered remotely versus in person in fall 2020 showed similar properties (Kuhfeld, Lewis, et al., 2020), our results from learning lag analyses in South Carolina, where we did have a student-level indicator of where students completed the assessment for most students, are more consistent with findings from Renaissance Learning (2021)—specifically, that there may be notable differences in scores between remote and in-person testers in the winter. We found that students who completed the winter interim assessment remotely experienced greater learning lag than those who completed the assessment in person (Meyer et al., 2021). However, we did not have the data in South Carolina to tease out whether this was a function of taking the assessment remotely or learning remotely/at home. Nevertheless, we believe the California results presented here could differ depending on whether students completed the assessment remotely or in person—if we had the data to differentiate by this factor. Future research on COVID-19 impacts on learning should prioritize obtaining and analyzing any student-level data on assessment location and learning environment.

Furthermore, it is also the case that we have a slightly smaller sample in the COVID-affected year than the pre-COVID-19 years. This opens up some possibility of bias if the smaller sample in the COVID-affected year is due to student assessment data being *missing not at random*. However, it is important to note a couple of things. First, there should only be bias if students are missing due to variables relevant to student achievement but *not* already controlled for in the growth model. For example, there should not be bias in our learning lag estimates if students are missing from the COVID-affected sample due to prior achievement, given that prior achievement is controlled for in the growth model. Second, the fact that the demographic composition of students stays mostly the same from year to year is at least suggestive that the sample of students is broadly similar between the COVID-affected and pre-COVID-19 years. The only exception is students with disabilities, which is proportionally smaller in the COVID-affected year. Note, however, that disability is controlled for in the growth model and should not directly cause bias in the learning lag measures.

Our findings generally align with those of other recent studies (e.g., Curriculum Associates, 2020, 2021; Dorn et al., 2020; Kuhfeld, Tarasawa, et al., 2020; Renaissance Learning, 2020), with one exception: these studies generally found greater learning lag in math than in ELA, where we tended to see evidence of learning lag in both ELA and math. From the studies examining winter interim assessment data, Curriculum Associates (2021) reported learning lag in both subjects on the i-Ready, except for Grade 8 ELA; Renaissance Learning (2021) reported *improvements* in both subjects on the Star but less progress for students of color, students with disabilities, and students who were English learners.

Our findings may differ from those of other studies due to differences in the sample, selected methodology, assessments used, and the metric we used to report the results (i.e., months of learning). Studies using nationwide samples (e.g., Curriculum Associates, 2020, 2021; Dorn et al., 2020; Kuhfeld, Tarasawa, et al., 2020; Renaissance Learning, 2020, 2021) may find different patterns than the ones we identified specifically for the California districts in our sample, as they may average across patterns *within* specific states when drawing conclusions that are generalizable *across* different states. Given the differences we noted in our results by assessment type, grade, and student subgroup, it seems beneficial to have both LEA- and state-specific results for informing policymaking and decision-making at those levels, as well as nationwide results to inform efforts at the federal level.

Conclusion

Students and educators across the country have experienced a loss of instructional opportunities due to COVID-related school closures. Yet, given that California accounted for nearly half of all students in the U.S. who were still attending schools with fully remote instruction in winter 2021 (Burbio School and Community Events Data Platform, 2021), it is imperative to understand the effect of these lost opportunities on California students' learning. We found evidence that students in the California districts in our sample experienced a learning lag in Grades 4–8 math and ELA since the onset of the pandemic and through winter 2021. Crucially, students who are most often underserved by our educational system are experiencing more of this learning lag than their peers; students who are economically disadvantaged, English learners, and Latinx experience greater learning lag, which exacerbates existing opportunity gaps that were problematic and concerning prepandemic.

The demographic composition of students in our sample did shift slightly over time, but changes do not appear to be due to a dramatic shift in the students assessed in COVID-affected years relative to pre-COVID-19 years. The exception is students with disabilities, who were underrepresented in the COVID-affected growth year relative to the pre-COVID-19 growth years. Thus, our estimates of learning lag for these students may be less reliable.

There are several reasons to interpret the findings here with some caution. As previously mentioned, we did not have data available to distinguish whether students completed these assessments remotely or in person, nor did we have student-level data indicating whether students received any in-person instruction during the 2020–21 school year. Another caution is that our results here are presented in the converted *months of learning* scale for intuitiveness and interpretability across different assessments; despite the positive properties of this metric, it is also an approximation that should not be literally interpreted to correspond to a specific number of weeks or months of instruction.

Finally, we wish to emphasize that the learning change results presented here are not causal estimates of schools' or LEAs' impacts on student learning; rather, they reflect the contributions of schools and families, given that students have been learning partially or fully at home. There are far too many factors outside the control of educators—including students' access to a reliable internet connection, students' responsibilities for other children in their family, students' access to an adult to help with their schoolwork when needed—that are relevant during COVID-19. Although student-level control variables (such as prior achievement) typically do a good job of controlling for these differences in pre-COVID-19 school years (Kane & Staiger, 2008; Chetty et al., 2014; Deming, 2014; Angrist et al., 2017), it is likely that during COVID-19, there were other factors not captured by these variables that would affect students' learning. Therefore, these measures capture the combined effects of schools and families—and thus could be thought of as *community-level indicators* of students' learning while COVID-19 continues to limit instructional time and in-person instructional opportunities. Given this, these results can be useful for guiding decision-making and resource allocation at the state and LEA levels. More immediately, they can be used to inform decisions about participation in interventions designed to offset the negative effects of COVID-19 on learning (e.g., summer academic recovery programs).

At Education Analytics, we are continuing to refine our approach for estimating and interpreting learning lag measures. This includes exploring additional modeling approaches (such as including school fixed effects), conducting further robustness checks of our results, and gathering more data from additional LEAs, additional assessment types, and additional assessment administrations (e.g., spring 2021). Looking forward, we aim to monitor the degree to which students experience learning recovery in response to the policies and interventions that districts and states are currently planning as we emerge from the pandemic. Our goal is to continue to deepen our understanding of how COVID-19 is affecting student learning within the states where we work and of its impact for the students who are most at risk of being inequitably affected, as well as to share those findings as they emerge to inform policymakers and educational stakeholders grappling with how to accelerate student learning this summer, next school year, and beyond.

References

Angrist, J., Hull, P., Pathak, P., & Walters, C. (2017). Leveraging lotteries for school value-added: Testing and estimation. *Quarterly Journal of Economics*, *132*(2), 871–919.

Burbio School and Community Events Data Platform. (2021, March 22). *K–12 school reopening trends*. Burbio. https://info.burbio.com/school-tracker-update-mar-22

California Department of Education. (2019). *2019 California School Dashboard technical guide: Final version (2019–20 school year)*. https://www.cde.ca.gov/ta/ac/cm/documents/dashboardguide19.pdf

The Center for Research on Education Outcomes. (2020). *Estimates of learning loss in the 2019–2020 school year*. https://credo.stanford.edu/sites/g/files/sbiybj6481/f/short_brief_on_learning_loss_final_v.3.pdf

Chetty, R., Friedman, J., & Rockoff, H. (2014). Measuring the impacts of teachers I: Evaluating bias in teacher value-added estimates. *American Economic Review*, *104*(9), 2593–2632.

Curriculum Associates. (2020). *Understanding student needs*. https://www.curriculumassociates.com/-/media/mainsite/files/i-ready/iready-diagnostic-results-understanding-student-needs-paper-2020.pdf

Curriculum Associates. (2021). *What we've learned about unfinished learning*. https://www.curriculumassociates.com/-/media/mainsite/files/i-ready/iready-understanding-student-needs-paper-winter-results-2021.pdf

Dadey, N., & Gong, B. (2017). *Using interim assessments in place of summative assessments? Consideration of an ESSA option*. The National Center for the Improvement of Educational Assessment. https://www.nciea.org/sites/default/files/publications/ASR%20ESSA%20Interim%20Considerations-April%202017.pdf

Deming, D. (2014). Using school choice lotteries to test measures of school effectiveness. *American Economic Review: Papers and Proceedings*, *104*(5), 406–411.

Domingue, B. W., Hough, H. J., Lang, D., & Yeatman, J. D. (2021, March). *Changing patterns of growth in oral reading fluency during the COVID-19 pandemic* [Policy Brief, Working Paper]. Policy Analysis for California Education. https://edpolicyinca.org/publications/changing-patterns-growth-oral-reading-fluency-during-covid-19-pandemic

Dorn, E., Hancock, B., Sarakatsannis, J., & Viruleg, E. (2020, December). *COVID-19 and learning loss—Disparities grow and students need help*. McKinsey & Company. https://www.mckinsey.com/industries/public-and-social-sector/our-insights/covid-19-and-learning-loss-disparities-grow-and-students-need-help#

Fuller, W. (1987). *Measurement error models*. John Wiley and Sons.

Gao, N., Lafortune, J., & Hill, L. (2020). *Who is losing ground with distance learning in California?* Public Policy Institute of California. https://www.ppic.org/wp-content/uploads/who-is-losing-ground-with-distance-learning-in-california-october-2020.pdf

Kane, T., & Staiger, D. (2008). *Estimating teacher impacts on student achievement: An experimental evaluation.* National Bureau of Economic Research Working Paper #14607. https://www.nber.org/papers/w14607

Kogan, V., & Lavertu, S. (2021). *The COVID-19 pandemic and student achievement on Ohio's third-grade English language arts assessment*. http://glenn.osu.edu/educational-governance/reports

Kuhfeld, M., Lewis, K., Meyer, P., & Tarasawa, B. (2020). *Comparability analysis of remote and in-person MAP Growth testing in fall 2020.* NWEA. https://www.nwea.org/research/publication/comparability-analysis-of-remote-and-in-person-map-growth-testing-in-fall-2020

Kuhfeld, M., Soland, J., Tarasawa, B., Johnson, A., Ruzek, E., & Liu, J. (2020). Projecting the potential impact of COVID-19 school closures on academic achievement. *Educational Researcher, 49*(8), 549–565. doi:10.3102/0013189x20965918

Kuhfeld, M., Tarasawa, B., Johnson, A., Ruzek, E., & Lewis, K. (2020, November). *Learning during COVID-19: Initial findings on students' reading and math achievement and growth*. NWEA. https://www.nwea.org/content/uploads/2020/11/Collaborative-brief-Learning-during-COVID-19.NOV2020.pdf

Lee, J., Finn, J., & Liu, X. (2011). *Time-indexed effect size metric for K–12 reading and math education evaluation* [Conference paper]. Annual Meeting of the American Educational Research Association. https://files.eric.ed.gov/fulltext/ED525730.pdf

Meyer, R., Christian, M., Dominitz, J., & Wang, C. (2021, March). *Learning lag in student achievement during the coronavirus pandemic: Evidence from multiple assessments and states* [Conference paper]. Association of Education Finance and Policy, Online Conference.

O'Keefe, B., & Lewis, B. (2019). *The state of assessment: A look forward on innovation in state testing systems.* Bellwether Education Partners. https://files.eric.ed.gov/fulltext/ED596503.pdf

Pier, L., Hough, H. J., Christian, M., Bookman, N., Wilkenfeld, B., & Miller, R. (2021). *COVID-19 and the educational equity crisis: Evidence on learning loss from the CORE Data Collaborative* [Commentary]. Policy Analysis for California Education. https://edpolicyinca.org/newsroom/covid-19-and-educational-equity-crisis

Renaissance Learning. (2020). *How kids are performing: Tracking the impact of COVID-19 on reading and mathematics achievement.* Renaissance Learning. https://www.renaissance.com/how-kids-are-performing

Renaissance Learning. (2021). *How kids are performing: Tracking the midyear impact of COVID-19 on reading and mathematics achievement* (Special Report Series—Winter 2020–2021 Edition). Renaissance Learning. https://www.renaissance.com/how-kids-are-performing

Wang, C., Pier, L., Webster, N., & Meyer, R. H. (2021). *Student well-being and learning conditions in the pandemic: Evidence from the CORE districts* [Report]. Policy Analysis for California Education. https://edpolicyinca.org/publications/student-well-being-and-learning-conditions-pandemic

Willis, D. J., & Fensterwald, J. (2021, May 5). Over half of California public school students remain in distance learning: Students in wealthier schools 3 times likelier to be back in school full time. *EdSource.* https://edsource.org/2021/new-data-55-of-california-public-school-students-remain-in-distance-learning/653848

Appendix

Additional Fall-to-Winter Subgroup Results

Table A1 provides details on the sample by student subgroup for each growth year separately by assessment. Figures A1–A5 display the fall-to-winter results for English learners, students with disabilities, students of different racial/ethnic backgrounds, students with low prior achievement, and students experiencing homelessness.

Table A1. Percent (and Number) of Students in Each Student Subgroup by Assessment and by Year versus California State Student Population

Panel A: MAP

	2019–20 California State Population	Fall 2017 to Winter 2019		Fall 2018 to Winter 2020		Fall 2019 to Winter 2021	
		ELA	Math	ELA	Math	ELA	Math
Native American and Pacific Islander	< 1 (30,282)	< 1 (89)	< 1 (88)	< 1 (110)	< 1 (117)	<1 (97)	<1 (103)
Asian American	9 (575,067)	2 (613)	2 (616)	2 (435)	2 (445)	2 (351)	2 (351)
Black	5 (324,496)	5 (1,544)	5 (1,549)	4 (1,068)	4 (1,104)	3 (614)	3 (643)
Latinx	55 (3,381,198)	81 (27,711)	82 (27,926)	84 (24,161)	83 (24,000)	85 (18,968)	85 (18,982)
White	22 (1,381,737)	9 (3,145)	9 (3,042)	8 (2,284)	8 (2,448)	8 (1,807)	8 (1,737)
English Learners	19 (1,148,024)	28 (9,706)	29 (9,776)	27 (7,795)	25 (7,283)	28 (6,223)	27 (6,080)
Students with Disabilities	12 (721,198)	14 (4,884)	14 (4,933)	15 (4,377)	15 (4,300)	11 (2,442)	11 (2,457)
Economically Disadvantaged	61 (3,741,755)	85 (28,879)	85 (29,052)	85 (24,406)	84 (24,373)	87 (19,518)	88 (19,563)

Panel B: Star

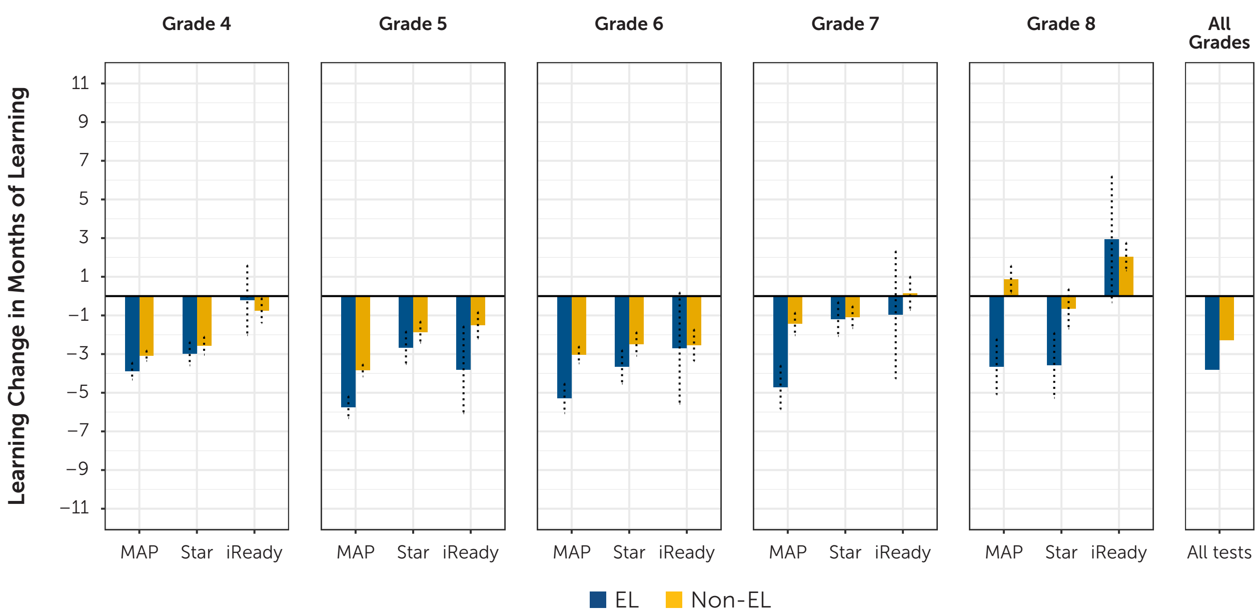
	2019–20 California State Population	Fall 2017 to Winter 2019		Fall 2018 to Winter 2020		Fall 2019 to Winter 2021	
		ELA	Math	ELA	Math	ELA	Math
Native American and Pacific Islander	< 1 (30,282)	< 1 (77)	< 1 (28)	< 1 (86)	< 1 (25)	< 1 (86)	< 1 (25)
Asian American	9 (575,067)	7 (1,153)	5 (146)	7 (1,252)	5 (155)	7 (1,162)	7 (237)
Black	5 (324,496)	8 (1,353)	5 (135)	8 (1,335)	3 (95)	7 (1,141)	4 (139)
Latinx	55 (3,381,198)	57 (9,244)	33 (974)	53 (9,331)	35 (1,014)	51 (8,379)	30 (1,061)
White	22 (1,381,737)	21 (3,380)	52 (1,537)	25 (4,291)	50 (1,451)	26 (4,313)	51 (1,817)
English Learners	19 (1,148,024)	23 (3,675)	13 (386)	22 (3,836)	16 (460)	22 (3,607)	13 (477)
Students with Disabilities	12 (721,198)	12 (1,904)	15 (449)	12 (2,015)	14 (414)	8 (1,367)	11 (377)
Economically Disadvantaged	61 (3,741,755)	67 (10,864)	40 (1,180)	63 (11,005)	40 (1,169)	58 (9,490)	36 (1,295)

Panel C: i-Ready

	2019–20 California State Population	Fall 2018 to Winter 2020		Fall 2019 to Winter 2021	
		ELA	Math	ELA	Math
Native American and Pacific Islander	< 1 (30,282)	< 1 (47)	n/a	< 1 (46)	n/a
Asian American	9 (575,067)	9 (1,036)	n/a	10 (1,107)	n/a
Black	5 (324,496)	5 (551)	n/a	4 (476)	n/a
Latinx	55 (3,381,198)	46 (5,443)	n/a	47 (5,453)	n/a
White	22 (1,381,737)	33 (3,949)	n/a	32 (3,709)	n/a
English Learners	19 (1,148,024)	10 (1,210)	n/a	12 (1,402)	n/a
Students with Disabilities	12 (721,198)	13 (1,591)	n/a	8 (968)	n/a
Economically Disadvantaged	61 (3,741,755)	43 (5,061)	n/a	48 (5,572)	n/a

Figure A1. Fall-to-Winter Results: English Learners

Panel A: English Language Arts: English Learners versus Non-English Learners



Panel B: Math: English Learners versus Non-English Learners

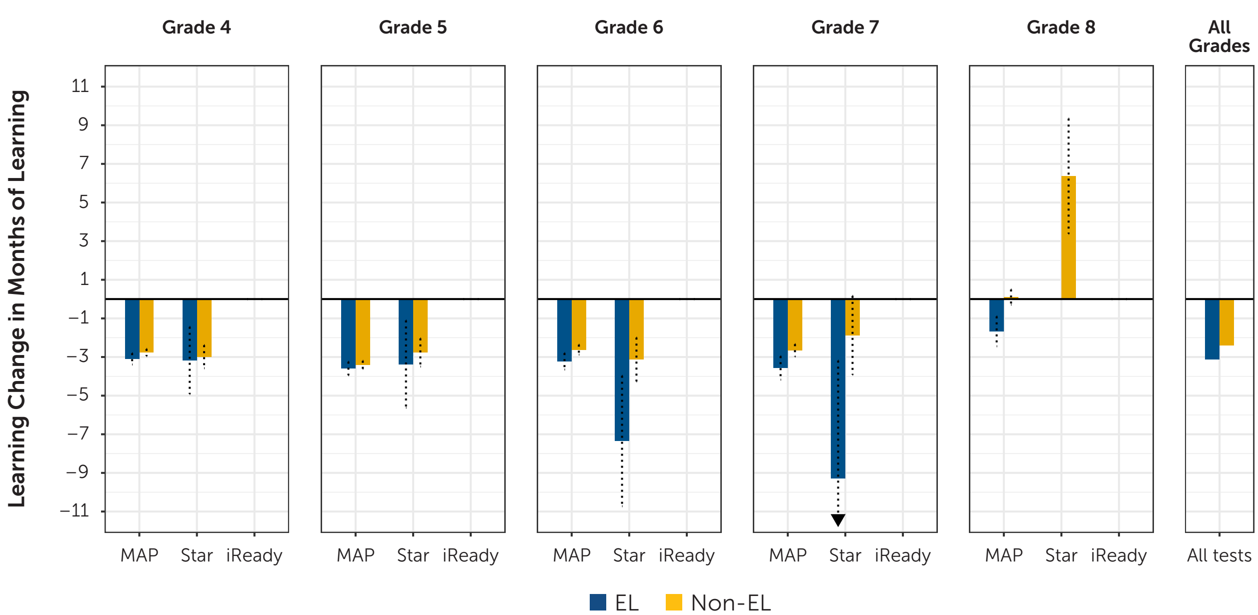
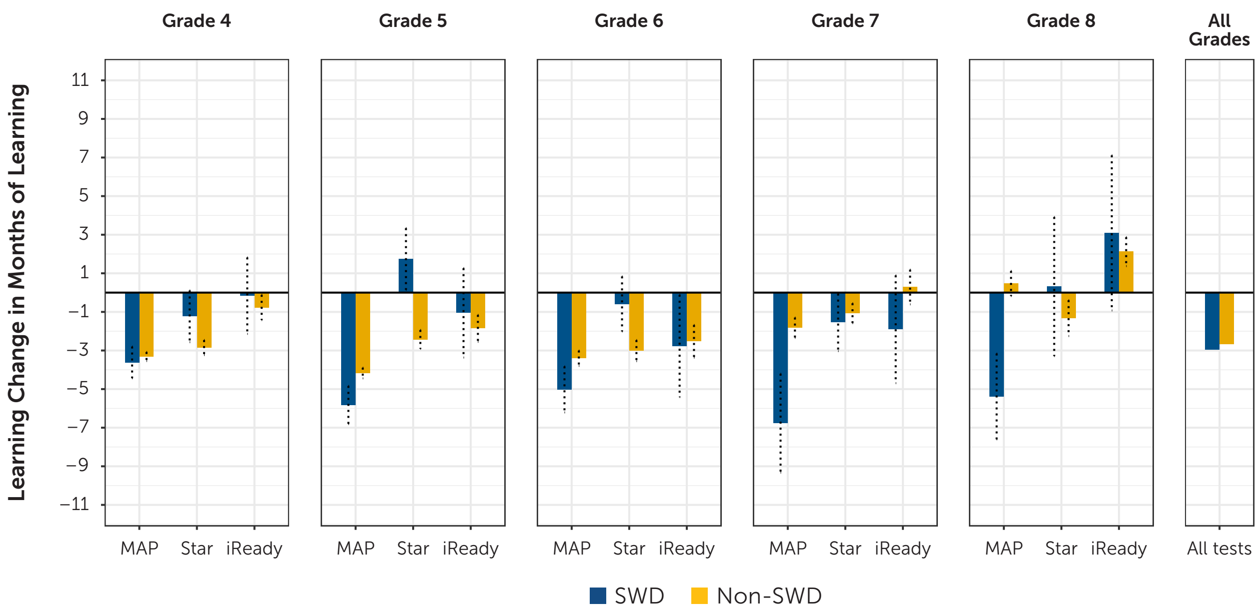


Figure A2. Fall-to-Winter Results: Students with Disabilities

Panel A: English Language Arts: Students with Disabilities versus Students without Disabilities



Panel B: Math: Students with Disabilities versus Students without Disabilities

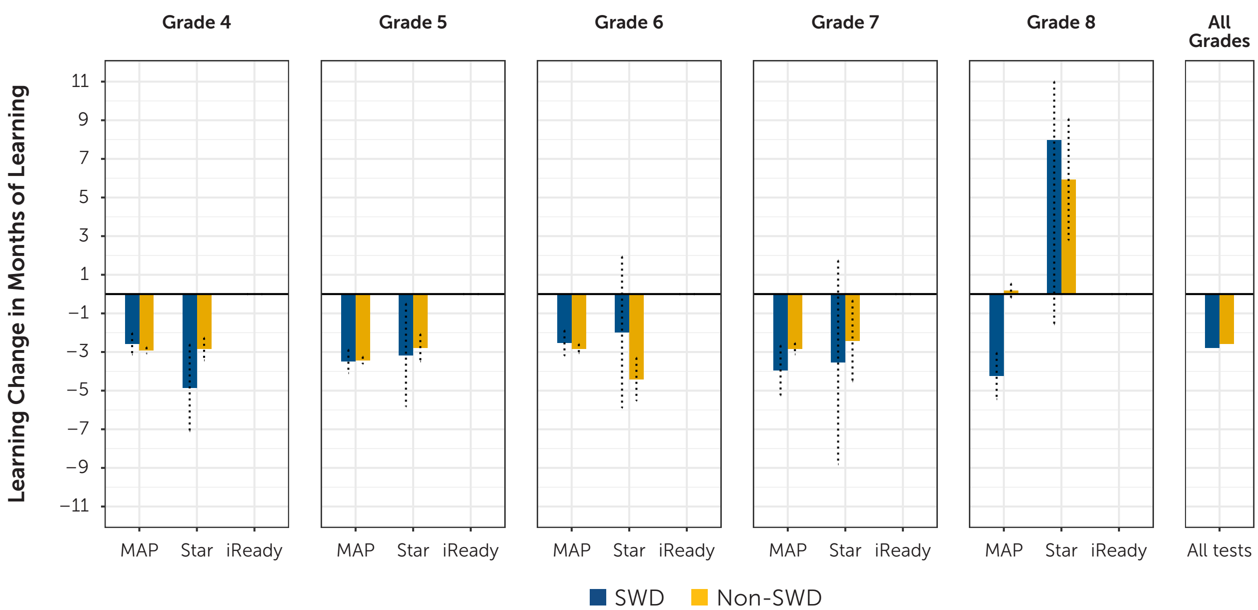
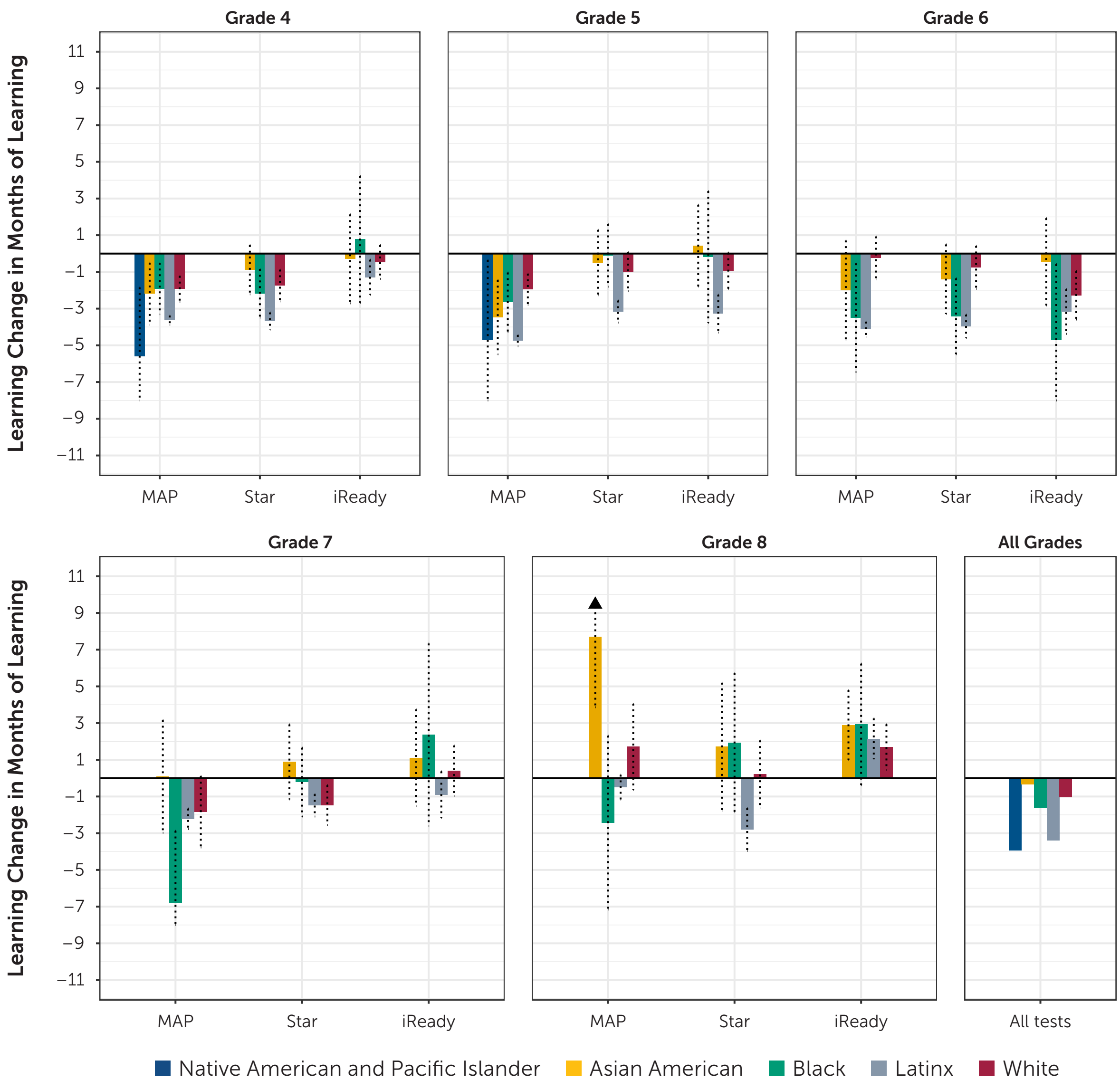


Figure A3. Fall-to-Winter Results: Race/Ethnicity

Panel A: English Language Arts: Race/Ethnicity



Panel B: Math: Race/Ethnicity

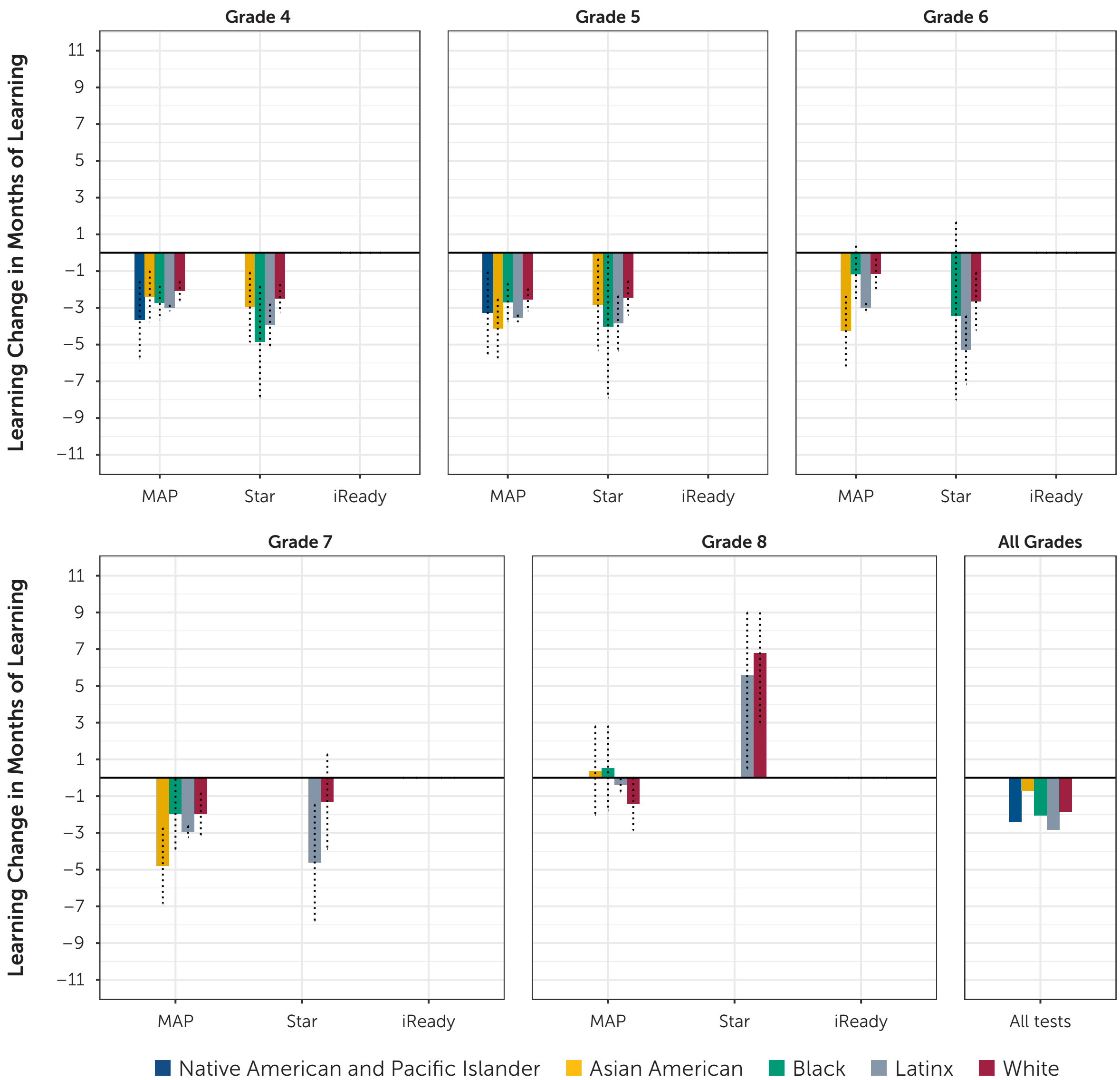
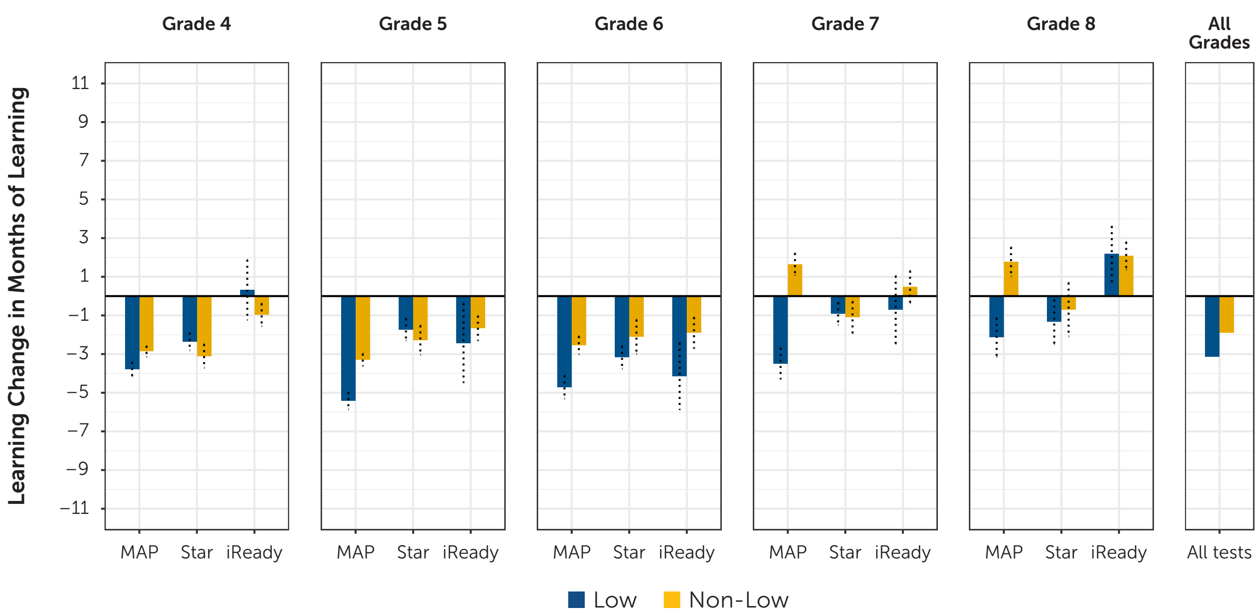


Figure A4. Fall-to-Winter Results: Prior Achievement

Panel A: English Language Arts: Non-Low Prior Achievement versus Low Prior Achievement



Panel B: Math: Non-Low Prior Achievement versus Low Prior Achievement

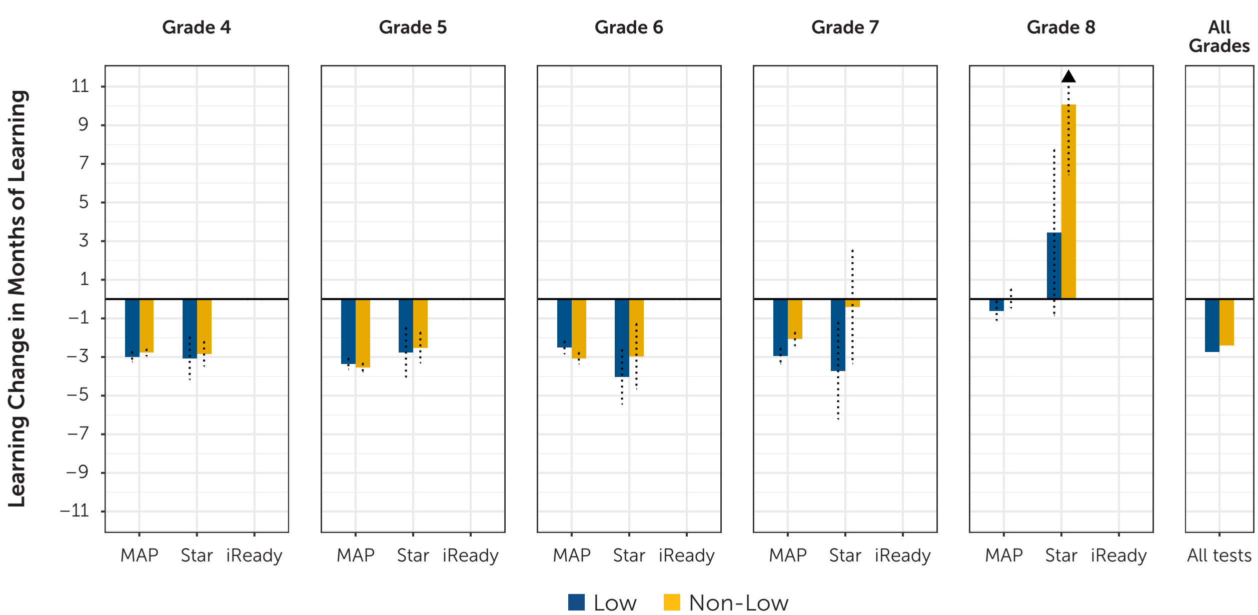
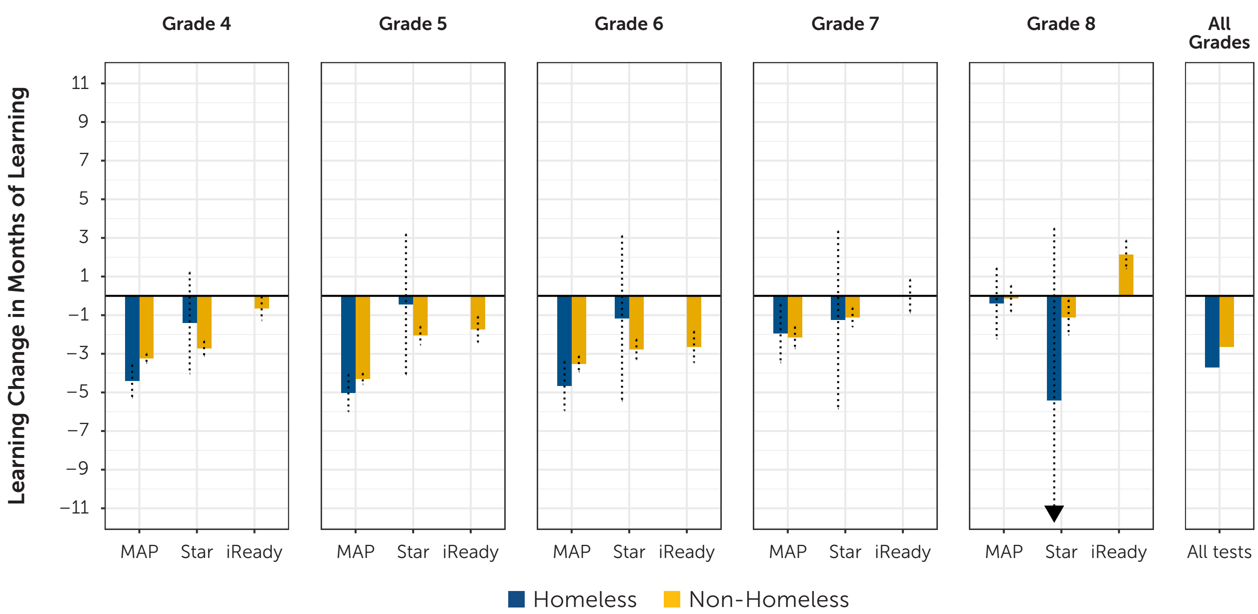
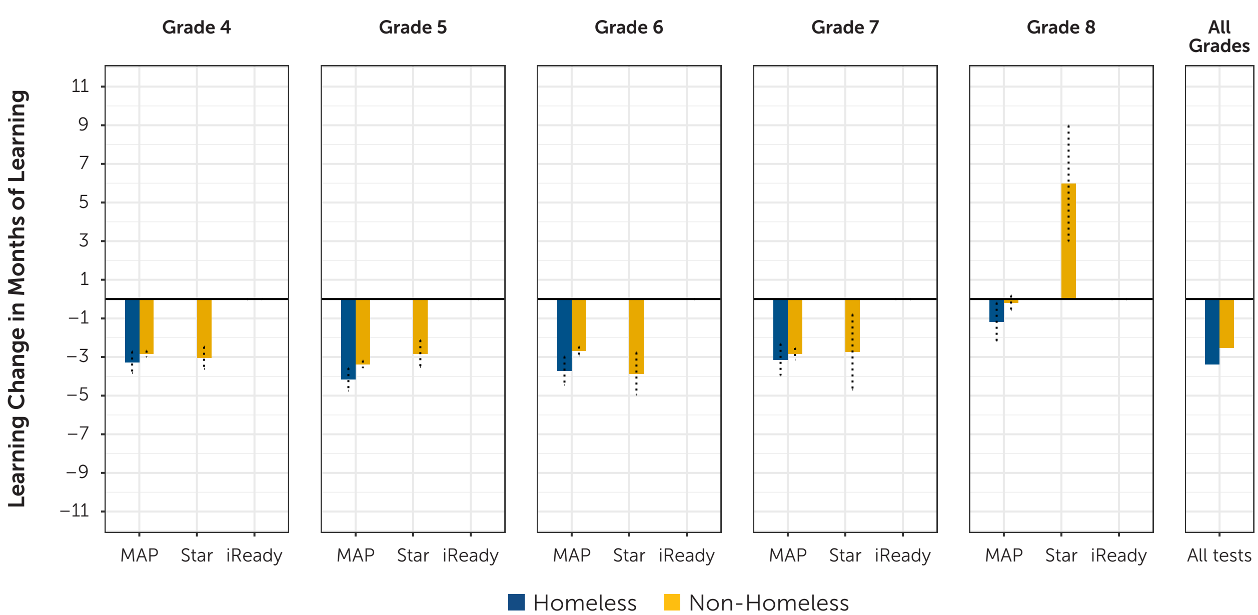


Figure A5. Fall-to-Winter Results: Homelessness

Panel A: English Language Arts: Homeless versus Non-Homeless



Panel B: Math: Homeless versus Non-Homeless



Fall-to-Fall Analyses

The sections that follow detail the analyses conducted to compare growth from fall 2019 to fall 2020 to fall-to-fall growth in prior years. Fall-to-fall results were previously reported in a PACE commentary. Figure A6 depicts the data requirements for LEAs to be included in the fall-to-fall models. Table A2 provides the size of the fall-to-fall sample by posttest grade, growth year, and assessment type, and Table A3 provides summary statistics for the fall-to-fall sample by student subgroup, year, and assessment type (and compares them to the 2019–20 California state sample).

Figure A6. Local Education Agency Data Requirements for Learning Change Model: Fall-to-Fall Models

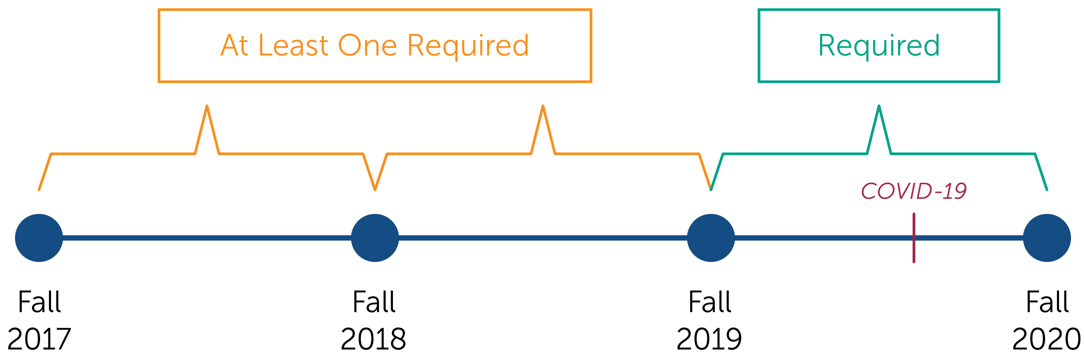


Table A2. Number of Students in Each Posttest Grade by Assessment and Growth Year: Fall-to-Fall Sample

Panel A: MAP

	Fall 2017 to Fall 2018		Fall 2018 to Fall 2019		Fall 2019 to Fall 2020	
Posttest Grade	ELA	Math	ELA	Math	ELA	Math
Grade 4	6,766	6,833	6,812	6,863	5,757	5,786
Grade 5	7,301	7,371	6,795	6,855	6,103	6,157
Grade 6	6,866	6,745	5,665	5,487	4,394	3,976
Grade 7	6,494	6,752	5,392	5,252	4,042	4,136
Grade 8	6,379	6,483	5,332	5,266	4,233	4,348
Total *n*	33,806	34,184	29,996	29,723	24,529	24,403

Panel B: Star

	Fall 2017 to Fall 2018		Fall 2018 to Fall 2019		Fall 2019 to Fall 2020	
Posttest Grade	ELA	Math	ELA	Math	ELA	Math
Grade 4	4,391	1,147	4,254	1,042	3,995	1,139
Grade 5	4,389	1,179	4,172	1,018	3,924	1,136
Grade 6	3,913	539	4,003	498	3,637	1,058
Grade 7	3,326	385	3,722	353	3,304	451
Grade 8	3,627	321	3,400	330	3,410	347
Total *n*	19,646	3,571	19,551	3,241	18,270	4,131

Panel C: i-Ready

	Fall 2018 to Fall 2019		Fall 2019 to Fall 2020	
Posttest grade	ELA	Math	ELA	Math
Grade 4	3,448	n/a	2,968	n/a
Grade 5	3,438	n/a	3,053	n/a
Grade 6	3,592	n/a	3,013	n/a
Grade 7	3,577	n/a	2,665	n/a
Grade 8	4,195	n/a	2,980	n/a
Total *n*	18,230	0	14,679	0

Table A3. Percent (and Number) of Students in Each Student Subgroup by Assessment and Year versus California State Student Population: Fall-to-Fall Sample

Panel A: MAP

	2019–20 California State Population	Fall 2017 to Fall 2018		Fall 2018 to Fall 2019		Fall 2019 to Fall 2020	
		ELA	Math	ELA	Math	ELA	Math
Native American and Pacific Islander	< 1 (30,282)	<1 (92)	<1 (91)	<1 (120)	<1 (120)	<1 (108)	<1 (112)
Asian American	9 (575,067)	2 (575)	2 (577)	2 (450)	1 (438)	2 (398)	2 (396)
Black	5 (324,496)	5 (1,550)	5 (1,594)	4 (1,261)	4 (1,249)	4 (876)	4 (895)
Latinx	55 (3,381,198)	82 (27,833)	83 (28,299)	83 (24,771)	83 (24,683)	83 (20,393)	83 (20,302)
White	22 (1,381,737)	8 (2,797)	8 (2,683)	8 (2,542)	8 (2,402)	9 (2,108)	8 (2,045)
English Learners	19 (1,148,024)	29 (9,772)	29 (9,919)	26 (7,691)	25 (7,467)	26 (6,491)	26 (6,312)
Students with Disabilities	12 (721,198)	14 (4,836)	14 (4,925)	15 (4,477)	15 (4,428)	10 (2,519)	10 (2,461)
Economically Disadvantaged	61 (3,741,755)	86 (29,033)	86 (29,499)	84 (25,237)	85 (25,173)	88 (21,517)	88 (21,443)

Panel B: Star

	2019–20 California State Population	Fall 2017 to Fall 2018		Fall 2018 to Fall 2019		Fall 2019 to Fall 2020	
		ELA	Math	ELA	Math	ELA	Math
Native American and Pacific Islander	< 1 (30,282)	<1 (92)	<1 (25)	<1 (99)	<1 (23)	<1 (93)	<1 (28)
Asian American	9 (575,067)	7 (1,381)	5 (167)	7 (1,359)	5 (158)	7 (1,272)	6 (266)
Black	5 (324,496)	8 (1,548)	5 (168)	7 (1,463)	3 (82)	7 (1,278)	4 (150)
Latinx	55 (3,381,198)	51 (10,032)	33 (1,165)	52 (10,061)	30 (972)	51 (9,351)	28 (1,165)
White	22 (1,381,737)	27 (5,323)	53 (1,887)	27 (5,250)	57 (1,839)	26 (4,827)	54 (2,219)
English Learners	19 (1,148,024)	20 (3,916)	13 (453)	21 (4,018)	12 (375)	21 (3,915)	13 (535)
Students with Disabilities	12 (721,198)	11 (2,205)	15 (544)	12 (2,296)	14 (468)	9 (1,563)	11 (449)
Economically Disadvantaged	61 (3,741,755)	61 (11,966)	40 (1,441)	61 (11,932)	35 (1,138)	59 (10,727)	35 (1,435)

Panel C: i-Ready

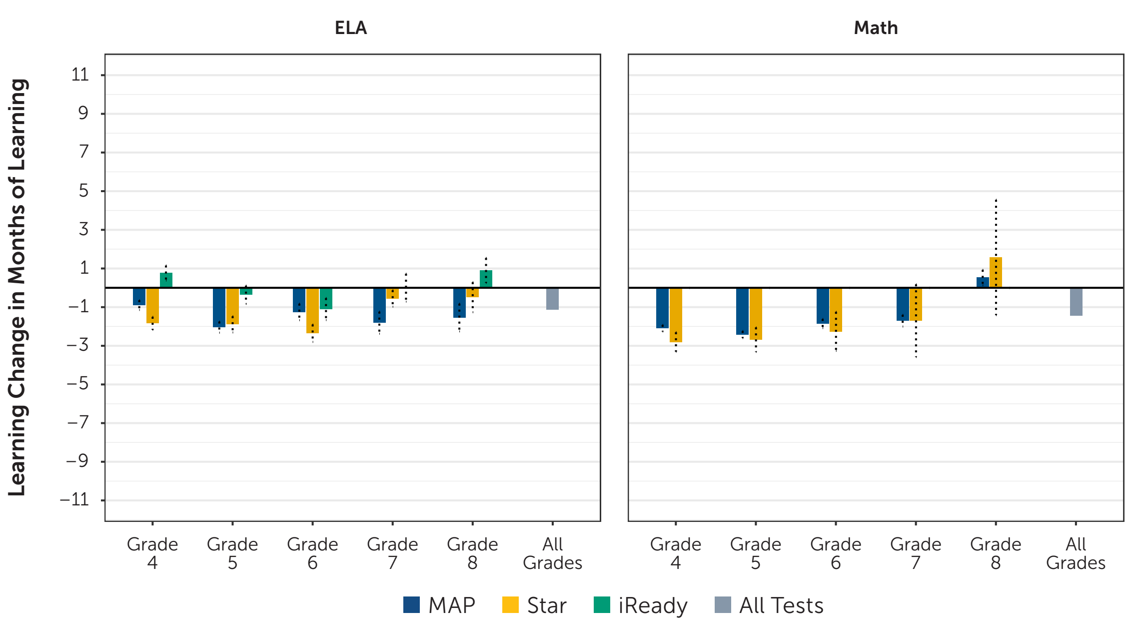
	2019–20 California State Population	Fall 2018 to Fall 2019		Fall 2019 to Fall 2020	
		ELA	Math	ELA	Math
Native American and Pacific Islander	< 1 (30,282)	<1 (69)	n/a	<1 (58)	n/a
Asian American	9 (575,067)	8 (1,540)	n/a	9 (1,315)	n/a
Black	5 (324,496)	4 (796)	n/a	4 (624)	n/a
Latinx	55 (3,381,198)	51 (9,290)	n/a	50 (7,273)	n/a
White	22 (1,381,737)	30 (5,420)	n/a	30 (4,426)	n/a
English Learners	19 (1,148,024)	13 (2,325)	n/a	12 (1,755)	n/a
Students with Disabilities	12 (721,198)	14 (2,526)	n/a	9 (1,262)	n/a
Economically Disadvantaged	61 (3,741,755)	47 (8,519)	n/a	49 (7,144)	n/a

Fall-to-Fall Results

Our fall-to-fall results answer the question: How much more or less did students grow academically from fall 2019 to fall 2020 than they did over the same time frame in prior school years? In other words, they measure the degree to which students grew faster or slower in the 2019–20 school year at the initial onset of COVID-19, compared to in pre-COVID-19 school years.

Figure A7 depicts results from the fall-to-fall learning change models across subjects, grades, and assessment types in units of *months of learning* (on the vertical axis). The results show a substantial learning lag in both math and ELA in nearly all cases. Using the inverse-variance weighted average of results across grades and assessments (which weights more heavily those results for a given grade-assessment combination that are estimated more precisely), we find that, compared to growth in prior years, students are experiencing a learning lag of approximately 1.1 months of learning in ELA and 1.4 months of learning in math. However, it is important to note that there are substantial differences in the learning change results across subjects, assessment types, and grades. Specifically, the results are *not* significantly different from zero in ELA for eighth graders on the Star and fifth and seventh graders on the i-Ready, nor in math for seventh graders and eighth graders on the Star. The only estimates indicating a statistically significant learning *acceleration*, rather than a learning lag, are for eighth graders in math on the MAP and for fourth and eighth graders in ELA on the i-Ready.

Figure A7. Fall-to-Fall Learning Change: Overall



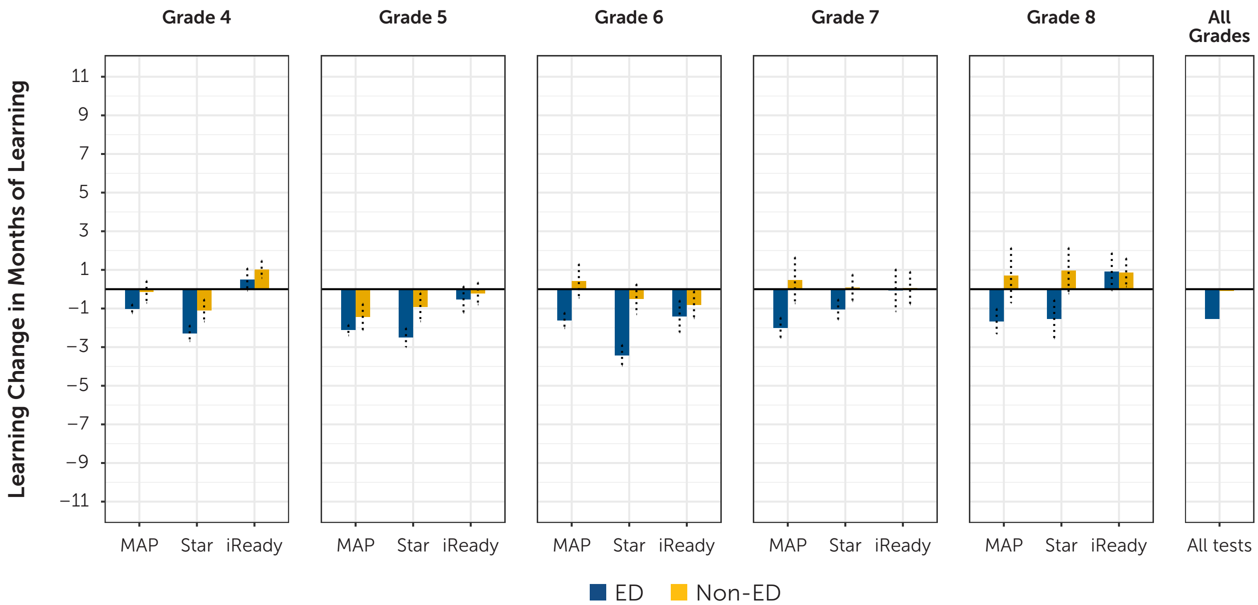
Results for Student Subgroups. We examined how our learning change results differ for different student subgroups by examining whether a particular subgroup (for instance, English learners) experienced significantly more or less learning change from fall to fall (relative to prior years) than their peers who were not in the subgroup.

Figure A8 depicts the fall-to-fall results for students who were economically disadvantaged. The top panel displays results for ELA, and the bottom panel displays results for math. Blue bars indicate learning change for students who were economically disadvantaged, and yellow bars indicate learning change for students who were not economically disadvantaged. Students' posttest grade is indicated at the top of each panel, and the assessment type is indicated at the bottom of each panel. Results are displayed in the *months of learning* metric. We depicted 95 percent confidence intervals as black dotted lines; these indicate that results were not statistically significantly different from zero if they cross the horizontal axis. It is important to note that the difference in learning change between the two groups may still be significantly different even if the dotted lines over the blue and yellow bars overlap with each other to some degree. If the dotted lines do not overlap at all, it is necessarily the case that learning change is significantly different between the two groups. For example, for the Grade 5 Star assessment in ELA (the second pair of bars within the Grade 5 panel), students who were economically disadvantaged (the blue bar) grew by approximately 2.5 months of learning less than they did in the past, whereas non-economically disadvantaged students grew by approximately one month of learning less than they did in the past, and this difference is statistically significant (as indicated by the non-overlapping bars).

Students who were economically disadvantaged experienced, on average, 1.6 months of learning lag in ELA and 1.7 months of learning lag in math, whereas students who were non-economically disadvantaged experienced, on average, 0.1 months of learning lag in ELA and 0.8 months of learning lag in math. Economically disadvantaged students experienced significantly more learning lag than non-economically disadvantaged students in all grades and assessments on the MAP and Star assessments in ELA *except* on the Grade 5 MAP. No statistically significant differences were observed in ELA on the i-Ready. The only statistically significant differences observed in math were on the Star in Grades 4–6.

Figure A8. Fall-to-Fall Learning Change: Economic Disadvantage

Panel A: English Language Arts: Economically Disadvantaged versus Non-Economically Disadvantaged



Panel B: Math: Economically Disadvantaged versus Non-Economically Disadvantaged

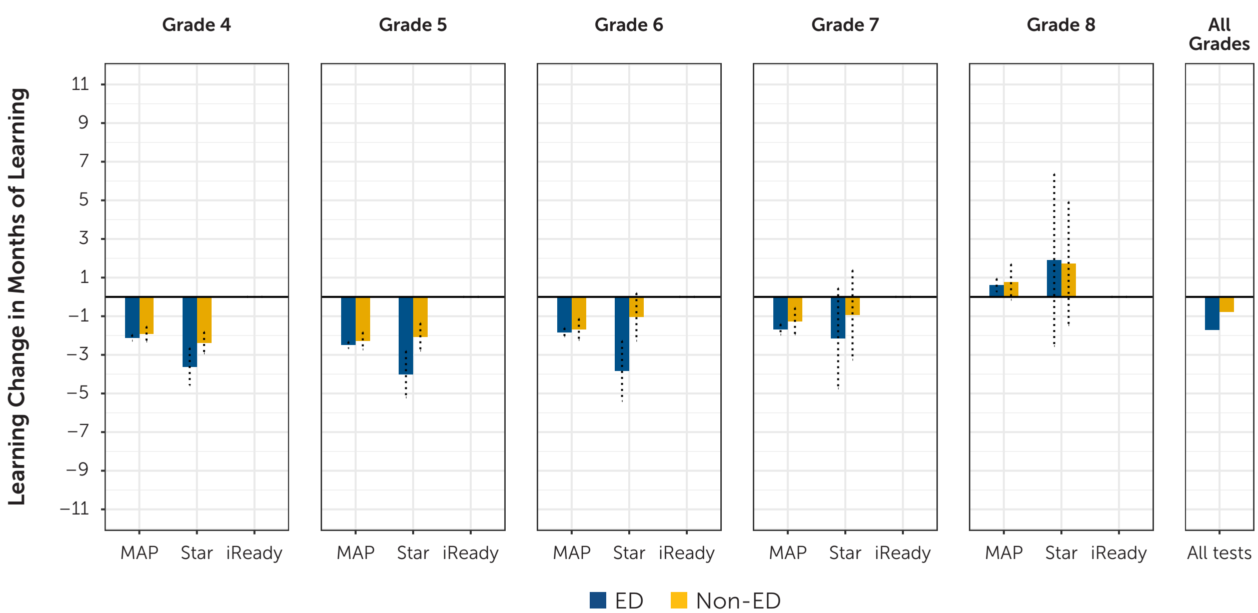
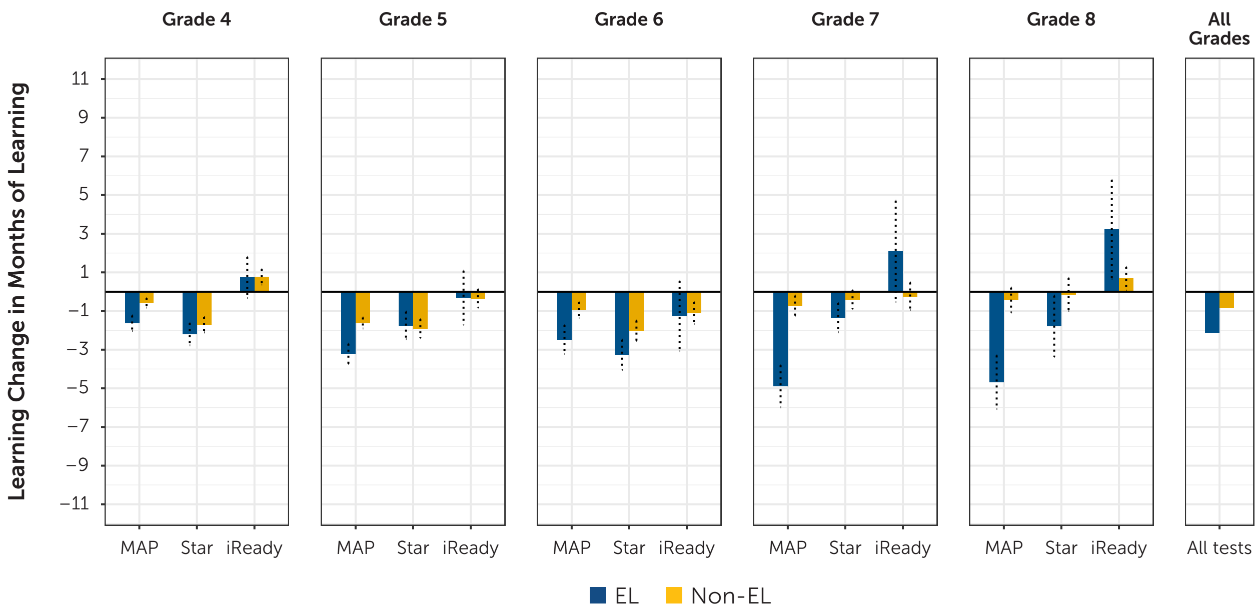


Figure A9 depicts fall-to-fall results for English learners and non-English learners. Students who were English learners experienced, on average, 2.1 months of learning lag in ELA and 1.9 months of learning lag in math, while students who were not English learners experienced, on average, 0.8 months of learning lag in ELA and 1.4 months of learning lag in math.

Figure A9. Fall-to-Fall Results: English Learners

Panel A: English Language Arts: English Learners versus Non-English Learners



Panel B: Math: English Learners versus Non-English Learners

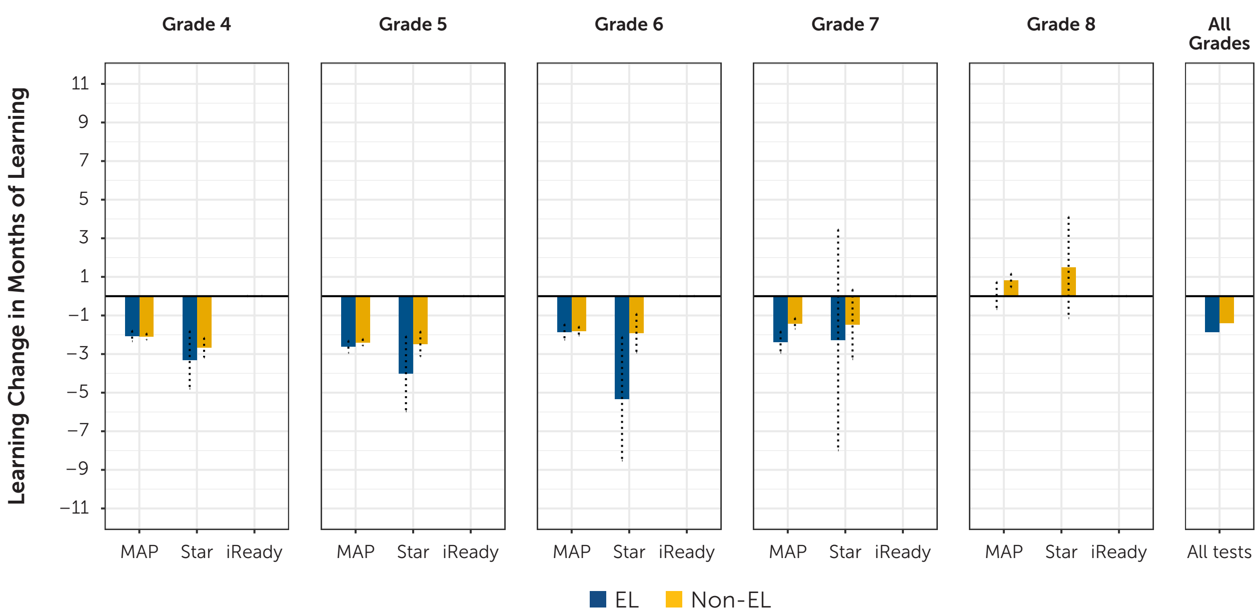
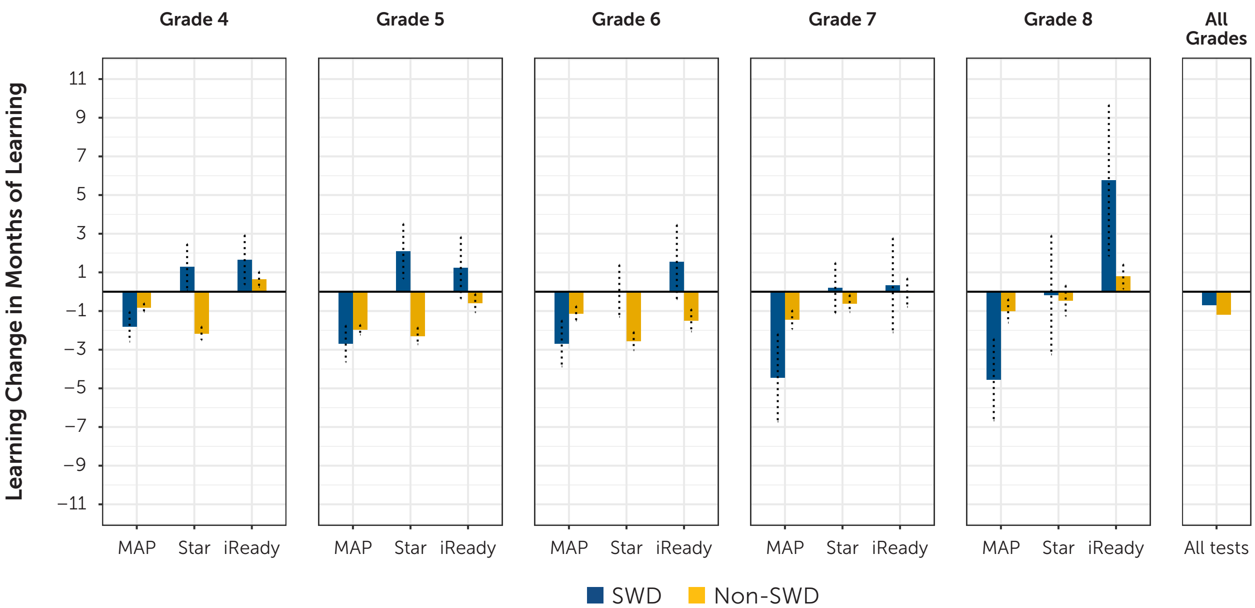


Figure A10 depicts fall-to-fall results for students with disabilities and students without disabilities. Students with disabilities experienced, on average, 0.7 months of learning lag in ELA and 1.3 months of learning lag in math, while students without disabilities experienced, on average, 1.2 months of learning lag in ELA and 1.6 months of learning lag in math.

Figure A10. Fall-to-Fall Results: Students with Disabilities

Panel A: English Language Arts: Students with Disabilities versus Students without Disabilities



Panel B: Math: Students with Disabilities versus Students without Disabilities

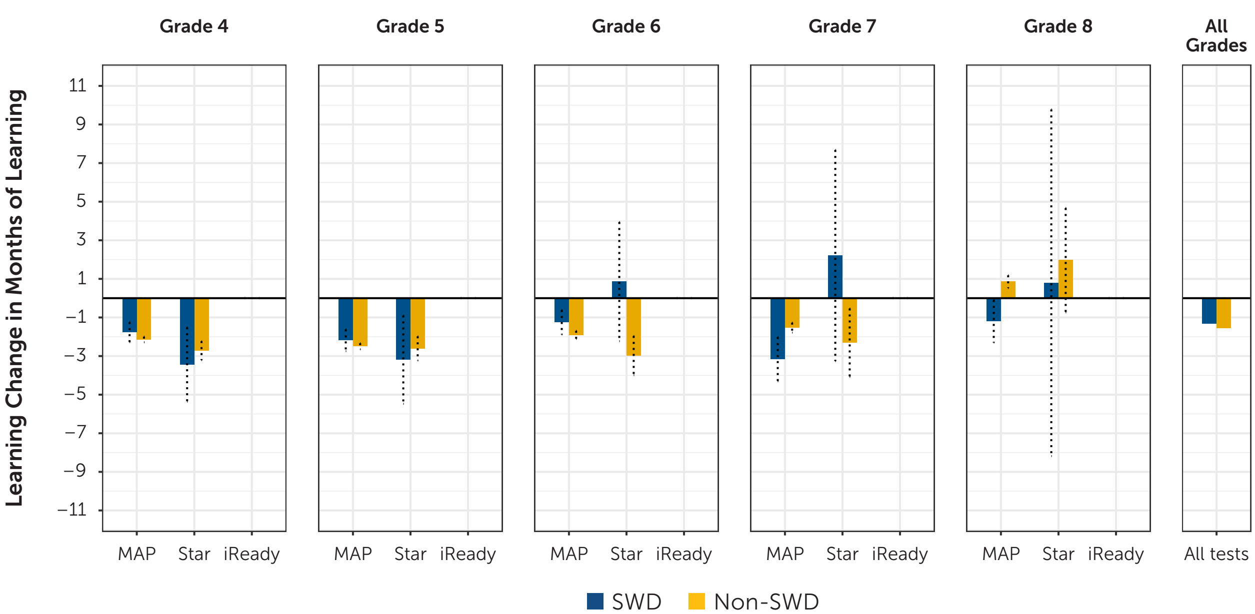
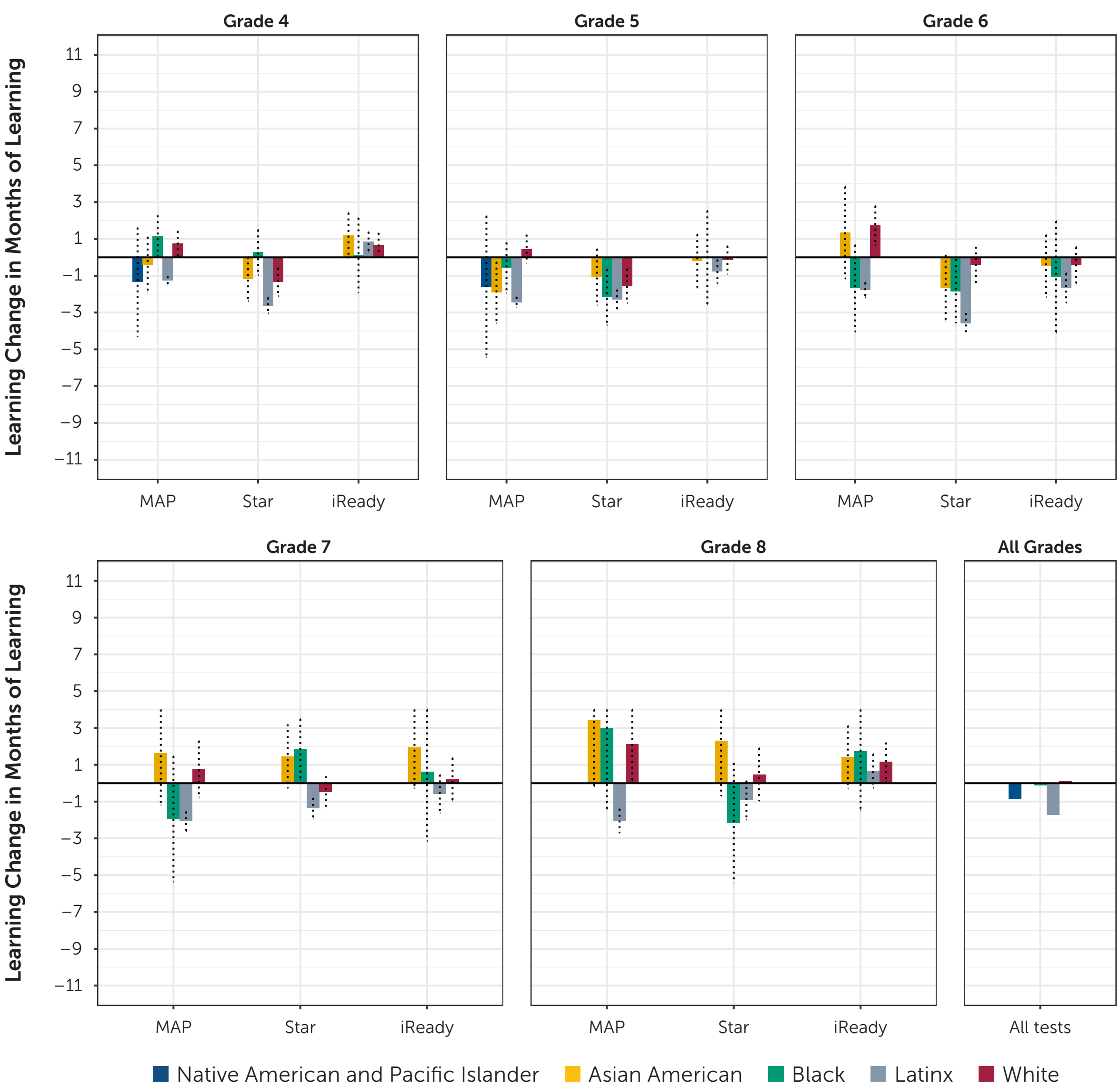


Figure A11 depicts fall-to-fall results for students of different racial and ethnic backgrounds. In ELA, on average, across grades and assessment types, the learning lag experienced was 0.9 months of learning for Native American and Pacific Islander students, 0.0 months of learning for Asian American students, 0.1 months of learning for Black students, and 1.7 months of learning for Latinx students; White students experienced 0.1 months of learning *acceleration* in ELA, on average. In math, on average, across grades and assessment types, the learning lag experienced was 2.0 months of learning for Native American and Pacific Islander students, 0.0 months of learning for Asian American students, 0.8 months of learning for Black students, 1.8 months of learning for Latinx students, and 0.9 months of learning for White students.

Figure A11. Fall-to-Fall Results: Race/Ethnicity

Panel A: English Language Arts: Race/Ethnicity



Panel B: Math: Race/Ethnicity

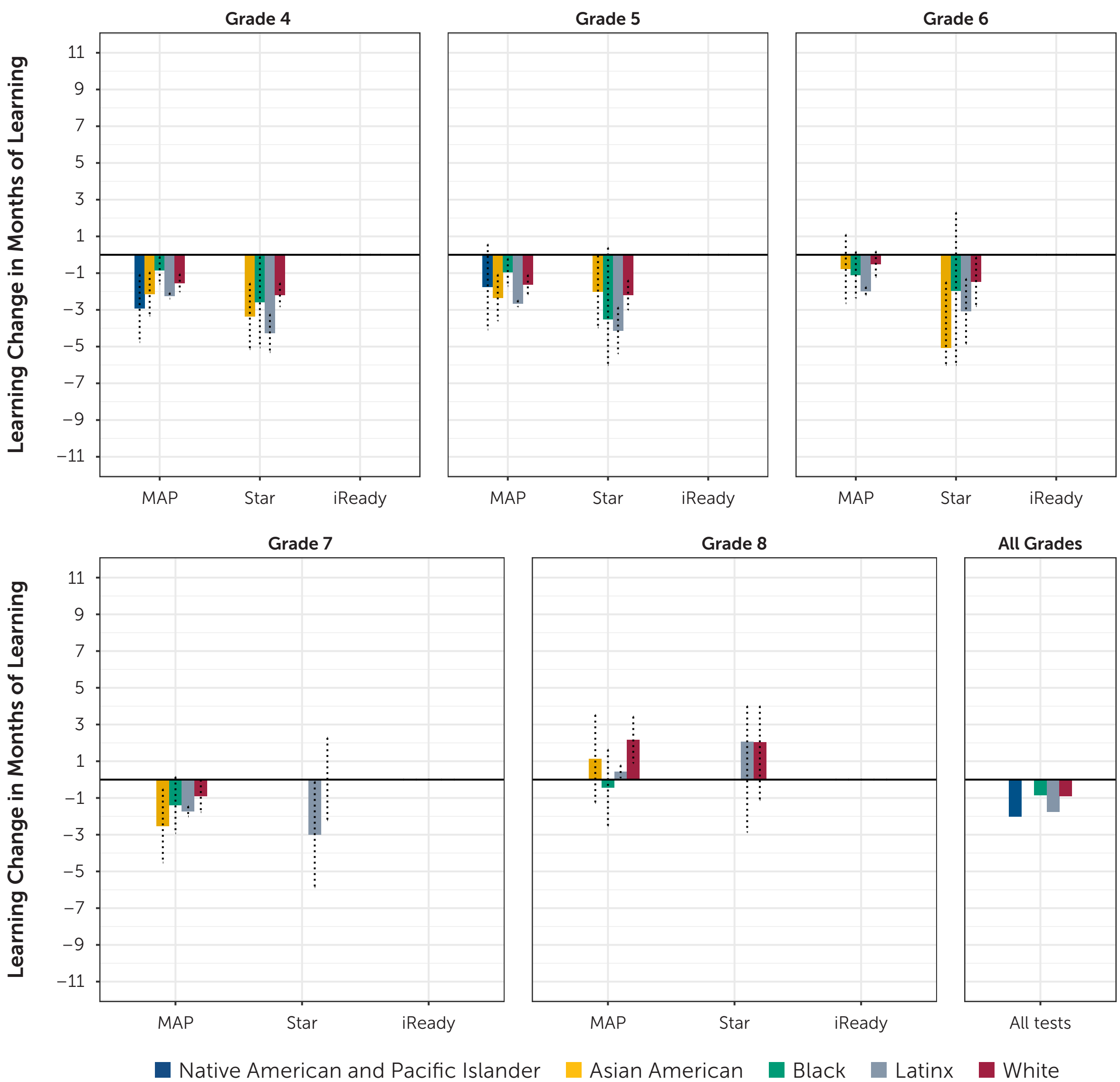
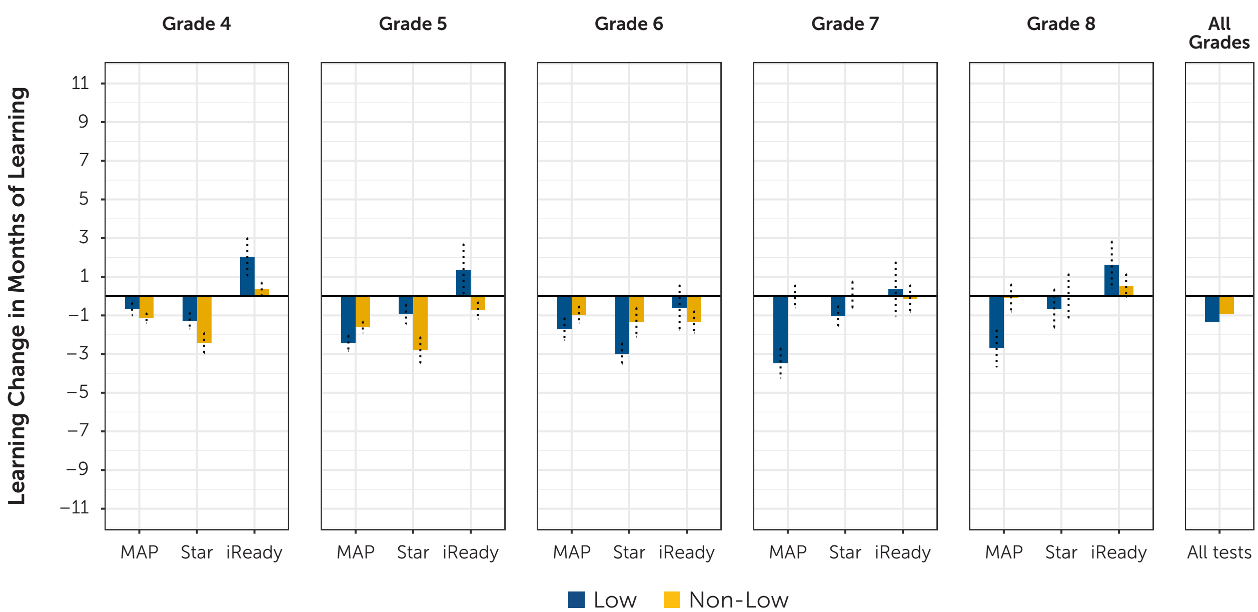


Figure A12 depicts fall-to-fall results for students with low prior achievement (defined as students scoring in the bottom two performance categories on each assessment[10]) and students with non-low prior achievement (defined as students scoring in the other performance categories on each assessment). Students with low prior achievement experienced, on average, 1.4 months of learning lag in ELA and 1.6 months of learning lag in math, while students with non-low prior achievement experienced, on average, 0.9 months of learning lag in ELA and 1.5 months of learning lag in math.

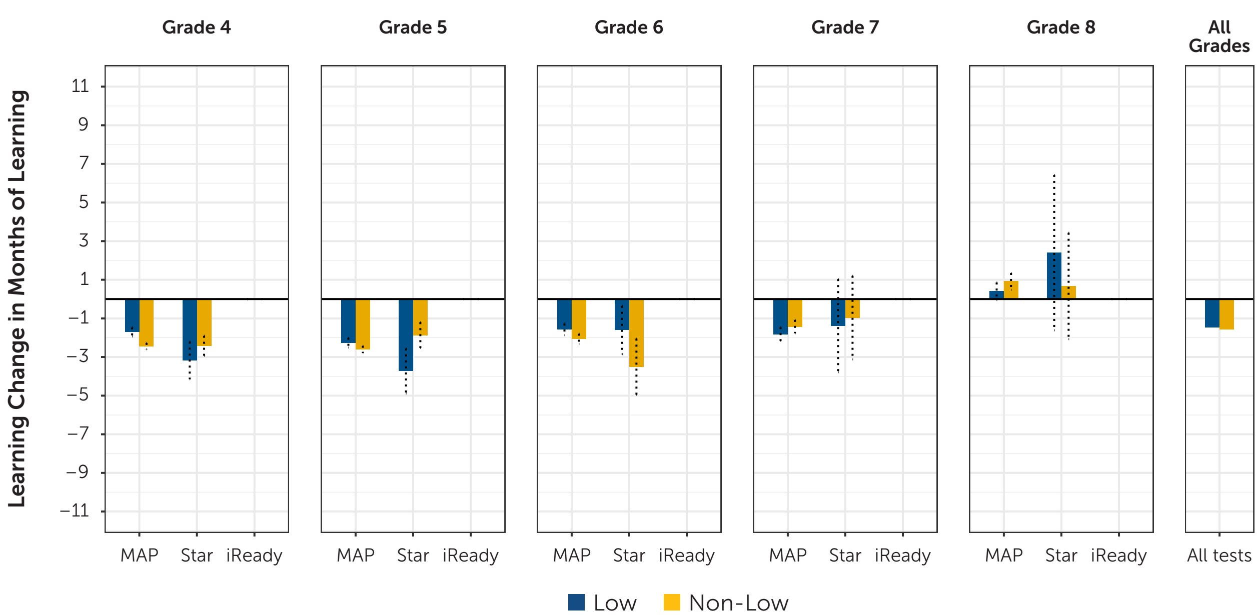
[10] The MAP performance categories are based on quintiles, such that students in the bottom two categories correspond to students in the 40th percentile or lower. The two bottom performance categories on the Star include "Did not meet standard" and "Nearly met standard," and on the i-Ready include "Three or more grade levels below" and "Two grade levels below."

Figure A12. Fall-to-Fall Results: Prior Achievement

Panel A: English Language Arts: Non-Low Prior Achievement versus Low Prior Achievement



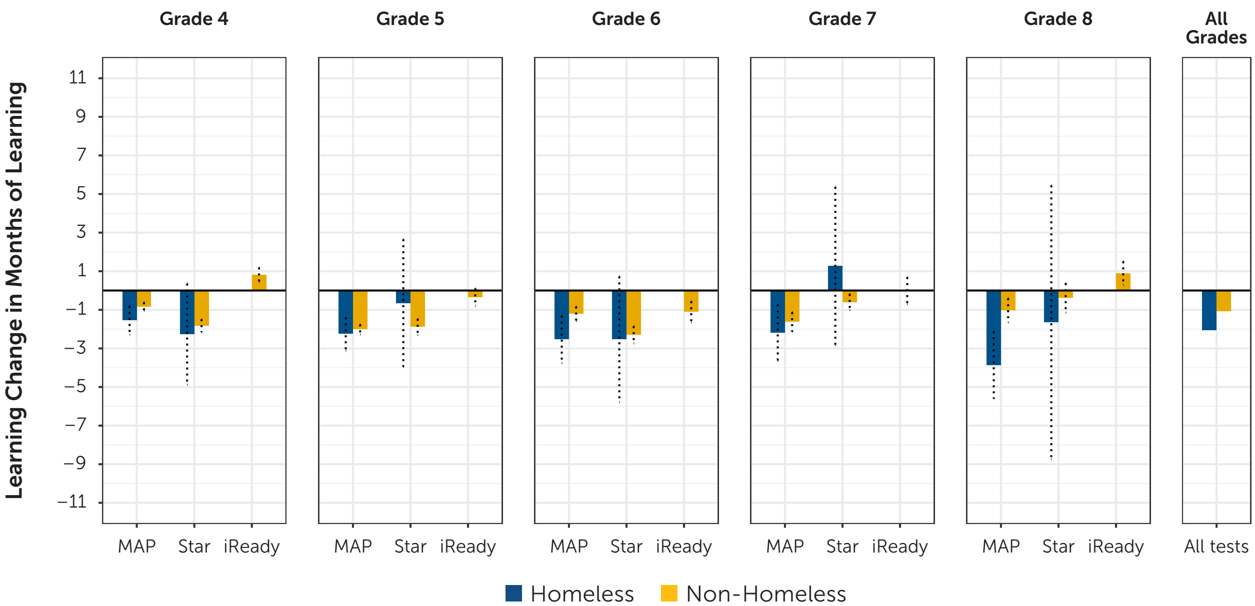
Panel B: Math: Non-Low Prior Achievement versus Low Prior Achievement



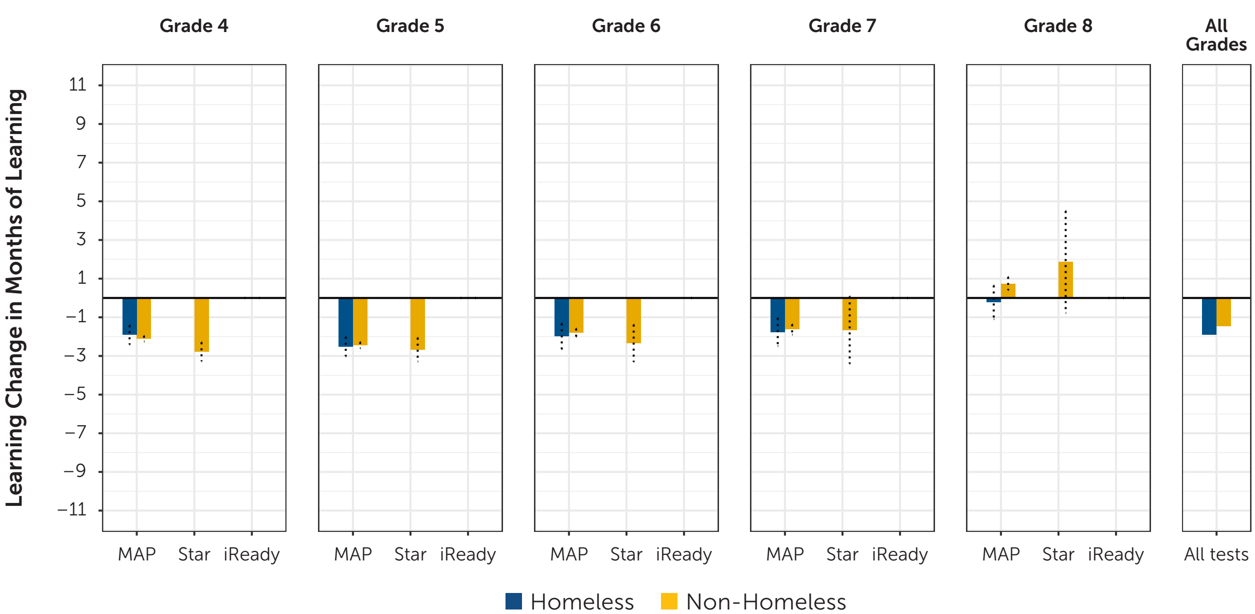
Finally, Figure A13 depicts fall-to-fall results for students experiencing homelessness and students not experiencing homelessness. Students experiencing homelessness experienced, on average, 2.1 months of learning lag in ELA and 1.9 months of learning lag in math, while students not experiencing homelessness experienced, on average, 1.1 months of learning lag in ELA and 1.5 months of learning lag in math.

Figure A13. Fall-to-Fall Results: Homelessness

Panel A: English Language Arts: Homelessness versus Non-Homelessness



Panel B: Math: Homelessness versus Non-Homelessness



To summarize, we observed more fall-to-fall learning lag for students who were economically disadvantaged, English learners, and Latinx (with these results frequently statistically significant on the MAP and Star assessments). We also observed more fall-to-fall learning lag among economically disadvantaged and Latinx students in ELA on the i-Ready, although these results are not statistically significant in any single grade. We found mixed results for students with disabilities, as they experienced more learning lag on the MAP (relative to students without disabilities) but less learning lag on the Star in both subjects as well as on the i-Ready in ELA.

Fall-to-Fall and Fall-to-Winter Results

It is worth noting that we observed more average learning lag in the fall-to-winter results than in the fall-to-fall results. Although this suggests a continued learning lag in the 2020–21 school year beyond the learning lag experienced in the 2019–20 school year, we caution readers against directly comparing the magnitude of the results from the fall-to-fall models with those from the fall-to-winter models. This is because these two models use a sample of students that is not longitudinal (which we use in order to maximize our sample size and bring as much student data as we can into our analysis) and because it can be challenging to precisely measure growth over such a short time span (i.e., from fall 2020 to winter 2020–21).

To probe the robustness of our results to this first issue, we restricted our fall-to-winter models to a matched sample of students also included in the fall-to-fall models. We found that, overall, the differences between fall-to-fall and fall-to-winter learning change were robust to this restriction in models with the MAP in ELA, the MAP in math, and the Star in ELA, suggesting that the difference in fall-to-fall and fall-to-winter learning change was not due to differences in the fall-to-fall and fall-to-winter samples used for these assessments and subjects. In contrast, we found that the difference between fall-to-fall and fall-to-winter learning change *was* more sensitive to this restriction in the smaller samples used for the Star in math and for the i-Ready; that stated, the broad result of measuring more learning lag over the fall-to-winter period in comparison to the fall-to-fall period held both with and without the sample restriction. Although we feel this is further evidence of continued learning lag this school year, we still caution against a direct comparison of the magnitudes of the results from each model, given that it is still difficult to measure and compare growth over the short same-year fall-to-winter period.

Policy Analysis for California Education (PACE)

Improving education policy and practice and advancing equity through evidence

PACE is an independent, non-partisan research center led by faculty directors at Stanford University, the University of Southern California, the University of California Davis, the University of California Los Angeles, and the University of California Berkeley. Founded in 1983, PACE bridges the gap between research, policy, and practice, working with scholars from California's leading universities and with state and local decision makers to achieve improvement in performance and more equitable outcomes at all levels of California's education system, from early childhood to postsecondary education and training. We do this through:

1. bringing evidence to bear on the most critical issues facing our state;
2. making research evidence accessible; and
3. leveraging partnership and collaboration to drive system improvement.

PACE
Policy Analysis for California Education
CORE-PACE RESEARCH PARTNERSHIP

Stanford Graduate School of Education
520 Galvez Mall, Suite 444
Stanford, CA 94305
Phone: (650) 724-2832 • Fax: (650) 723-9931

edpolicyinca.org