PUBLIC POLICY INSTITUTE OF CALIFORNIA

Targeted K–12 Funding and Student Outcomes

Evaluating the Local Control Funding Formula

Technical Appendices

CONTENTS

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Appendix A. Data Sources and Sample Construction

Data Sources

This report uses a variety of data sources publicly provided by the California Department of Education (CDE) and the Stanford Education Data Archive. There are three main types of data: district-level financial data; school-level enrollment and demographic records; school, district, and state-level student outcome data; and school-level expenditure data. We describe each below:

District-level financial data: For 2003–onwards, financial data are reported at the district level through the Standardized Account Code Structure (SACS). The CDE maintains unaudited databases of district finances using this accounting system. These data allow for detailed accounting of revenue streams, spending categories, and fund balances. The data also contain annual average daily attendance (ADA) totals for each district, which are used to construct per pupil spending measures.

To construct measures of district-level per pupil expenditures we follow the conventions of Bruno (2018) in aggregating categories in the financial data.[1] We exclude all district revenue sources, transfers between districts, and net pension liabilities. We also exclude charter schools filing independently of their affiliated district's general fund, as well as charter-specific funds that account for operations of charters filing through an affiliated district, but outside of its general fund.[2] A small share of charter schools report financial information through an affiliated district's general fund; we therefore include ADA for these schools in the ADA of the affiliated district.[3]

We then aggregate to the district-year level to construct district-year total expenditures. K–12 student spending is a subset of total expenditures that excludes pre-K and adult education, Public Employees' Retirement System (PERS) reductions, capital expenditures (minus equipment replacement), retiree benefits, non-agency spending, and debt service. Other expenditures subcategories are defined based on the relevant SACS "object" codes.

We also rely on LCFF summary data in the 2018–19 and 2019–20 fiscal years, available from CDE. These data are used to get actual LCFF supplemental and concentration grant totals for each district.

School-level enrollment and demographic records: Data on school and district enrollment, English Learner (EL) status, and student socio-demographic characteristics are also maintained by the CDE. Data on the "unduplicated" count of students, relevant for LCFF supplemental and concentration grant calculations, are available at the school and district levels beginning in 2013, the first year of LCFF. School-by-grade enrollment, both overall and broken down by race/ethnicity/gender, as well as by EL status, is available going back to 1982. We collect school and district-level free and reduced price lunch meal (FRPM) totals from three different files: for 2004–2019, we use the FRPM files, while for 2003, we use the AFDC files, which are available back to 1988.

School-level financial records: School-level expenditure data reporting became mandatory under the federal Every Student Succeeds Act (ESSA), and the first year of California data (2018-19) are publicly available from the California Department of Education. The data contain per-student expenditures for each school, broken down into central and school-site specific expenditures. The data then report expenditure levels for each category via federal or state and local funding sources.

[1] Despite minor differences in sample construction from Bruno (2018) (detailed below), my calculations of mean total and student expenditures per pupil are within $40 (0.25%) and $65 (0.5%) of his calculations for 2016–17, respectively.
[2] For more information on spending in charter schools and the data limitations that make these calculations difficult, see Atchison et al. (2018).
[3] Charter school ADA is not available in the SACS data in 2008 and earlier. Fortunately, the charter share in the early 2000s was small, and most still reported financial information independently of the general fund of an affiliated district, meaning this limitation has a negligible impact on overall results.

Student test score outcomes: We rely on test score data publicly available from the CDE. Data are available at multiple levels of aggregation: the lowest being the school-grade-subject-subgroup-year, and the highest being the state-subject-year. Scores from 2002-03 through 2012-13 come from the California Standards Test (CST), while data from 2014-15 to 2018-19 are from the Smarter Balanced (SBAC) exams.[4] We examine both scores in terms of the share meeting grade level standards (often deemed the "percent proficient") and the mean scale scores; scale scores are standardized by the statewide student-level mean and standard deviation to ensure comparability of the scores (as relative measures, within grade-year-subject) over time. In Appendix B, we also use district-grade-subject level test score data from the Stanford Education Data Archive (SEDA), which covers the years from 2008-09 to 2017-18.

Graduation outcomes: We rely on two sources of data for graduation and A-G completion rates.[5] First, statewide comparisons of adjusted cohort rates (starting in 2016-17)[6] were collected information from the CDE's DataQuest. To enable longer-term comparisons, we rely on the CDE's graduates files, which give counts of graduates by year at the school-subgroup level. We construct graduation and A-G completion rates from these data by dividing the total number of graduates (or A-G completers) by the 9th grade enrollment in the same school or district (depending on the level of aggregation used in the analysis) four years prior.

English Learner Reclassification: We use data from CDE on the number of EL students who are reclassified in a given school-year, from 2011-12 to 2019-20. We construct reclassification rates by dividing the number of reclassified students by the total number of current EL and formerly EL students reclassified in that year. For district-level analyses, we aggregate these rates across schools to the district-year level.

Sample Restrictions

In order to reduce the impact of measurement error and extreme outliers on the analyses in this report, we restrict the sample in the following ways, depending on the level of analysis and outcome under consideration.

District financial outcomes: Across most analyses, we restrict attention only to those districts with an average daily attendance (ADA) of at least 250 in every year. While small districts are an important and often understudied population, district financial operations and staffing patterns are often quite different from larger districts, making it difficult to compare.[7] The 250 ADA cutoff is fairly common in the literature comparing finances of districts across the state; it is used by Bruno (2018) and others in earlier work. We also exclude districts that have atypically high or low per pupil student expenditures in a given year. District-years where per pupil student spending is above 500% or below 20% of the California mean in that year are excluded. There are very few such spending outliers (less than 0.1% of observations).[8]

Taken together, these are not trivial restrictions. 37% of district-years are excluded, most of them from very small districts: in total, these districts enroll only 2% of the state's public K–12 students. Thus, the main analysis sample covers 98% of students in the state.

Graduation / A-G outcomes: As mentioned above, graduation and A-G completion rates are constructed by dividing the total number of completers at a school/district by the 9th grade enrollment four years prior. Schools and districts with missing prior enrollment are excluded, as this rate cannot be constructed. This is an imperfect

[4] There was no comparable statewide test for 2013-14, due to the switch from CST to SBAC.
[5] CDE data are only available for the graduates "meeting UC/CSU requirements", which we interpret as A-G completion rates, though these are not always exactly equivalent.
[6] Earlier cohort-level graduation and A-G completion rates are available, but the CDE notes that the underlying methodologies are not consistent, and do not recommend comparing these to the new data.
[7] These small districts are most often rural or remote districts, which generally have very different cost structures than the typical district.
[8] Some of these appear to be coding errors, although it is difficult to verify or correct these, and thus we exclude these observations.

measure: it does not account for migration into and out of the district between 9th and 12th grade. In some cases, this results in completion rates that are greater than 1; for those that are between 1 and 1.1 we censor the rate at 1, but we exclude those that are greater than 1.1.

Test score outcomes: Test score records are only publicly available for cell sizes with 10 or more students. Cells (e.g. a district-grade-subject-year) with fewer than 10 students are therefore excluded from all test score analyses.

School-level expenditure analyses: For school-level expenditure analyses using the ESSA data, we make a small number of exclusions, mostly due to missing data or implausibly high expenditure levels. First, we exclude a small number of schools (116) we could not merge to the enrollment data described above. Next, some schools did not report expenditure data; these schools are excluded, and we exclude any districts for which non-reporting schools make up more than 5% of total student enrollment. This excludes 37 districts (364 schools). This leaves us with 8,339 schools in 953 districts.

When examining how within-district spending patterns relate to LCFF spending, we restrict to the 826 districts (7,432 schools) that we can merge to "LCFF Snapshot" financial records available from CDE. We further exclude small schools with fewer than 50 students (which may have very different expenditure patterns), schools with total school spending greater than $100,000 per student (which we deem implausible), and, to further restrict the influence of outliers, we exclude schools that spend less than 20% or more than 500% of the mean school spending in the data (equivalent to the exclusion criteria mentioned above for district-level financial records). For analyses where a district-level relationship between school spending and LCFF funding is estimated, we rely only on those districts with 10 or more schools.

Appendix B. Estimating Effects on Student Outcomes

Estimating the impact of additional LCFF funding requires one to be careful to account for contemporaneous changes and trends that were not due to the formula. Most importantly, funding increased substantially for all districts following 2012-13 due to the improved economic situation in the state (Figure 2). For this reason, we rely on *relative* comparisons across districts that received different funding increases under LCFF to identify the effect of these *relative* funding increases on student outcomes. Specifically, we rely on "differences-in-differences" (DiD) and "Regression Kink Discontinuity" (RKD) designs; these are described in detail below.

Differences-in-Differences

Comparing trends in outcomes over time, even within the same district, confounds the effect of the LCFF formula due to other contemporaneous changes in funding and/or policy. To determine the effect of LCFF funding increases due to the formula, we can compare the trends in outcomes between districts that received small increases in funding (and have low shares of high-need students) to those that received significant amounts of additional funding (due to high shares of high-need students). Under a "parallel trends" assumption that these districts would have trended similarly in the absence of LCFF, we can interpret any relative differences in outcomes as due to the effect of the formula. Importantly, this assumption is fundamentally untestable, but we can examine relative trends in outcomes and other intermediate inputs prior LCFF's implementation: indeed, spending and revenues trended similarly across districts of varying need prior to LCFF (Lafortune 2019; Figures B3 and B4 below).

For these differences-in-differences comparisons, we rely on a regression approach that compares the evolution of outcomes within districts over time – before and after LCFF – between concentration districts with 55-80% high need and those with 80% or above high-need. Non-concentration districts with less than 55% high-need students are the relative "control" group, as they experienced relatively smaller spending increases (Figure 2; see also, Lafortune 2019). Notably, we opted to combine districts with low shares of high-need students (0-30%) and those with higher shares (30-55%) into a single control group, as financial evidence shows these two groups had very similar changes in revenues, spending, and the composition of spending (Figures 2, 3, 4).[9] District need is fixed based on the initial levels in 2013-14, the first year of LCFF, to treatment and control groupings consistent over time.

We estimate these changes using the following regression equation:

$$(1)\ \ Y_{d,y} = \alpha_d + \sum_{y_{min}}^{y_{max}} \sum_{j=2}^{3} \beta_{y,j(d)}\ \gamma_y * LCFF_{j(d)} + \gamma_y + \Gamma X_{d,y}\ \epsilon_{d,y}$$

Here, $\beta_{y,j(d)}$ estimates the impact of the funding formula change on an outcome $Y_{d,y}$, for district *d* in year in high-need districts (the "treatment group"), *relative to* the change in lower-need districts (the "control group"; 0-55% high-need). $LCFF_{j(d)}$ is an indicator for the LCFF "treatment group": 55-80% high need (group 2) and 80%+ high-need (group 3). The model also includes fixed effects for district, α_d, and fixed effects for year, γ_y. For test score outcomes at the district-grade-subject level, we include additional fixed effects for each grade-subject combination. Standard errors are clustered at the district-level in all regressions, to account for serial correlation in district outcomes over time.

[9] In spirit, this differences-in-differences approach is similar to the simulated instruments approach used by Johnson and Tanner (2018) and Lee, Fuller, and Rabe-Hesketh, (*Forthcoming*), which relies on the formula itself to generate predicted changes in spending that net out potential confounds, such as increasing state revenues that affect finances across districts of varying need.

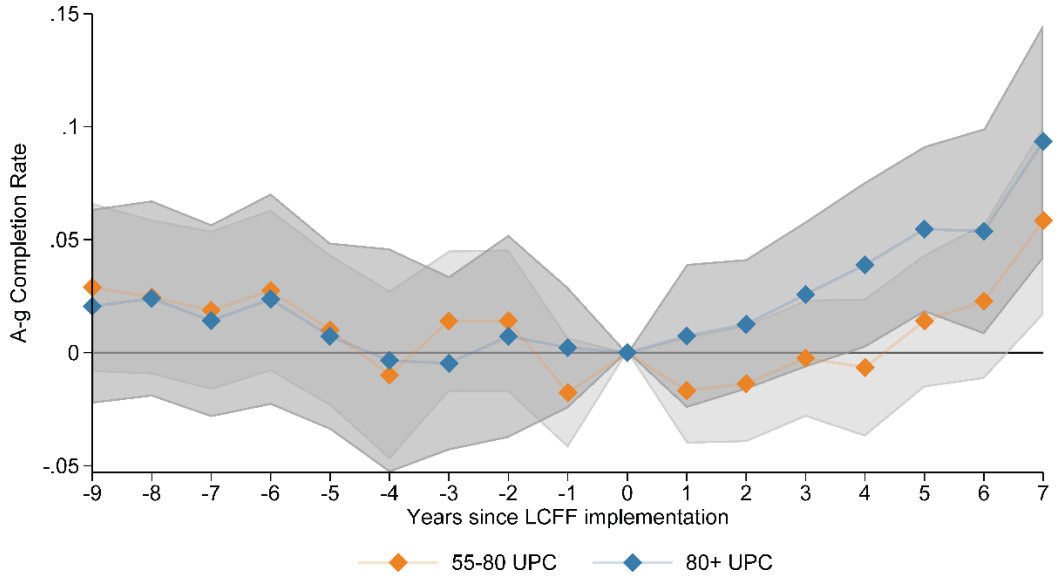
Estimates of $\beta_{y,j(d)}$ prior to LCFF represent falsification tests of the assumption of parallel trends in outcomes (2012–13, the year prior to LCFF, is excluded). Any non-zero coefficients indicate differences in outcomes prior to LCFF, which may mean indicate that outcomes would not have trended in parallel, and the estimates of $\beta_{y,j(d)}$ in post-LCFF years may therefore be biased estimates of the true *causal* impact of the additional funding for high-need districts.

Finally, equation (1) also includes controls for time-varying district outcomes, $X_{d,y}$. These controls are: district enrollment in each grade level, district share eligible for free and/or reduced price meals, and the district shares African American, American Indian, Asian American, Filipino, Hispanic/Latino, Pacific Islander, and White. Given that we rely on aggregate and not student-level data, these controls are included to address any changes in enrollment or the composition of enrollment within districts that may affect aggregate district-level outcomes.

Non-test score outcomes: Estimates of $\beta_{y,j(d)}$ for graduation and A-G completion are reported in Figures 9 and 10 in the main text. Below, we present analogous estimates with 95% confidence intervals for A-G completion rates (Figure B1), high school graduation rates (Figure B2), funding formula revenues per pupil (Figure B3), student spending per pupil (Figure B4), and EL reclassification rates (Figure B5) as the outcomes of interest.

FIGURE B1

DiD estimates for A–G completion (corresponding to Figure 9)

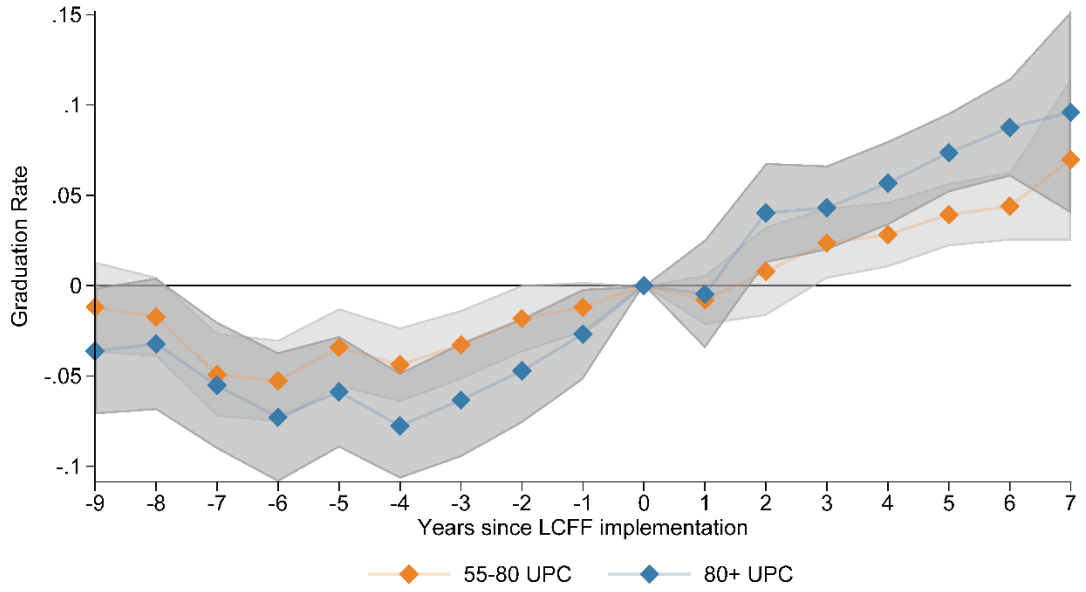


SOURCE: California Department of Education, enrollment and graduates files; Authors' calculations.

NOTE: Figure reports differences-in-differences estimates for A–G completion rate, separately for high-need (55%–80%) and very high-need (80%+) districts. Shaded areas show 95 percent confidence intervals; the darker (lighter) shaded area corresponds to the point estimates for very high-need (high-need) districts. Estimates control for enrollment by grade, racial/ethnic shares, share eligible for free or reduced-price meals, for time-invariant district characteristics, and for differences across years. Standard errors are clustered by district. See equation (1) in Technical Appendix B for the full specification.

FIGURE B2

DiD estimates for graduation rates (corresponding to Figure 10)

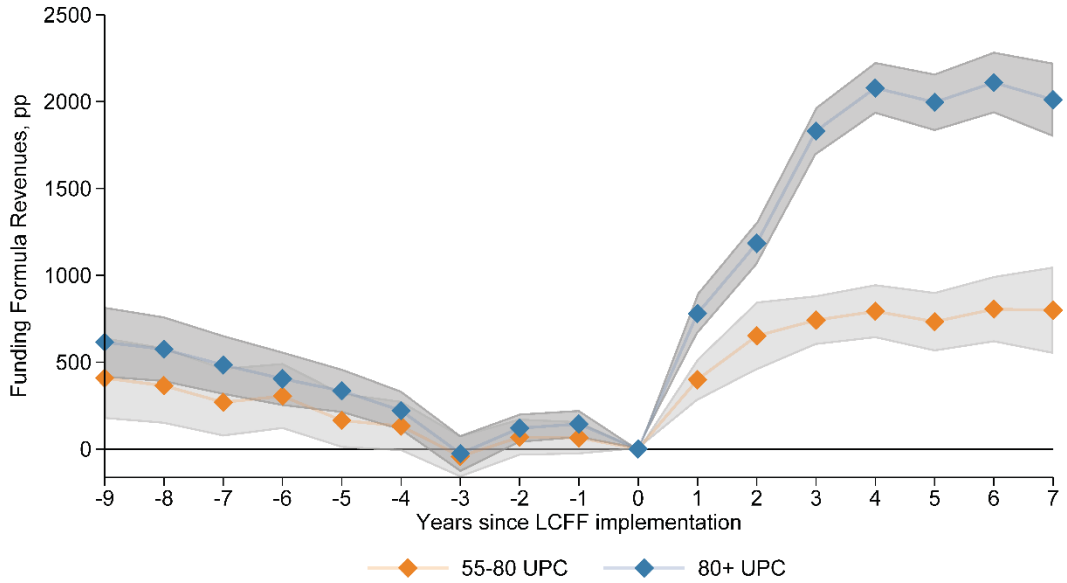


SOURCE: California Department of Education, enrollment and graduates files; Authors' calculations.

NOTE: Figure reports differences-in-differences estimates for graduation rates, separately for high-need (55%–80%) and very high-need (80%+) districts. Shaded areas show 95 percent confidence intervals; the darker (lighter) shaded area corresponds to the point estimates for very high-need (high-need) districts. Estimates control for enrollment by grade, racial/ethnic shares, share eligible for free or reduced-price meals, for time-invariant district characteristics, and for differences across years. Standard errors are clustered by district. See equation (1) in Technical Appendix B for the full specification.

FIGURE B3

DiD estimates for funding formula revenues (per pupil)

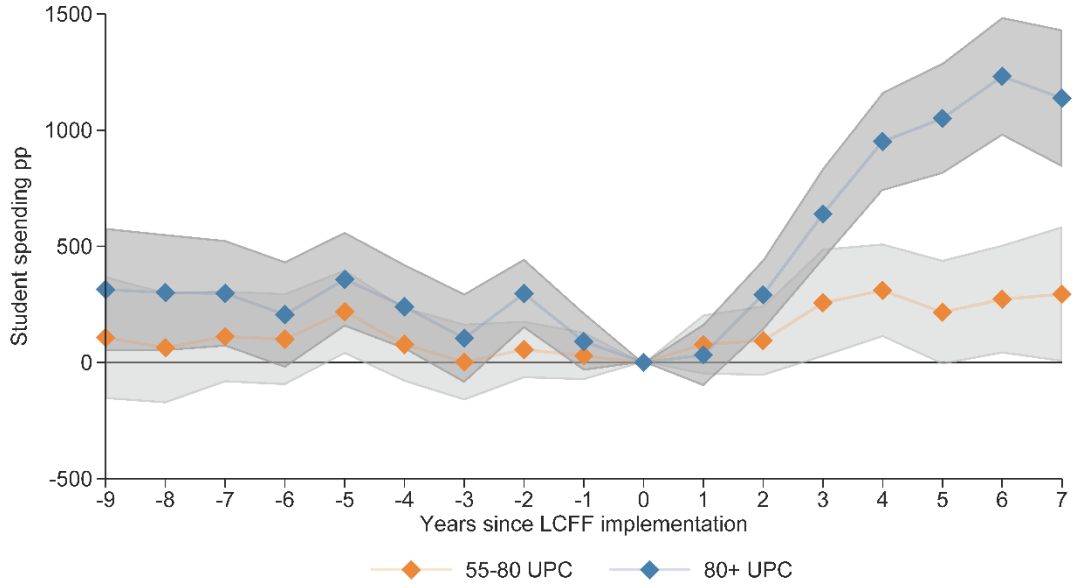


SOURCE: California Department of Education, enrollment and SACS district finance data; Author's calculations.

NOTE: Figure reports differences-in-differences estimates from equation (1) for funding formula revenues per pupil, separately for high-need (55-80%) and very high-need (80%+) districts. Shaded areas show 95% confidence intervals; the darker (lighter) shaded area corresponds to the point estimates for very high-need (high-need) districts. Estimates control for enrollment by grade, racial/ethnic shares, share eligible for free or reduced price meals, for time-invariant district characteristics, and for differences across years. Standard errors are clustered by district. See equation (1) in Technical Appendix B for the full specification.

FIGURE B4

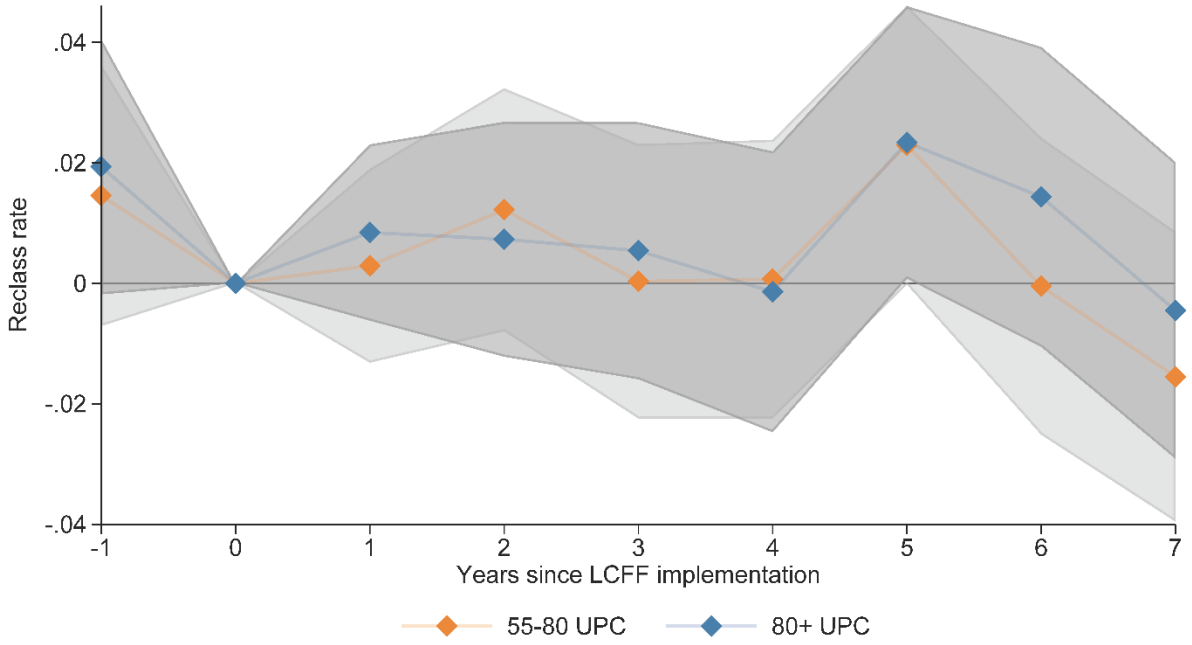
DiD estimates for K-12 student spending (per pupil)



SOURCE: California Department of Education, enrollment and SACS district finance data; Author's calculations.

NOTE: Figure reports differences-in-differences estimates from equation (1) for student spending per pupil, separately for high-need (55-80%) and very high-need (80%+) districts. Shaded areas show 95% confidence intervals; the darker (lighter) shaded area corresponds to the point estimates for very high-need (high-need) districts. Estimates control for enrollment by grade, racial/ethnic shares, share eligible for free or reduced price meals, for time-invariant district characteristics, and for differences across years. Standard errors are clustered by district. See equation (1) in Technical Appendix B for the full specification.

FIGURE B5
DiD estimates for EL reclassification



SOURCE: California Department of Education, enrollment and reclassification files; Author's calculations.

NOTE: Figure reports differences-in-differences estimates from equation (1) for district-year reclassification rates, separately for high-need (55-80%) and very high-need (80%+) districts. Shaded areas show 95% confidence intervals; the darker (lighter) shaded area corresponds to the point estimates for very high-need (high-need) districts. Estimates control for enrollment by grade, racial/ethnic shares, share eligible for free or reduced price meals, for time-invariant district characteristics, and for differences across years. Standard errors are clustered by district. See equation (1) in Technical Appendix B for the full specification.

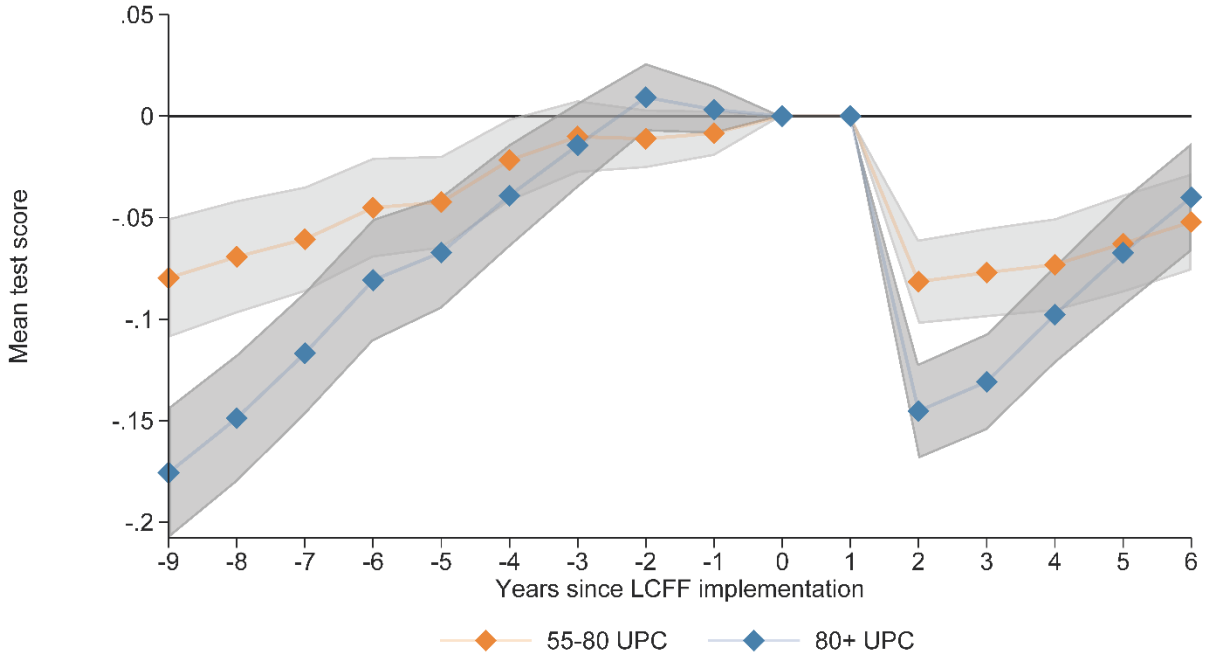
Test score outcomes: Estimates of equation (1) with grade 3-7 test scores as outcomes reveal evidence of prior trends and a discontinuous change in relative performance between high-need and lower-need districts in the first SBAC year. Both of these cast doubt on the validity of the design for test score outcomes in elementary and middle school. Figure B6 shows that there was a significant trend in the gap between higher and lower-need districts: the gap between the highest-need districts (80%+ high-need) and non-concentration districts narrowed by roughly 18% of a standard deviation from 2002-03 to 2009-10; the analogous gap for 55-80% high need districts narrowed by roughly 8% of a standard deviation in the same time period. On the other hand, there was no significant differential trend in the four years prior to LCFF, which is more reassuring for the validity of the differences-in-differences design to estimate the effect of LCFF on test scores.

A larger concern, however, is the fact that gaps between high-need and lower-need districts increase dramatically (9% and 15% of a standard deviation, for 55-80% and 80%+ high-need, respectively) following the switch from CST to SBAC. This is consistent with evidence from that time (Hill and Ugo, 2016), and could be due to multiple factors, such as: (1) SBAC may be a more difficult test for higher-need students, perhaps due to the fact that it is computer adaptive; (2) SBAC may be measuring achievement gaps more accurately, because the old CST tests were easier to "game" by preparing students for specific types of questions; (3) SBAC relies on the Common Core standards, which may be more difficult for higher-need students and/or may not have been implemented as recently in higher-need districts. Regardless of the exact cause, each of these three reasons would also imply that improvements may occur faster in higher-need districts for reasons that have nothing to do with LCFF and the additional funding for high-need districts under the formula. Indeed, by 2018-19 higher-need districts had

recovered most of the initial increase in the test score gap that emerged in the first SBAC year (Figure B6). This may very well reflect the effect of additional funding, but without additional information we cannot disentangle how much of these increases may have been due to these other factors mentioned above.

FIGURE B6

DiD estimates for average test scores (in standard deviation units)



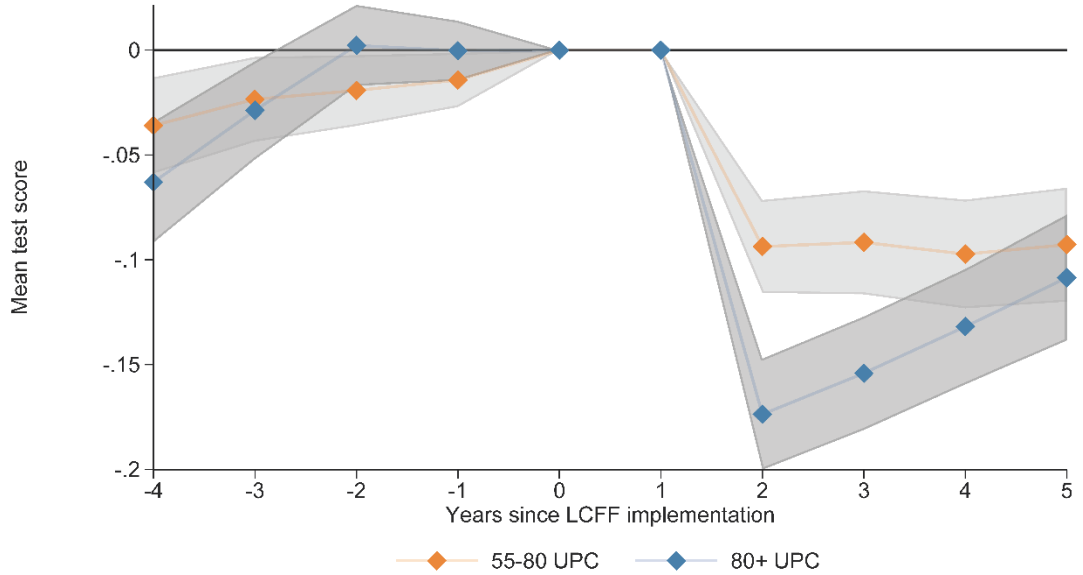
SOURCE: California Department of Education, California Assessment of Student Progress and Performance research files, enrollment files; Authors' calculations.

NOTE: Figure reports differences-in-differences estimates from equation (1) for test scores in standard deviation units, separately for high-need (55-80%) and very high-need (80%+) districts. Shaded areas show 95% confidence intervals; the darker (lighter) shaded area corresponds to the point estimates for very high-need (high-need) districts. Estimates control for enrollment by grade, racial/ethnic shares, share eligible for free or reduced price meals, for time-invariant district characteristics, for time-invariant grade-subject differences, and for differences across years. Standard errors are clustered by district. See equation (1) in Technical Appendix B for the full specification.

To ensure that these patterns are not affected by our standardization of the test score data within each year (described in Appendix A), we also estimate equation (1) using data from the Stanford Education Data Archive (SEDA), which is standardized for comparability over time and normed to the same scale across states using data from the National Assessment of Educational Progress (NAEP). These data are only available from 2008-09 to 2017-18, but reveal the same pattern: a notable increase in the gap between districts with higher and lower shares of high-need students in the first SBAC year, and a subsequent narrowing of the gap in the following years (Figure B7). For these reasons, we do not rely on differences-in-differences comparisons of test scores across years to examine the impact of LCFF on test scores.

FIGURE B7

DiD estimates for average test scores using SEDA data (in standard deviation units)



SOURCE: California Department of Education, school enrollment files; Stanford Education Data Archive 4.0; Authors' calculations.

NOTE: Figure reports differences-in-differences estimates from equation (1) for test scores in standard deviation units, separately for high-need (55-80%) and very high-need (80%+) districts. Shaded areas show 95% confidence intervals; the darker (lighter) shaded area corresponds to the point estimates for very high-need (high-need) districts. Estimates control for enrollment by grade, racial/ethnic shares, share eligible for free or reduced price meals, for time-invariant district characteristics, for time-invariant grade-subject differences, and for differences across years. Standard errors are clustered by district. See equation (1) in Technical Appendix B for the full specification.

Regression (Kink) Discontinuity

As mentioned above, the switch from CST to SBAC complicates attempts to use relative trends in test scores over time to analyze the impact of LCFF funding on student outcomes. Instead, we rely on an alternative strategy that only uses within-year comparisons across districts. Specifically, we employ a "Regression Kink Design" (RKD) that estimates whether the slope of test scores with respect to district share high-need changes across the concentration grant threshold at 55%. The intuition is as follows: the funding formula has a "kink" at 55% high-need, above which each additional high-need student provides even greater funding to the school district. If the additional funding for these districts – specifically the concentration grant funding for districts with more than 55% high-need – has impacts on student outcomes we would expect to see a kink in the relationship between district share high-need and outcomes emerge.

Key for this design to estimate the causal impact of the funding formula is the assumption that the changes at the 55% threshold are as good as random. For example, there should be no discontinuous changes at the kink point between other district characteristics (such as racial/ethnic shares, the share eligible for free and/or reduced price lunch, etc.) and the district share high-need; Figure B15 provides evidence that this is indeed the case.

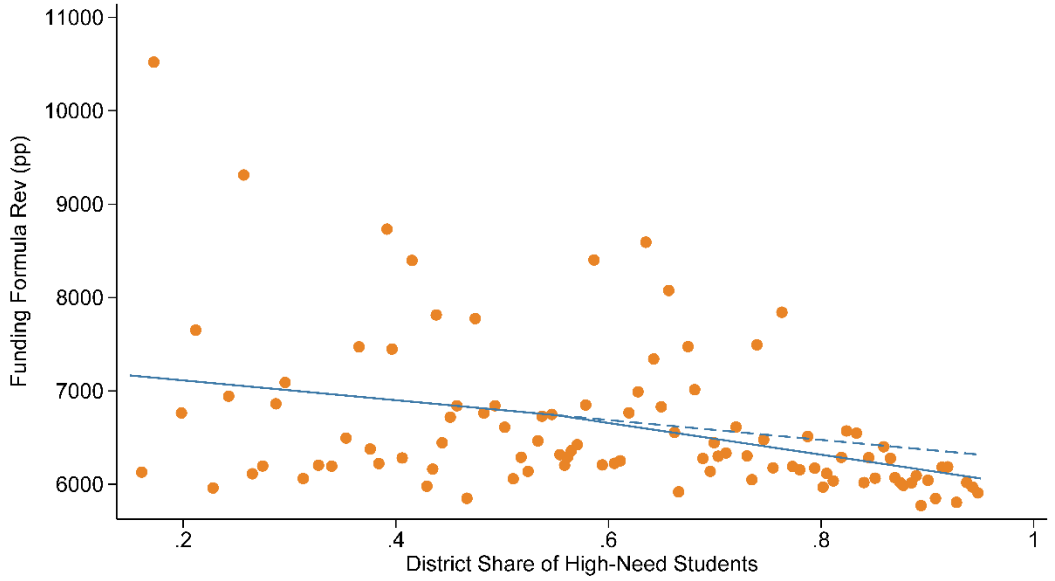
Figure B8 provides motivation for this empirical design. As expected under the revenue limit system which did not fund schools based on their share high-need, there is no discontinuous relationship between funding and share high-need in 2012-13.[10] However, 7 years later in 2019-20 after LCFF had become fully funded, there is indeed a notable kink in the slope between funding and share high-need, as would be expected given funding formula.

[10] We use a district's share high-need in 2013-14, the first year for which data are available.

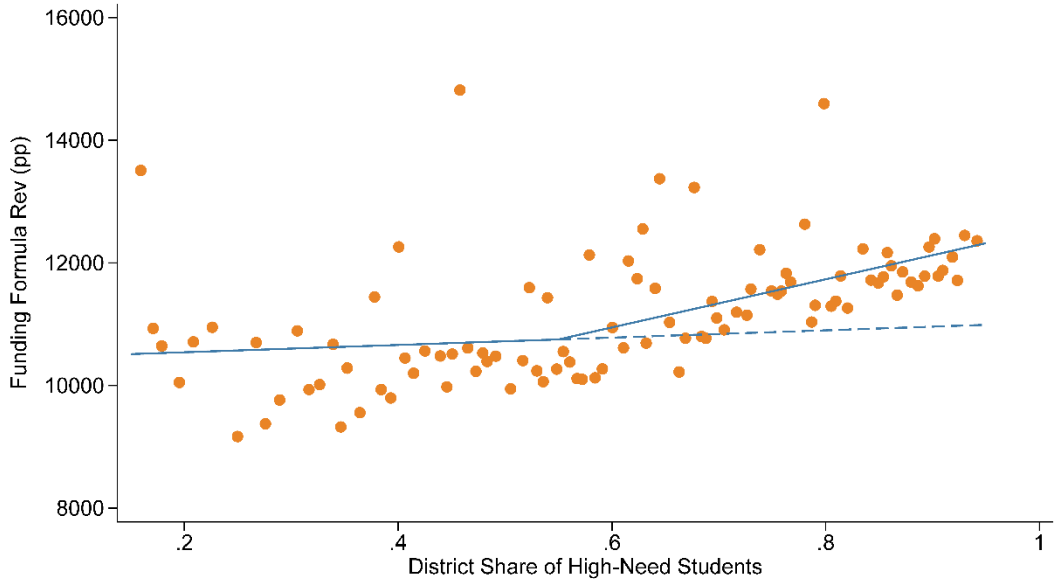
FIGURE B8

Relationship between formula revenues and district share high-need, 2012-13 and 2019-20 (bandwidth=40%)

Panel 1: 2012-13



Panel 2: 2019-20



SOURCE: California Department of Education, enrollment and SACS district finance data; Author's calculations.

NOTE: Each dot is a "bin" depicting mean funding formula revenues per pupil in 2012-13 (top panel) and 2019-20 (bottom panel), within a narrow range of share high need, the share meeting standards in 2012–13 (top panel) and 2018–19 (bottom panel). Only districts within 40% of the cutoff on either side are shown. Solid blue line displays the line of best fit above and below the 55% cutoff; the dashed blue line extrapolates the line of best fit from below the 55% cutoff. Each dot contains an equal number of districts (unweighted), and shows the average for different values of high-need share.

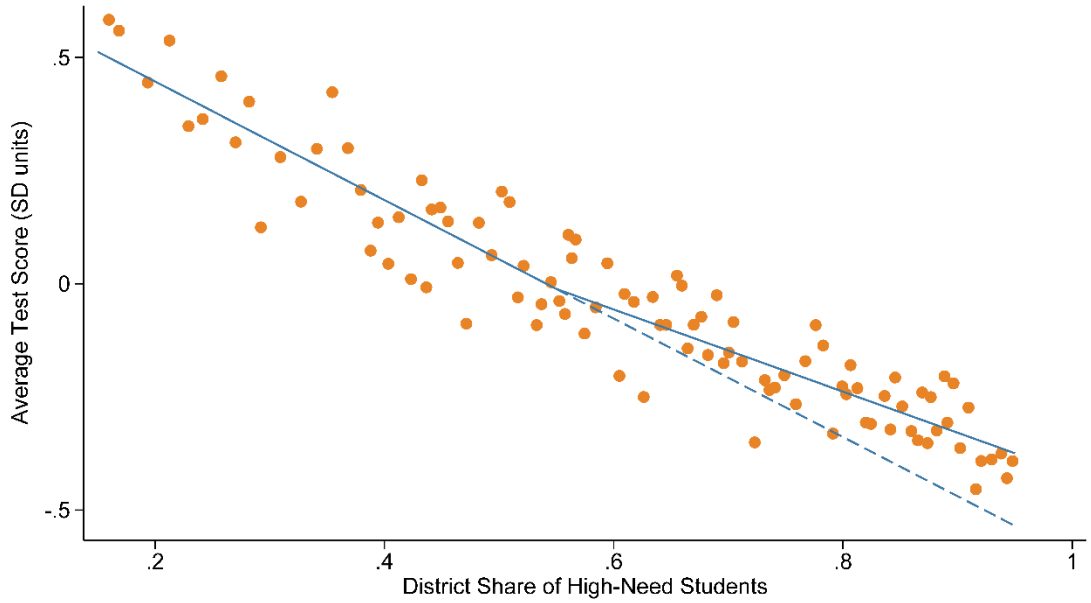
Figures 10 in the main text (percent meeting standards) and Figure B9 (average standardized scale scores) show the analogous relationships between district share high-need and student test scores, in 2012-13 and 2018-19, including data within 40 percentage points on either side of the 55% cutoff. The visual difference is less striking, but the change in slope at the kink point is apparent. There is a slight discontinuity in the slope in 2012-13 at the

kink point, but this is not statistically significant, and the corresponding change in slope is much larger. Thus, just looking at the raw data, it appears as though the *change in slope* at the 55% threshold is increasing over time after LCFF, providing suggestive evidence that the additional concentration grant dollars are indeed leading to increases in student academic performance.

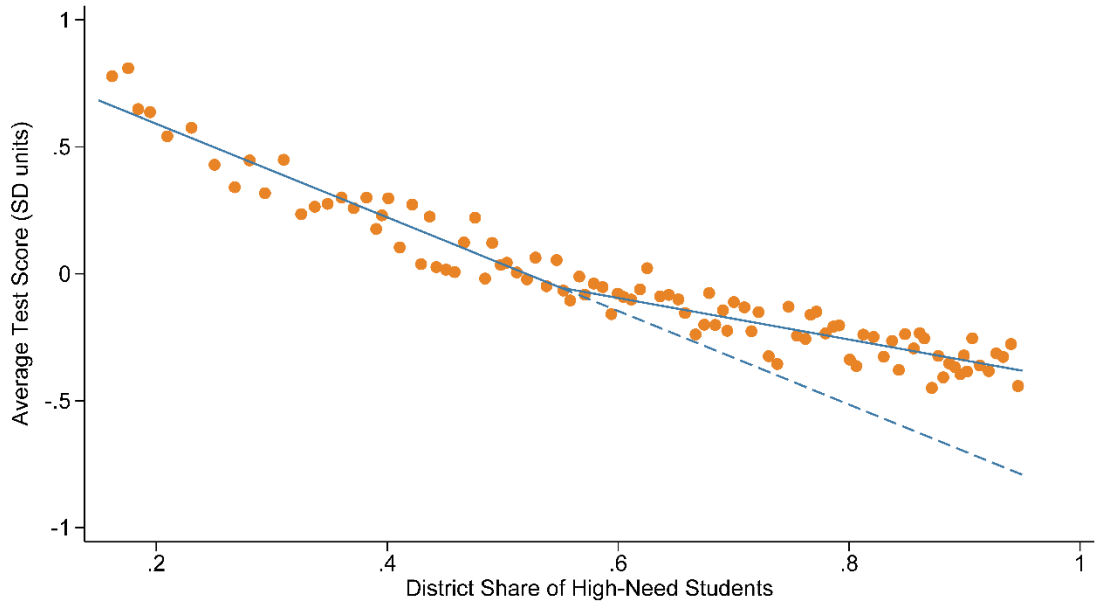
FIGURE B9

Relationship between mean scale scores and district share high-need, 2012-13 and 2018-19 (bandwidth=40%)

Panel 1: 2012-13



Panel 2: 2018-19



SOURCE: California Department of Education, California Assessment of Student Progress and Performance research files, enrollment files; Authors' calculations.

NOTE: Each dot is a "bin" depicting mean test scores per pupil in 2012-13 (top panel) and 2019-20 (bottom panel), within a narrow range of share high need, the share meeting standards in 2012–13 (top panel) and 2018–19 (bottom panel). Only districts within 40% of the cutoff on

either side are shown. For comparability over time, only test scores in grades 3–7 are included. Solid blue line displays the line of best fit above and below the 55% cutoff; the dashed blue line extrapolates the line of best fit from below the 55% cutoff. Each dot contains an equal number of district-grade-subject observations (unweighted); binned averages and lines of best fit are adjusted for average differences in the share meeting standards across grade-subject exams.

To formally estimate these relationships, we estimate regressions separately for each year of data using a linear slope in the share high-need relative to the 55% kink point. Specifically, we estimate equation (2):

$$(2)\ \ y_{d,gs} = \alpha + \beta_1(x_d - 0.55) + \beta_2(x_d - 0.55) * 1[x_d > 0.55] + \Gamma X_d + \gamma_{gs} + \phi_{c(d)} + \epsilon_{dgs}$$

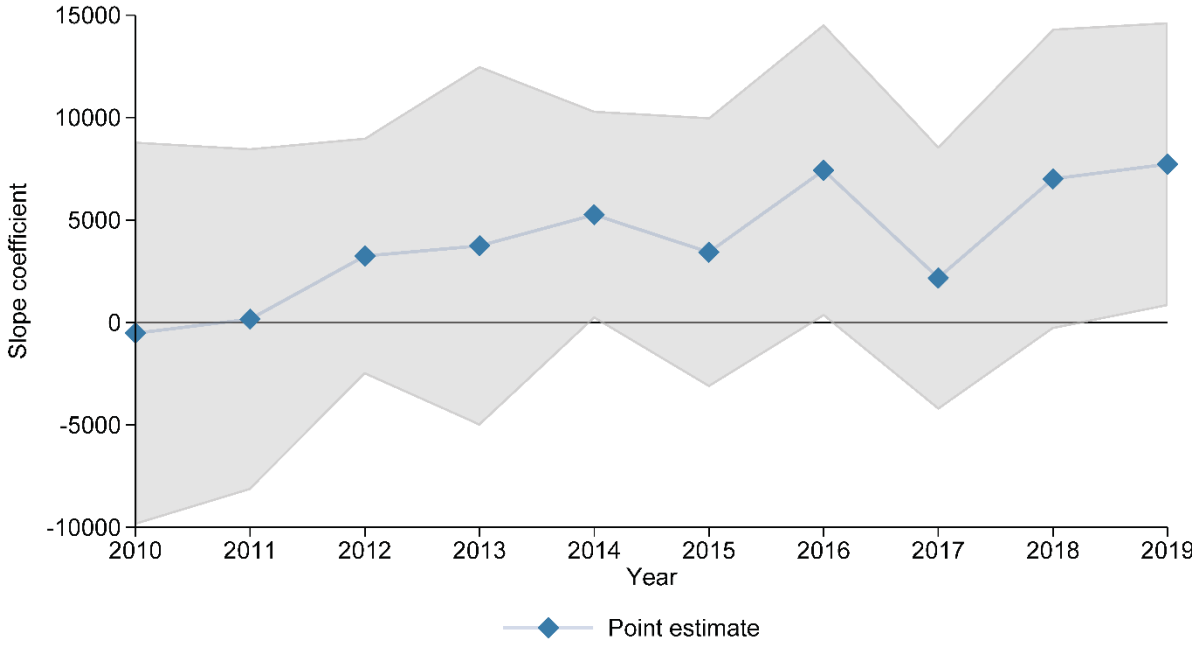
Where $y_{d,gs}$ is a test score outcome in a given year for a district-grade-subject combination, and x_d is the district share high-need in a given year. Here, β_1 gives the slope of the outcome with respect to district share high-need, while β_2 estimates the change in slope – or the kink. We also include grade-subject fixed effects γ_{gs} , county fixed effects $\phi_{c(d)}$, and district-level controls X_d. For non-test score regressions using district level outcomes, we exclude these fixed effects but still use controls. Standard errors are clustered by district. In our main specifications we estimate equation (2) using a bandwidth of +/- 20%. Smaller bandwidths produce similar but noisier estimates. Estimates are also similar for larger bandwidths (Figures B13 and B14), but we select smaller bandwidths due to concern over bias in the linear specification.[11]

Figure B10 reports estimates of β_1 for per pupil funding formula revenues. Point estimates are noisy, but are statistically significant at the 5% level in 3 of the 6 post-LCFF years, and statistically significant at the 10% level in one other year (2018-19). The point estimate in 2019-20 is $7,732, implying that a 45% increase in the share high-need above 55% (equivalent to going from 55% to 100% high-need) would increase funding per pupil by nearly $3,500. The adjusted base grant per pupil ranged from $7,818 to $9,572 depending on the grade level; per the formula this implies an increase in funding ranging from roughly $2,500 to $3,000 per pupil going from 55% to 100% high-need. The RKD estimates for funding are therefore consistent, though slightly higher, than what would be expected under the formula.

[11] Indeed, for larger bandwidths some of the point estimates in the early LCFF years or even before LCFF are statistically significant. For smaller bandwidths, point estimates for pre-LCFF years are always small and never statistically significant, providing evidence that equation (2) is not erroneously finding effects due to nonlinearities in the relationship between test scores and share high-need.

FIGURE B10

RKD estimates for funding, by year (bandwidth =20%)



SOURCE: California Department of Education, SACS district finance data, enrollment files; Authors' calculations.

NOTE: Figure shows equation (2) estimates of the change in slope (kink) at the cutoff for funding formula revenues per pupil, by year. Year corresponds to fall year. Shaded area shows 95% confidence interval; standard errors are clustered by district.

Figure 11 and Figure B11 report estimates for test scores – Figure 11 in the main text reports estimates for the share at or above grade level standards, while Figure B11 below reports analogous estimates for mean test scores in standard deviation units. Estimates of equation (2) that correspond to Figure 10 are included below in Table B1. Both test score measures show a similar pattern – estimates are small and insignificant, and only several years after LCFF do they become large and statistically significant (2017-18 and 2018-19). This provides evidence supporting the validity of the RKD design, as there is no discontinuous relationship in outcomes around the cutoff in the early years of LCFF nor the years prior to the implementation of LCFF.

We report estimates of heterogeneity by grade, subject, student subgroup, and school characteristics in Tables B2-B5. Regressions by grade and subject, and are equivalent to equation (2), with the slope and kink in slope interacted with grade or subject indicator variables. For heterogeneity by student subgroup, we rely on regressions analogous to equation (2) that are at the district-grade-subject-subgroup level and also include indicator variables for subgroup separately and interacted with the main slope and kink variables. Finally, columns 5 and 6 in Table B3 split effects by whether a school is concentration (UPP>=55%) or not (UPP<55%). Here, these regressions are at the *school-grade-subject* level, and include demographic controls at the school rather than district level.

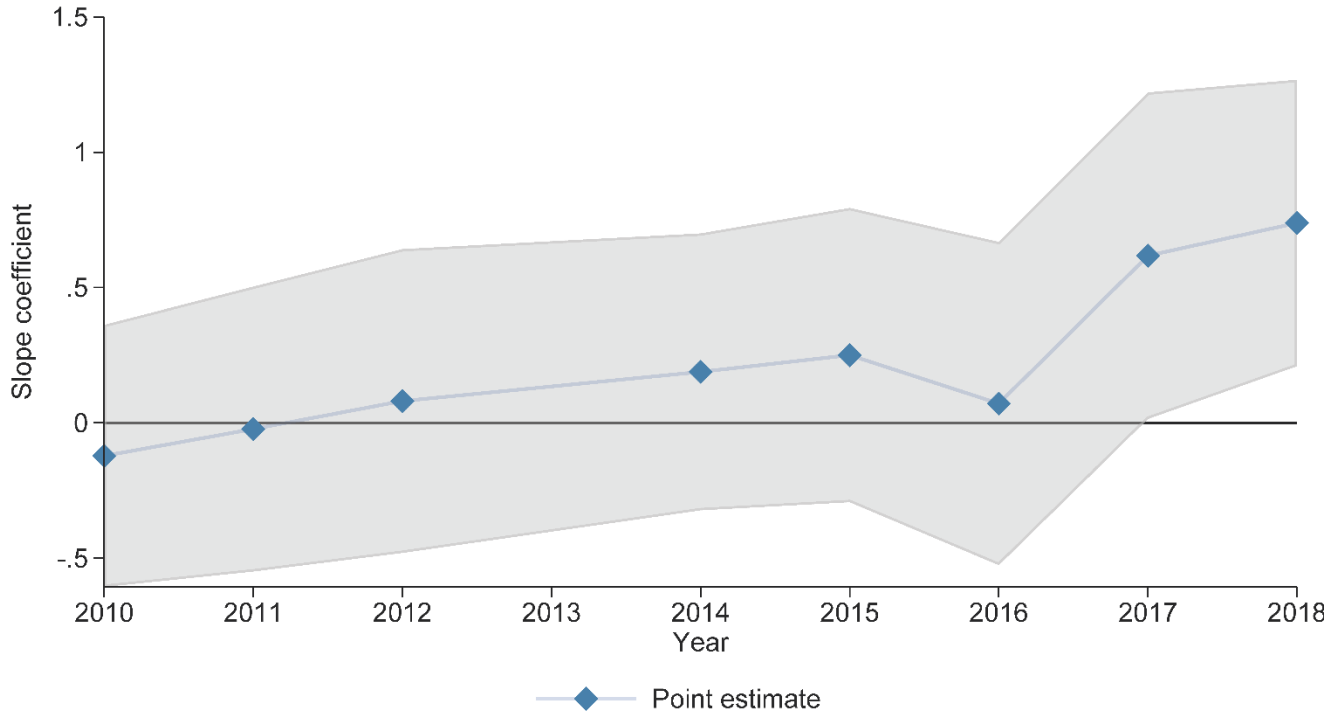
We also report estimates of effects for revenues and test scores (in share at or above standards) by bandwidth for 2018-19, the most recent year for which we have test score data (Figures B12 and B13). Estimates are similar across bandwidths, although estimates are far noisier for small bandwidths. We ultimately select a bandwidth of 20% as our baseline specification, to minimize potential biases from nonlinearities as we increase the bandwidth.

Estimates of equation (2) are also reported for graduation and A-G completion rates (Figures B14 and B15, respectively). We find no evidence of any significant effects in any year – though estimates are too noisy to rule out effects of the same magnitude as those estimated in the differences-in-differences models (Figures 9 and 10).

Finally, placebo estimates of district-level demographics provide little evidence of other changes at the threshold (Figure B16). Only one variable (the district share white) is statistically significant at the 10% level. Nevertheless, we still control for these variables in all regressions.

FIGURE B11

RKD estimates for test scores in standard deviation units, by year (bandwidth=20%)



SOURCE: California Department of Education, California Assessment of Student Progress and Performance research files, enrollment files; Authors' calculations.

NOTE: Figure shows equation (2) estimates of the change in slope (kink) at the cutoff for test scores in standard deviation units, by year. Year corresponds to fall year. Shaded area shows 95% confidence interval; standard errors are clustered by district.

TABLE B1

Estimates of equation (3) for share at or above standard (corresponding to Figure 11; bandwidth=20%)

	2010	2011	2012	2014	2015	2016	2017	2018
UPP Slope	-13.21	-21.65**	-44.81***	-48.27**	-69.91**	-68.88**	-98.84***	-90.54***
	(8.697)	(10.36)	(9.995)	(19.97)	(22.46)	(22.42)	(15.18)	(25.55)
Change in Slope (Kink)	-2.128	2.256	7.830	12.93	16.41	9.812	29.55**	36.39***
	(10.35)	(11.06)	(11.79)	(11.15)	(12.14)	(13.08)	(12.81)	(12.01)
Observations	4570	4592	4610	3982	4002	4069	4076	4063
Grade-Subject Fixed Effects	X	X	X	X	X	X	X	X
County Fixed Effects	X	X	X	X	X	X	X	X
Demographic Controls	X	X	X	X	X	X	X	X

SOURCES: California Department of Education, California Assessment of Student Progress and Performance research files, enrollment files; Authors' calculations.

NOTES: Table reports estimates of Beta 1 and Beta 2 from equation (2) for the share at or above standard. Standard errors are in parentheses, and are clustered by district. * p<.10, ** p<.05, *** p<.01.

TABLE B2

Effects by grade level (2018-19, bandwidth=20%)

	G3	G4	G5	G6	G7	G8	G11
UPP Slope	-86.18**	-88.19**	-102.2***	-80.15**	-94.71***	-96.41***	-86.49**
	(26.13)	(27.01)	(27.32)	(25.92)	(25.87)	(26.64)	(26.28)
Change in Slope (Kink)	39.69*	52.90**	41.29*	20.19	27.31	38.92*	36.65*
	(17.38)	(16.05)	(16.14)	(16.14)	(17.35)	(19.05)	(16.98)
Observations	4063	4063	4063	4063	4063	4063	4063
Grade-Subject Fixed Effects	X	X	X	X	X	X	X
County Fixed Effects	X	X	X	X	X	X	X
Demographic Controls	X	X	X	X	X	X	X

SOURCES: California Department of Education, California Assessment of Student Progress and Performance research files, enrollment files; Authors' calculations.

NOTES: Table reports estimates of Beta 1 and Beta 2 from a single regression equivalent to equation (2) where Beta 1 and Beta 2 are interacted with grade level, and data are at the district-grade-subject-subgroup level. Dependent variable is the share at or above standard in 2018-19. Standard errors are in parentheses, and are clustered by district. * p<.10, ** p<.05, *** p<.01.

TABLE B3

Effects by subject, student income, and school share high-need (2018-19; bandwidth=20%)

	ELA	Math	Low-income	Non-low-income	Concentration School	Non-concentration School
UPP Slope	-91.50***	-89.59***	-105.3***	-125.2***	-15.58	-1.609
	(25.52)	(25.78)	(28.08)	(27.25)	(10.12)	(11.49)
Change in Slope (Kink)	39.52**	33.25**	9.982	18.77	49.46*	3.410
	(12.56)	(12.63)	(13.57)	(14.76)	(19.34)	(17.79)
Observations	4063	4063	6779	6779	25130	25130
Grade-Subject Fixed Effects	X	X	X	X	X	X
County Fixed Effects	X	X	X	X	X	X
Demographic Controls	X	X	X	X	X	X

SOURCES: California Department of Education, California Assessment of Student Progress and Performance research files, enrollment files; Authors' calculations.

NOTES: Table reports estimates of Beta 1 and Beta 2 from regressions equivalent to equation (2) where Beta 1 and Beta 2 are interacted with subject, student income, or school high-need status. Student subgroup regressions rely on district-grade-subject-subgroup scores; school income regressions rely on school-grade-subject level scores. Dependent variable is the share at or above standard in 2018-19. Standard errors are in parentheses, and are clustered by district. * p<.10, ** p<.05, *** p<.01.

TABLE B4

Effects by student race (2018-19; bandwidth=20%)

	Asian	African American	Hispanic/Latino	Filipino	White
UPP Slope	-110.5***	-119.7***	-115.8***	-116.5***	-105.2**
	(32.64)	(29.30)	(34.03)	(32.04)	(32.76)
Change in Slope (Kink)	-27.05	8.064	31.80*	19.07	23.45
	(25.72)	(24.02)	(14.86)	(23.51)	(16.77)
Observations	10737	10737	10737	10737	10737
Grade-Subject Fixed Effects	X	X	X	X	X
County Fixed Effects	X	X	X	X	X
Demographic Controls	X	X	X	X	X

SOURCES: California Department of Education, California Assessment of Student Progress and Performance research files, enrollment files; Authors' calculations.

NOTES: Table reports estimates of Beta 1 and Beta 2 from a single regression equivalent to equation (2) where Beta 1 and Beta 2 are interacted with student race, and data are at the district-grade-subject-subgroup level. Dependent variable is the share at or above standard in 2018-19. Standard errors are in parentheses, and are clustered by district. * p<.10, ** p<.05, *** p<.01.

TABLE B5

Effects by student EL status (2018-19; bandwidth=20%)

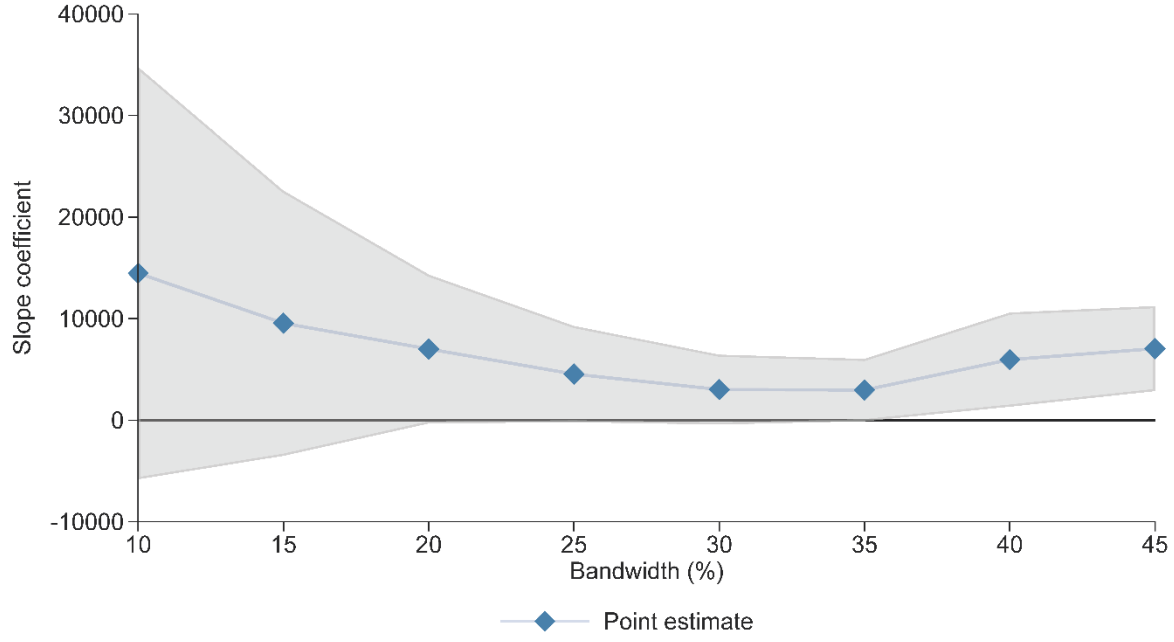
	Fluent English Proficient/ English Only	Initially Fluent English Proficient	Reclassified EL	EL	Ever EL
UPP Slope	-61.35*	-60.14*	-37.78	-51.23	-41.43
	(29.18)	(30.38)	(28.07)	(31.01)	(29.95)
Change in Slope (Kink)	27.57	-6.200	41.63	43.54**	50.29***
	(14.78)	(20.87)	(21.25)	(16.25)	(14.68)
Observations	X	X	X	X	X
Grade-Subject Fixed Effects	X	X	X	X	X
County Fixed Effects	X	X	X	X	X
Demographic Controls	X	X	X	X	X

SOURCES: California Department of Education, California Assessment of Student Progress and Performance research files, enrollment files; Authors' calculations.

NOTES: Table reports estimates of Beta 1 and Beta 2 from a single regression equivalent to equation (2) where Beta 1 and Beta 2 are interacted with student race, and data are at the district-grade-subject-subgroup level. Dependent variable is the share at or above standard in 2018-19. Standard errors are in parentheses, and are clustered by district. * p<.10, ** p<.05, *** p<.01.

FIGURE B12

RKD estimates for revenues, 2018-19, by bandwidth

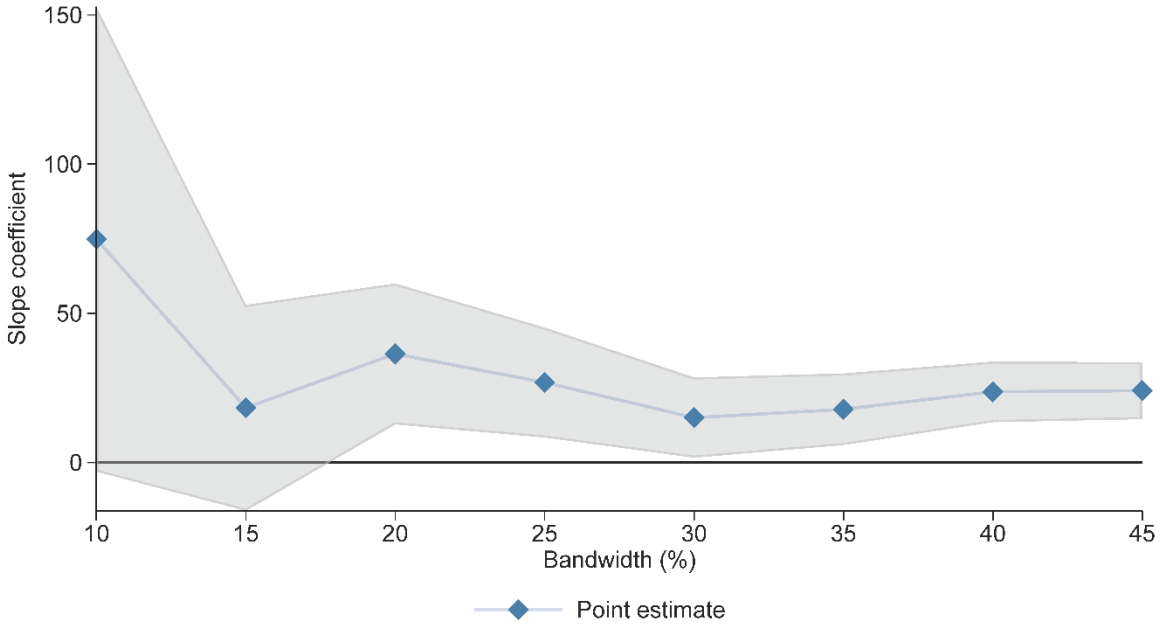


SOURCE: California Department of Education, SACS district finance data, enrollment files; Authors' calculations.

NOTE: Figure shows equation (2) estimates of the change in slope (kink) at the cutoff for funding formula revenues per pupil, for different bandwidths. Estimates only shown for 2018-19. Shaded area shows 95% confidence interval; standard errors are clustered by district.

FIGURE B13

RKD estimates for test scores, 2018-19, by bandwidth (share at or above standard)

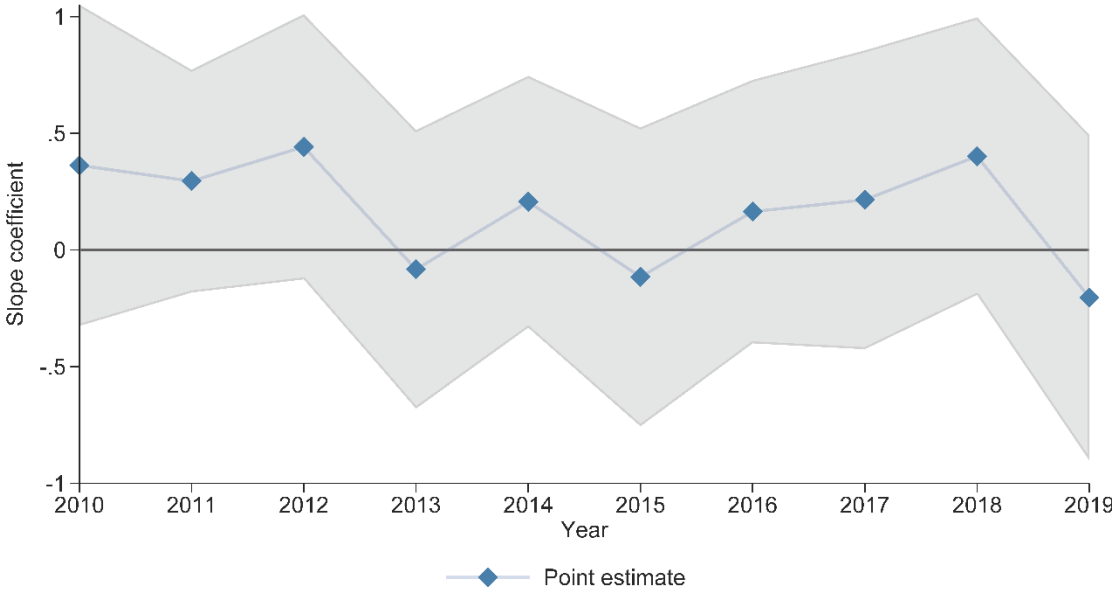


SOURCE: California Department of Education, California Assessment of Student Progress and Performance research files, enrollment files; Authors' calculations.

NOTE: Figure shows equation (2) estimates of the change in slope (kink) at the cutoff for the mean share at or above standards on the 2018-19 SBAC, for different bandwidths. Shaded area shows 95% confidence interval; standard errors are clustered by district.

FIGURE B14

RKD estimates for AG completion, by year (bandwidth=20%)

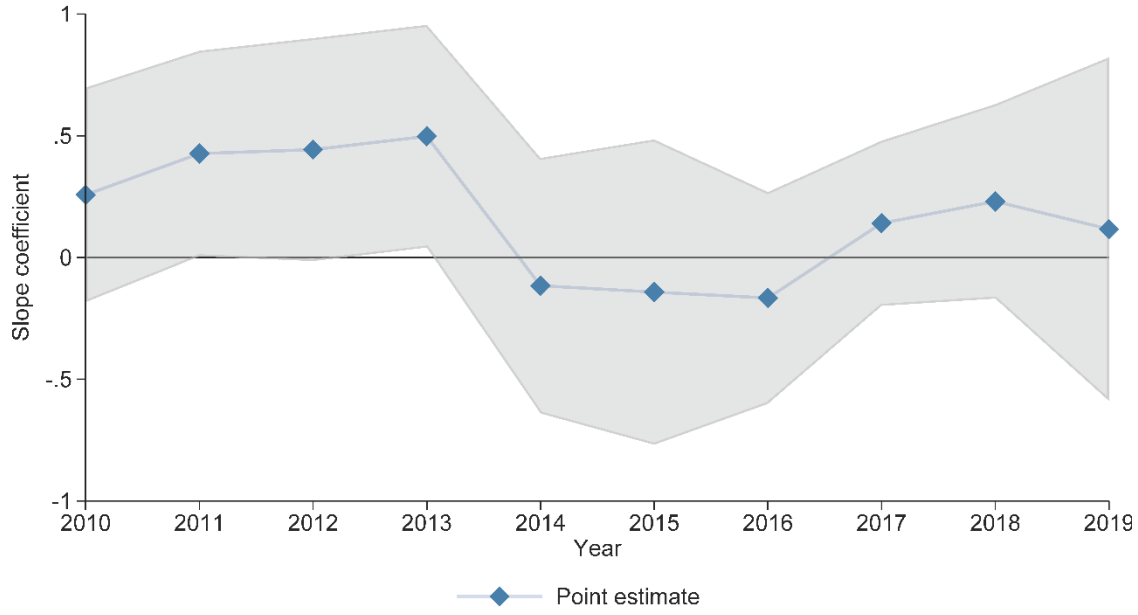


SOURCE: California Department of Education, California Assessment of Student Progress and Performance research files, enrollment files; Authors' calculations.

NOTE: Figure shows equation (2) estimates of the change in slope (kink) at the cutoff for the mean A-G completion rate among graduates, separately by year. Years denote fall year. Bandwidth = 20%. Shaded area shows 95% confidence interval; standard errors are clustered by district.

FIGURE B15

RKD estimates for graduation, by year (bandwidth=20%)

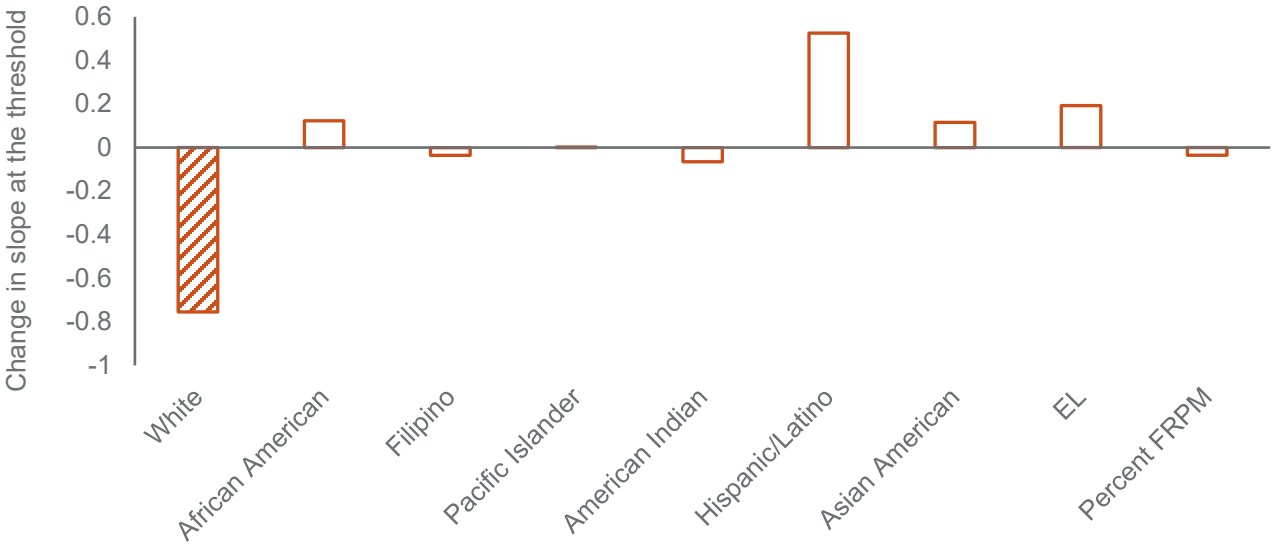


SOURCE: California Department of Education, California Assessment of Student Progress and Performance research files, enrollment files; Authors' calculations.

NOTE: Figure shows equation (2) estimates of the change in slope (kink) at the cutoff for the mean graduation rate, separately by year. Years denote fall year. Bandwidth = 20%. Shaded area shows 95% confidence interval; standard errors are clustered by district.

FIGURE B16

RKD estimates for race/income, 2018-19 (bandwidth=20%)



SOURCE: California Department of Education, school enrollment files; Authors' calculations.

NOTE: Figure shows equation (2) estimates of the change in slope (kink) at the cutoff for different demographic characteristics in 2018-19. Solid bars denote statistical significance at the 5% level, diagonal lines denote significance at the 10% level; standard errors are clustered by district.

Appendix C. Estimating Targeting Using School Site Spending Data

There is no formal accounting mechanism for tracking how and where supplemental and concentration (hereafter S&C) dollars are spent by districts across the state. However, using school site spending data and information on schools' high-need shares, we can understand the extent to which spending is higher in schools that have higher shares of high-need students – and therefore generate S&C dollars for their districts.

To do this, we rely on the "LCFF Snapshot" data for 2018-19 (the same year of the ESSA school site spending data) provided by CDE, which, among other things, details the amount of S&C grant funding received by a district. Then, using the number of high-need students at each school site in a district, we calculate the S&C grant funding generated by a school site: we allocate total S&C dollars within a district based on the number of high-need students at each site, and then divide the total S&C dollars at each school site by that school's total enrollment.

We then estimate the relationship between school site spending from local and state sources[12] and the S&C dollars generated at a school site. Specifically, we estimate equation (3):

$$(3)\ \ SiteSpend_{s(d)} = \alpha + \beta_1 S\&C_{s(d)}^{fund} + +\Gamma X_{s(d)} + \gamma_d + \epsilon_{s(d)}$$

In our primary specifications we include district fixed effects, as we are interested in the *within*-district change in spending given different levels of S&C funding generated at a site. In our most preferred specification, we also include school-level controls for enrollment in the various grade ranges that determine base grant funding (K-3, 4-6, 7-8, and 9-12), $X_{s(d)}$, which also account for any differences in spending patterns by school level.

Table C1 reports these estimates. Table C2 reports analogous estimates where total LCFF funding per student generated at a site (S&C funding plus base grant funding) is the explanatory variable of interest instead of S&C funding. Intuitively, β_1 estimates by how many dollars site-level spending increases for an additional dollar of funding generated at a school site. A coefficient of 1 would be consistent with perfect targeting of S&C dollars: for every dollar in funding a school site generates under the LCFF formula, the district spends 1 dollar more at that site.

There are some caveats to this exercise. First, this is based only on one year of expenditure data. Second, it relies on the assumption that all centrally administered spending is equally allocated across school sites. This may not always hold in practice; for example, a central expense like educational software to use districtwide to help English Learner students would show up as a central expense even if its specific purpose is targeted towards improving outcomes for high-need students.

Third, and more generally, we cannot look explicitly at how and where S&C dollars are spent; we only have access to overall site spending from state and local funding sources. This means that how districts spend their other funding sources will influence this relationship. If districts also spend more on high-need school sites from their other funding sources, we might expect a coefficient that is even greater than one. On the other hand, if districts spend less on high-need students out of their other funding sources, then a district could technically perfectly target their S&C funding but still have a β_1 coefficient less than 1. However, this would indicate that S&C funding crowds out other funding, which would violate the spirit of LCFF – that additional dollars should be used to increase services for high-need students, not supplant spending that they would have otherwise received.

[12] We exclude spending from federal funding sources, as this would operate outside of the funding formula. We also exclude central expenses, as by definition in the school site spending data, are constant across all schools in the same district.

Finally, we estimate separate regressions for each district – analogous to equation (3), but excluding the fixed effects – to estimate a district-specific relationship between spending and S&C funding, β_1^d. This estimation is restricted only to districts with 10 or more schools. The distribution of β_1^d is reported in Table 2 in the main text.

TABLE C1

Regression estimates for supplemental and concentration funding

S&C Dollars Per Pupil	0.27702	0.72148	0.552256
	0.210331	0.172063	0.138313
School K-3 Enrollment			-4.45475
			0.460216
School 4-6 Enrollment			-3.16419
			0.286417
School 7-8 Enrollment			-2.4321
			0.208396
School 9-12 Enrollment			-0.98388
			0.121903
N	6790	6790	6790
District Fixed Effects		X	X

SOURCES: California Department of Education, ESSA school site spending reports, school enrollment files; Authors' calculations.

NOTES: Regression estimates via equation (3). Columns 2 and 3 include district fixed effects. Standard errors are clustered by district.

TABLE C2

Regression estimates for total LCFF funding

LCFF Dollars Per Pupil	0.425929	0.609374	0.670389	0.572567
	0.134997	0.035504	0.064273	0.123803
School K-3 Enrollment			-4.03294	-3.90799
			0.446235	0.559982
School 4-6 Enrollment			-2.53156	-2.3527
			0.330319	0.468431
School 7-8 Enrollment			-1.99006	-1.86365
			0.227762	0.360808
School 9-12 Enrollment			-1.21128	-1.29962
			0.147547	0.112769
School Base Grant Per Pupil				0.31524
				0.38033
N	6790	6790	6790	6790
District Fixed Effects		X	X	X

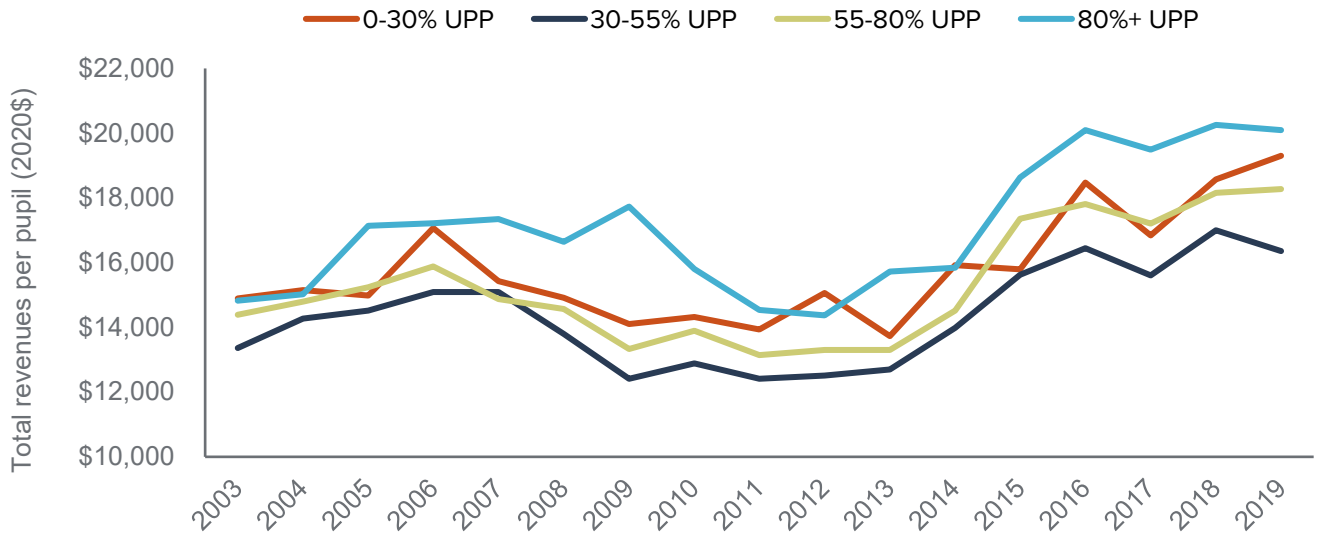
SOURCES: California Department of Education, ESSA school site spending reports, school enrollment files; Authors' calculations.

NOTES: Regression estimates via equation (3). Columns 2 and 3 include district fixed effects. Standard errors are clustered by district.

Appendix D. Supplemental Tables and Figures

FIGURE D1

Time series of total revenue, by UPP

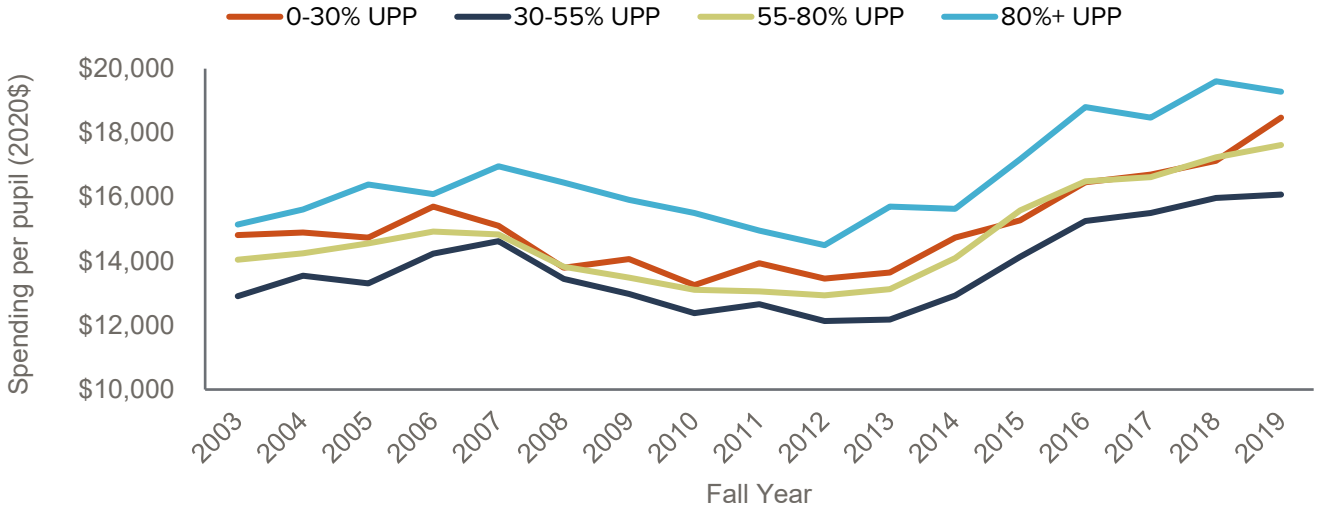


SOURCE: California Department of Education, SACS district finance data and enrollment files; Author's calculations.

NOTE: Figure plots the yearly funding formula revenues per pupil, in inflation-adjusted 2020 dollars. UPP refers to the "unduplicated pupil percentage" of low-income, English Learner, and foster youth in a district. Averages are weighted by average daily attendance (ADA). Districts with ADA less than 250 are excluded. Districts with greater than 500% or less than 20% of California mean spending per pupil or funding formula revenues per pupil are excluded. See Technical Appendix A for further detail on data sources and sample restrictions.

FIGURE D2

Time series of total spending, by UPP

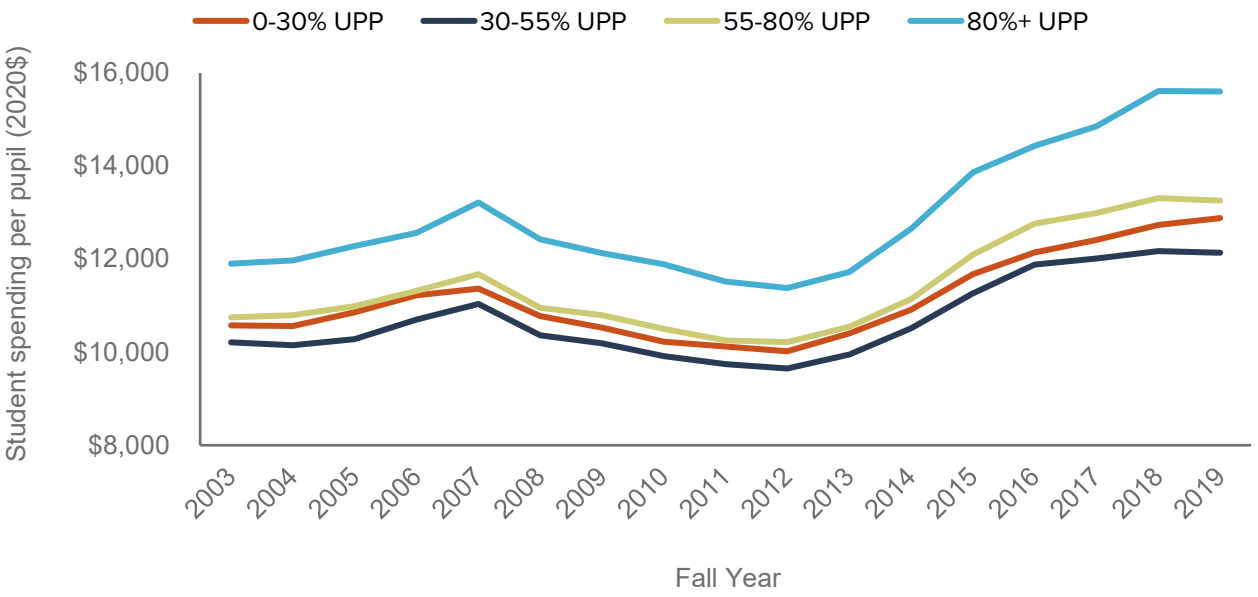


SOURCE: California Department of Education, SACS district finance data and enrollment files; Author's calculations.

NOTE: Figure plots the yearly funding formula revenues per pupil, in inflation-adjusted 2020 dollars. UPP refers to the "unduplicated pupil percentage" of low-income, English Learner, and foster youth in a district. Averages are weighted by average daily attendance (ADA). Districts with ADA less than 250 are excluded. Districts with greater than 500% or less than 20% of California mean spending per pupil or funding formula revenues per pupil are excluded. See Technical Appendix A for further detail on data sources and sample restrictions.

FIGURE D3

Time series of K-12 student spending, by UPP

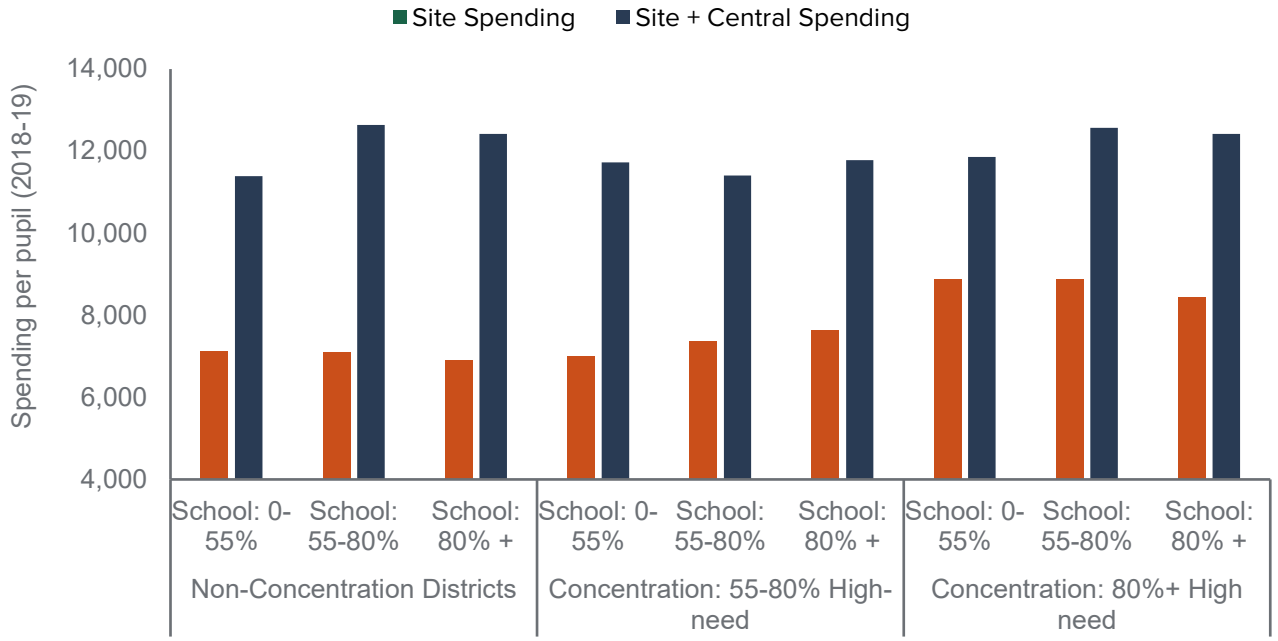


SOURCE: California Department of Education, SACS district finance data and enrollment files; Author's calculations.

NOTE: Figure plots the yearly funding formula revenues per pupil, in inflation-adjusted 2020 dollars. UPP refers to the "unduplicated pupil percentage" of low-income, English Learner, and foster youth in a district. Averages are weighted by average daily attendance (ADA). Districts with ADA less than 250 are excluded. Districts with greater than 500% or less than 20% of California mean spending per pupil or funding formula revenues per pupil are excluded. See Technical Appendix A for further detail on data sources and sample restrictions.

FIGURE D4

School site spending highest among concentration districts

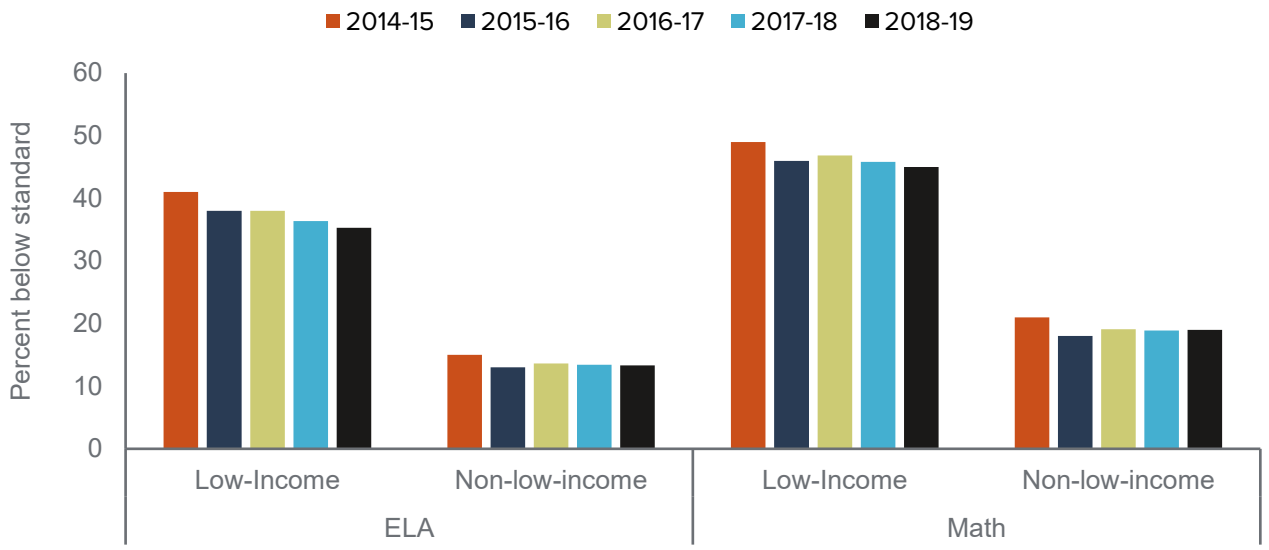


SOURCE: California Department of Education, ESSA school site spending reports; Authors' calculations.

NOTE: Figure reports mean school site spending per pupil from state and local sources, for schools and districts of varying levels of student need. Districts where school site spending is not reported for more than 5% of student enrollment are excluded. Schools with fewer than 50 students are excluded. See Technical Appendix A for further details on the data and sample restrictions.

FIGURE D5

Share below standards (lowest proficiency level), by student income

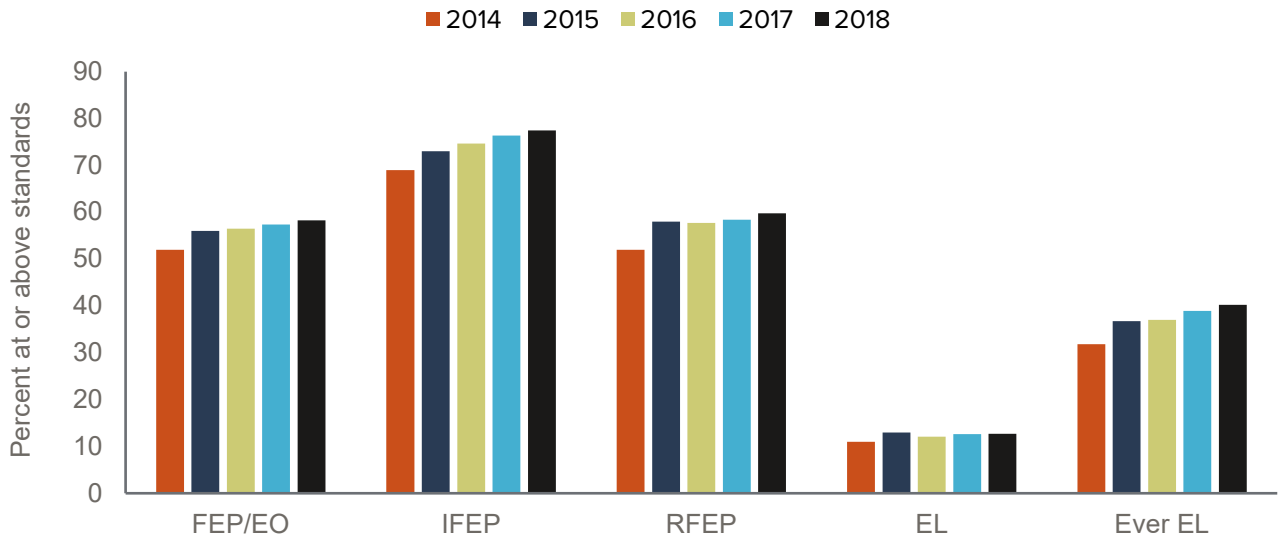


SOURCE: California Department of Education, California Assessment of Student Progress and Performance research files; Authors' calculations.

NOTE: Figure plots the statewide share below grade level standards (the lowest performance level) on the SBAC, in ELA and math, for low-income and non-low-income students. Low-income refers to economically disadvantaged students, per the California Department of Education's definition. See Technical Appendix A for more information on data sources.

FIGURE D6

Share at or above standard, by EL classification (ELA)

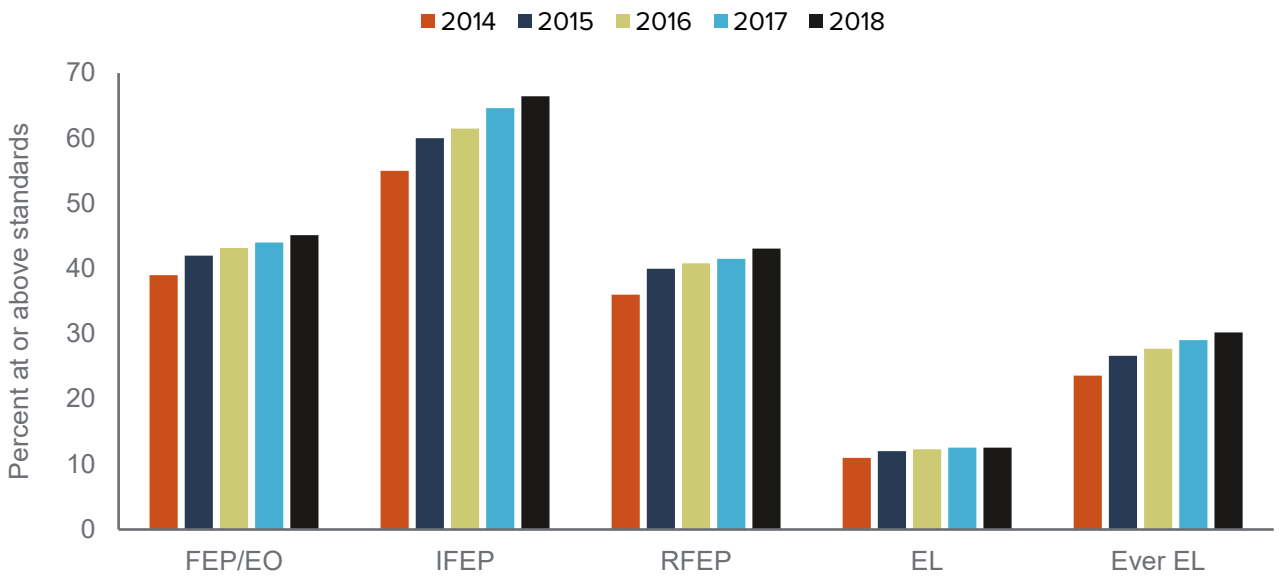


SOURCE: California Department of Education, California Assessment of Student Progress and Performance research files; Authors' calculations.

NOTE: Figure plots the statewide share below grade level standards (the lowest performance level) on the SBAC in ELA, for students of different EL status. FEP/EO is Fluent English Proficient / English Only; IFEP is Initial Fluent English Proficient; RFEP is Reclassified English Proficient. Ever EL includes current and reclassified EL students. Ever EL is calculated by taking the weighted average of EL and RFEP in 2014-15 and 2015-16; it is included in the data files in subsequent years. Low-income refers to economically disadvantaged students, per the California Department of Education's definition. See Technical Appendix A for more information on data sources.

FIGURE D7

Share at or above standard, by EL classification (Math)



SOURCE: California Department of Education, California Assessment of Student Progress and Performance research files; Authors' calculations.

NOTE: Figure plots the statewide share below grade level standards (the lowest performance level) on the SBAC in Math, for students of different EL status. FEP/EO is Fluent English Proficient / English Only; IFEP is Initial Fluent English Proficient; RFEP is Reclassified English Proficient. Ever EL includes current and reclassified EL students. Ever EL is calculated by taking the weighted average of EL and RFEP in 2014-15 and 2015-16; it is included in the data files in subsequent years. Low-income refers to economically disadvantaged students, per the California Department of Education's definition. See Technical Appendix A for more information on data sources.

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