PPIC PUBLIC POLICY INSTITUTE OF CALIFORNIA

25 YEARS

School Resources and the Local Control Funding Formula

Is Increased Spending Reaching High-Need Students?

Technical Appendices

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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). There are three main types of data: (1) district-level financial data; (2) staff-level demographic and assignment data; (3) school-level enrollment and demographic records. I describe each below:

District-level financial data: 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 and spending categories. In this report, I rely on the CDE SACS files for all district-level financial outcomes. Annual average daily attendance (ADA) totals for each district are also included in the SACS files, which are used to construct per pupil spending measures. SACS data are available beginning in the 2003 fiscal year.

To construct measures of district-level per pupil expenditures I follow the conventions of Bruno (2018) in aggregating categories in the SACS data.[1] I exclude all district revenue sources, transfers between districts, and net pension liabilities. I 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; I therefore include ADA for these schools in the ADA of the affiliated district.[3]

I then aggregate to the district-year level to construct district-year total expenditures. 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.

Staff-level demographic and assignment data: The CDE also maintains databases of staff-level data. These data give characteristics of individual "certificated"[4] staff member in each year. Crucially, these records contain school codes that make it possible to identify where a given staff member was assigned in a given year. However, it is not possible to link these data across time, meaning one cannot follow individual staff members longitudinally. For the 2012-2017 fiscal years, I merge staff records from the Staff FTE files, Staff Demographics files, and Staff Credentials files. For the years prior to 2012, I use the PAIF files, which contain roughly similar, but less comprehensive information. These are available back to 1997, but I only use records back to 2003 to maintain consistency with the sample window for the district financial records.

Together, these files contain data on the staff FTEs, school assignment(s), education, experience (both overall and within district), and credentials. Depending on the outcome, I either compute school- and district-level averages or totals. Averages are used for outcomes like experience, education, and credentials, and are weighted by FTE. Total FTEs for each school and district, by staff type (e.g. teacher, pupil support services, or administrator) are used to compute school and district-level measures of average pupil-staff ratios. For example, school-level pupil-teacher ratios are computed by dividing total school enrollment in a year by the total teacher FTEs in that school-year.

[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 an 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.

[4] Certificated staff include teachers, pupil support services (e.g., counselors, nurses, psychologists, social workers), and administrators.

School-level enrollment and demographic records: Data on school and district enrollment 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 beginning in 2013, the first year of LCFF. School-by-grade enrollment, both overall and broken down by race/ethnicity/gender, is available going back to 1982. I collect school and district-level free and reduced price lunch meal (FRPM) totals from three different files: for 2004-2017, I use the FRPM files, while for 2003, I use the AFDC files, which are available back to 1988.

Sample Restrictions

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

All outcomes: Across all analyses, I 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.[5] 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. I 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).

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.

School-level staffing outcomes: When measuring school-level outcomes, I exclude small schools with fewer than 40 students in a given year. These schools likely have very different staffing patterns and staffing ratios. This drops an additional 14% of schools, but only 0.2% of student enrollment.

Within-district, across school comparisons: For outcomes that rely on comparisons across schools in a district, it is necessary that there be enough schools in a district to facilitate a meaningful comparison. I choose a cutoff of 10 schools, and exclude district-years with fewer than 10 schools. Roughly 60% of districts have fewer than 10 schools, representing 23% of schools. However, the districts with more than 10 schools serve 84% of the students in the school sample.

Teacher salary sample: Teacher salary data are not collected by CDE, and I therefore estimate these data using salary schedules and teacher demographics (see Appendix B for more detail on this process). I only include district-years where I can reasonably estimate salaries for 95% or more of a districts' teachers. This excludes 28% of districts, and 39% of students in the state. Notably, Los Angeles Unified is one of the excluded districts due to a poor salary estimation rate.

[5] These small districts are most often rural or remote districts, which generally have very different cost structures than the typical district.

Appendix B. Estimating Teacher Salaries

Unfortunately, school-level financial data is not reported by the CDE nor is available for most California K–12 districts in any consistent fashion. Due to federal reporting requirements as a part of the Every Student Succeeds Act (ESSA), California will be required to submit and maintain school-level financial data starting in the 2018-19 fiscal year, although it remains to be see how this more granular level of school district accounting will be achieved in practice.

In lieu of actual school-level spending data, I use publicly available staff files from the CDE to measure the staffing resources and costs at the school level. I then merge each certificated teacher record to her district's salary schedule, and estimate the salary of each teacher based on their education, credentials, and years of experience. Staff assignments and demographic records are available in the staffing datasets described in Technical Appendix A. District-level salary schedule are available on the "J-90" forms collected and maintained by the CDE.

To assign teacher salaries based on their district salary schedules, I rely on the following matching hierarchy, assigning salaries to teachers based on a gradually coarser match. I start with the first step, and for all those who do not match, I move on to the next step. Where salary schedules are non-unique for a given set of demographic characteristics, I assign the highest salary.

1. Exact match based on all demographics: years of experience, education, credential(s), and additional semester hours.
2. Match on years of experience, education, and additional semester hours, excluding credentials.
3. Match on (2), but move down a step (year of experience).
4. Match on (2), but move up a step (year of experience).
5. Match on years of experience, education, and assume no additional semester hours.
6. Match on (5), but move education "down" a discrete category.
7. Match only on years of experience and education.
8. Match only on years of experience, assigning the minimum salary for a given step.

Where districts assign bonuses based on having master's or doctoral degrees, I then add that to the estimate of her salary. Overall, across all years I am able to match about 92% of all staff records that have schedule data, which correspond to 88% of teachers.

There are many caveats and difficulties to this approach. Perhaps most importantly, staff demographic data are much coarser than salary schedules. For example, while the CDE record for a teacher denotes whether the teacher had a BA, BA +30 semester hours, MA, MA + 30 semester hours, or a Doctorate[6], a district salary schedule will often have different categories, such as "BA" vs "BA +15" vs "BA +45". Second, teachers will sometimes get additional bonus pay based on additional credentials, such as an English Language Development (ELD), or Crosscultural, Language, and Academic Development (CLAD) credential. These are not consistently reported in the salary schedule data, and to the extent that a teacher receives additional pay for additional credentials, I will understate her pay. More generally, any bonus pay outside of the schedule will lead to an underestimation of the

[6] There are additional categories in some years, but this is the set of educational categories that I use that are consistently defined across all years of staffing data.

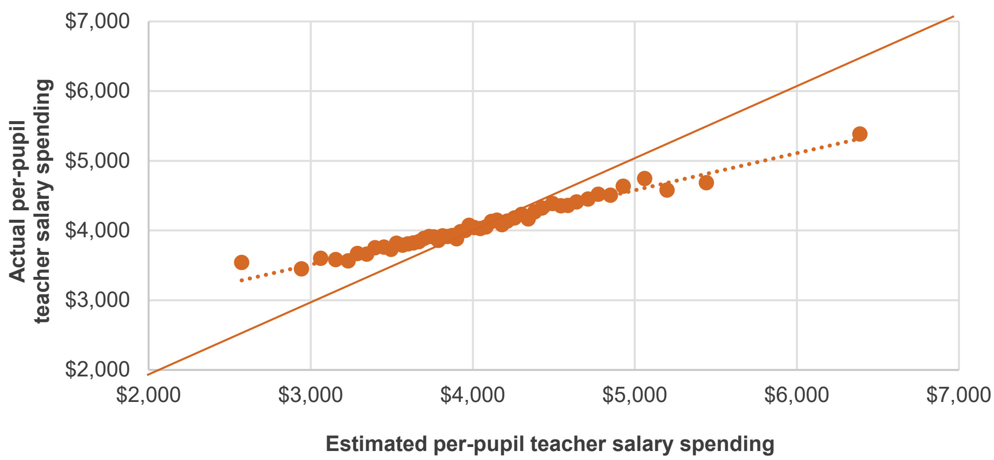
actual salary.[7] Finally, there is also the possibility of measurement error in the recording of individual staff demographics, staff FTEs, and district salary schedules. This also contributes to salary matching difficulties.

To compute school and district average salaries, I take the average in each year, weighted by FTEs. Teachers with greater than 200% FTE are excluded[8], and those with between 150% and 200% are censored at 150%. Per pupil salary spending is computed similarly, but is totaled rather than averaged, again weighted by FTE.

Overall, in districts with high match rates, I am able to relatively closely match teacher salary spending in the SACS data. Figure B1 below shows a binned scatterplot (each dot represents the average of the X and Y variable over multiple districts, so that each "bin", or dot, is equally weighted by the number of students) comparing total salary spending on teachers (at the school-level, excluding central office spending) against estimated teacher salary spending, per pupil. On average, estimated salaries are very close to actual district salaries – the average difference between estimated and actual total salary spending is only $24 (0.5%). Notably, the estimation error is greater in districts in the tails of the teacher salary spending distribution; total salary spending tends to be overestimated in high spending districts, and underestimated in low spending ones. Nonetheless, Figure B1 shows that while the estimation procedure is imperfect and likely introduces measurement error, it is able to reasonably approximate teacher salary spending, even in districts with different levels of spending.

FIGURE B1

Comparing estimated to actual district-level per pupil teacher salary spending



SOURCE: California Department of Education, staff demographics files, SACS financial records, and J-90 files; Author's calculations.

NOTE: Each dot includes multiple districts, and represents an equal number of students. The larger dashed line depicts the best linear fit, while the smaller dashed line is the 45 degree line. Figure shows per pupil spending on teacher salaries vs estimated per pupil spending on teacher salaries. Districts with a salary match rate below 95% are excluded. Districts with ADA less than 250 are excluded. Districts with greater than 500% or less than 20% of California mean spending per pupil are excluded. See Technical Appendix A for further detail on sample restrictions.

[7] To the extent that such bonus pay is disproportionately distributed in higher (or lower) poverty schools, this could affect measurements of progressivity. Reassuringly, however, such payments are typically a small portion of a teacher's overall salary, and thus this is unlikely to meaningfully affect measurement of the across-school differences in spending.

[8] Such cases are rare, and are likely due to coding errors in the data.

Appendix C. Regression Framework

In Tables 1 and 2, I estimate the extent to which district spending and resources change before and after the passage of LCFF. In the first three columns of both tables, I report estimates of the average change in district spending, relative to the level of spending in a district prior to LCFF. I estimate this using the linear regression specified in equation (1) below:

$$(1) \qquad Y_{d,y} = \alpha_d + \sum_{y=2013}^{\bar{Y}} \sum_{j=1}^{3} \beta_{y,j(d)}\ \gamma_y * LCFF_{j(d)} + \gamma_{\tilde{y}} + \epsilon_{d,y}$$

Here, an outcome $Y_{d,y}$, for district d in year y is regressed on $\gamma_y * LCFF_{j(d)}$, which is the product between indicators for the LCFF "treatment group" (e.g. 0-30% UPC, 30-55% UPC, and 55%+ UPC) and indicators for post-LCFF years. The model also includes fixed effects for district, α_d, and fixed effects for year, $\gamma_{\tilde{y}}$, which are included for only pre-LCFF years, defined as $\tilde{y}$.[9] The coefficients $\beta_{y,j(d)}$ provide estimates of the post-LCFF change in spending for a district of a given funding formula intensity. These amount to single-difference estimates, effectively comparing the average differences in districts before and after LCFF. In the first three columns of Tables 1 and 2, I report estimates for the year 2017, the most recent fiscal year in the financial and staffing data files.

However, we know that spending would have risen regardless of the funding formula change in most districts, due Prop 98 revenue increases resulting from the state's improved fiscal health. To measure the effect of the LCFF funding formula itself on these spending patterns, I use a difference-in-differences approach that compares those districts who benefitted little from the funding formula change (those with 0-30% high-need students), to those districts that saw a significant increase in revenues due to the funding formula (55%+ high-need students). The assumption required here for a causal interpretation of $\beta_{y,j(d)}$ coefficients is that there are parallel trends in district expenditures; i.e. that district expenditures would have evolved similarly in absence of LCFF in both the high- and low-need districts, after accounting for fixed differences between districts and across years. Indeed, the visual depiction of relative trends in student spending in the bottom panel of Figure 3 lends support to this assumption of parallel trends.

To implement this, I estimate a regression very similar to equation (1), except I omit the interaction between post-LCFF year effects and the low-need LCFF treatment dummy variable. Specifically, I estimate equation (2) below:

$$(2) \qquad Y_{d,y} = \alpha_d + \sum_{y=2013}^{\bar{Y}} \sum_{j=2}^{3} \beta_{y,j(d)}\ \gamma_y * LCFF_{j(d)} + \gamma_y + \epsilon_{d,y}$$

Here, $\beta_{y,j(d)}$ estimates the impact of the funding formula change on spending in high-need districts (the "treatment group"), *relative to* the change in spending in low-need districts (the "control group"). Note that this is equivalent to taking the difference between $\beta_{y,j(d)}$ coefficients for high- and low- need districts from the estimation of equation (1). Standard errors are clustered at the district-level in all regressions, to account for serial correlation in district outcomes over time.

Appendix D. Supplemental Tables and Figures

[9] Note that year effects for post-LCFF years are collinear with the year effects in the post-LCFF interaction, which includes indicators for all district types and is therefore fully saturated. In equation (2), there is no such collinearity problem: the coefficients here measure the relative effect of LCFF, relative to districts that have a 30% or lower share high-need students.

TABLE D1

Spending changes (in percentages) have been greatest for high-need districts, 2012–13 to 2017–18 (per pupil)

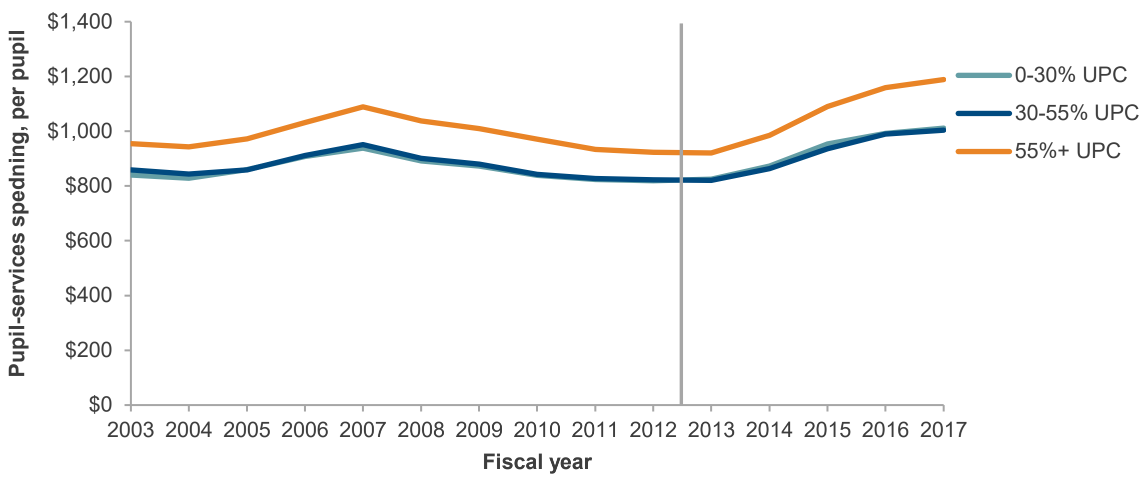
	Spending increase			Relative change	
	(1) Low need (0–30% UPC)	(2) Moderate need (30–55% UPC)	(3) High need (55%+ UPC)	(4) Moderate vs low need (30–55% vs 0–30%)	(5) High vs low need (55%+ vs 0–30%)
Total spending	**20%**	**23%**	**25%**	2%	4%
Student spending	**20%**	**21%**	**25%**	1%	**4%**
Instructional salaries	**16%**	**15%**	**16%**	-1%	0%
Pupil services and support staff salaries	**24%**	**23%**	**30%**	-1%	**4%**
Admin salaries	**24%**	**23%**	**29%**	0%	4%
Other staff salaries	**22%**	**19%**	**25%**	-2%	3%
Staff benefits	**32%**	**34%**	**38%**	2%	**5%**
Other student spending	**20%**	**23%**	**28%**	22%	**6%**
Non-student spending	**26%**	**27%**	**30%**	1%	3%

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

NOTES: Coefficients in bold are significant at the 5% level; those bold and italicized are significant at the 10% level. Table reports linear regression coefficients from equations (1) and (2) in Technical Appendix C, where dependent variables are the natural log of spending categories. Coefficients are transformed from logs into a percentage by exponentiation. UPC refers to the "unduplicated pupil count" of economically disadvantaged, English Learner, foster youth, and homeless students in a district. Averages are weighted by average daily attendance (ADA). Districts with ADA less than 250 are excluded. Districts with more than 500% or less than 20% of California mean spending per pupil are excluded. See Technical Appendix A for further detail on sample restrictions. See table 1 in the main text for changes in dollars.

FIGURE D1

Mean pupil services spending per pupil is greatest in high-need districts, and similar in low- and moderate-need districts

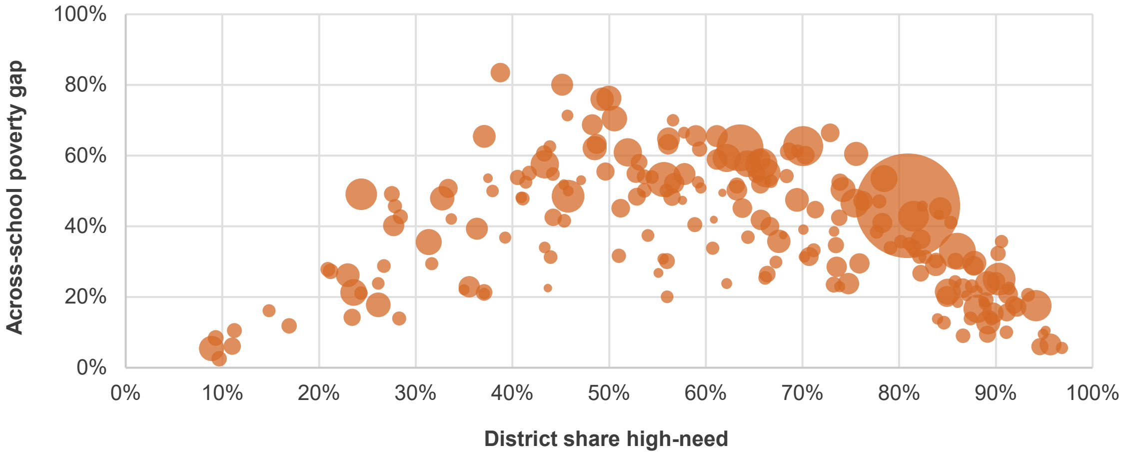


SOURCES: California Department of Education, SACS district finance data; Author's calculations.

NOTES: Figure plots the yearly average pupil services salaries spending per pupil, in inflation-adjusted 2017 dollars. UPC refers to the "unduplicated pupil count" of economically disadvantaged, English Learner, foster youth, and homeless students 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 are excluded. See Technical Appendix A for further detail on sample restrictions.

FIGURE D2

There are large income gaps between highest- and lowest-poverty schools in districts, even when including high schools

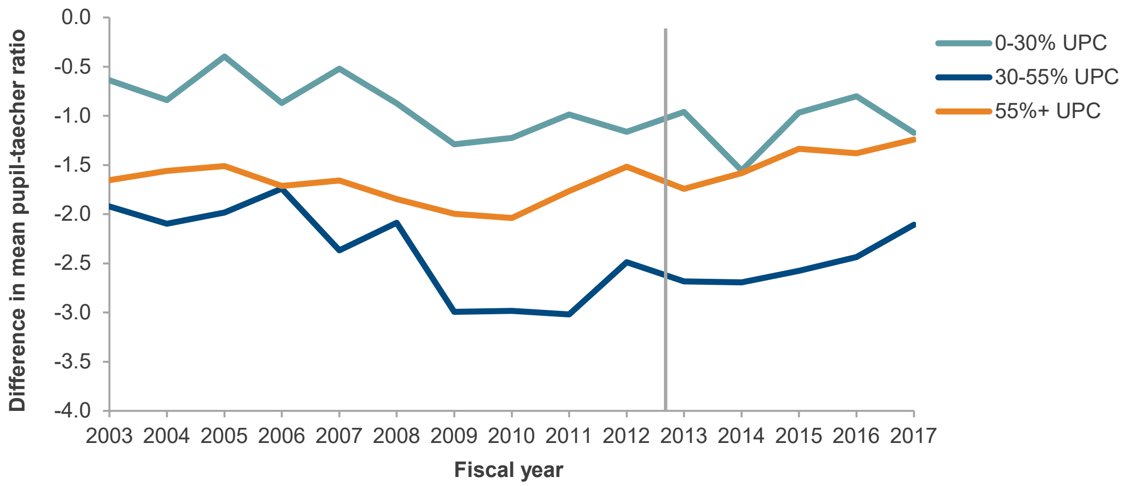


SOURCES: California Department of Education, Student FRPM and UPC data; Author's calculations.

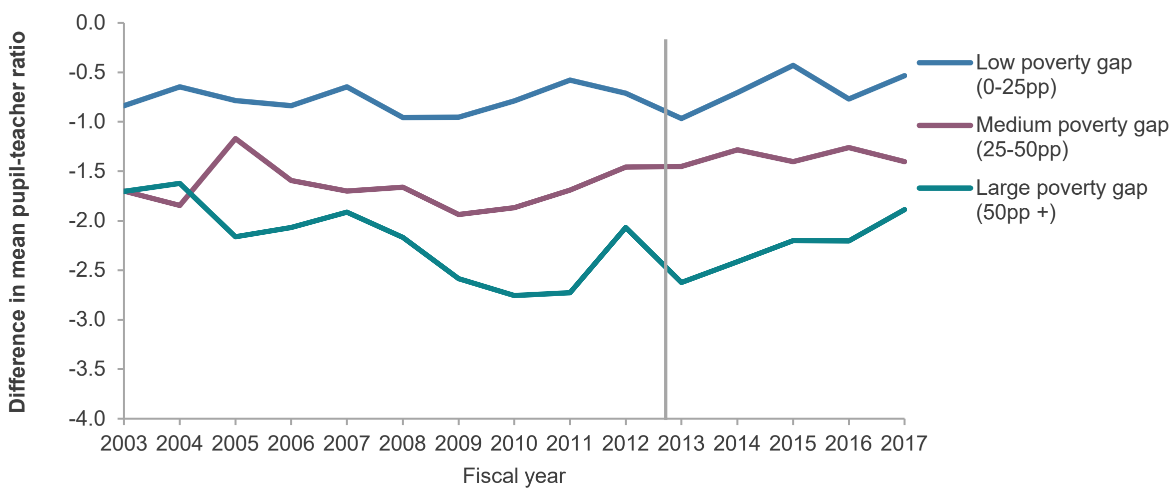
NOTES: Figure plots the gap in mean school share FRPM between the fourth and first quartiles of school FRPM within a district. Quartile means are weighted by enrollment. District data points are weighted by ADA, with larger bubbles indicating greater ADA. Districts with fewer than 10 schools are excluded Districts with ADA less than 250 are excluded. Districts with greater than 500% or less than 20% of California mean spending per pupil are excluded. See Technical Appendix A for further detail on sample restrictions.

FIGURE D3

Within-district pupil-teacher ratio gaps similar over time in high-need and non-high-need districts



Within-district pupil-teacher ratio gaps over time, in more and less segregated districts

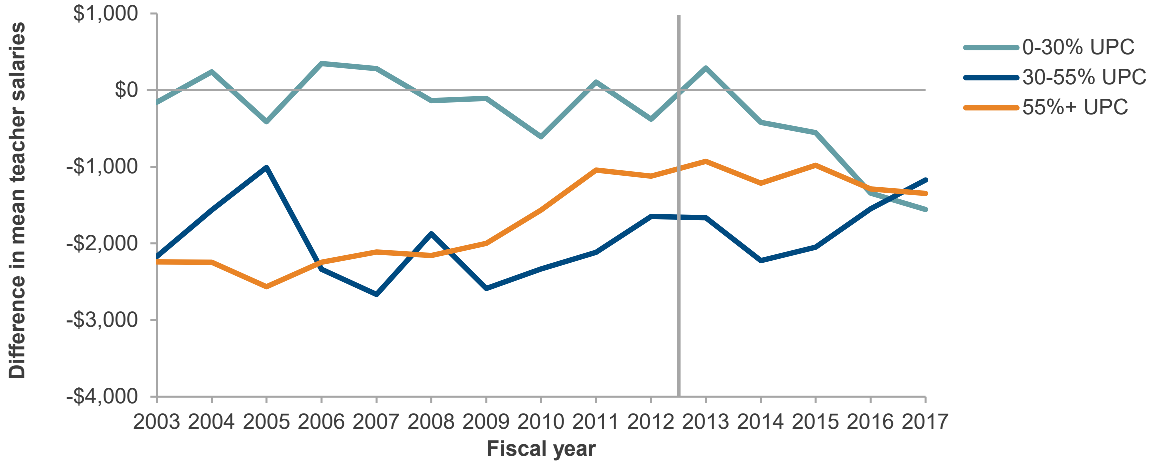


SOURCES: California Department of Education, staff demographics files, PAIF data files, student FRPM and UPC files; Author's calculations.

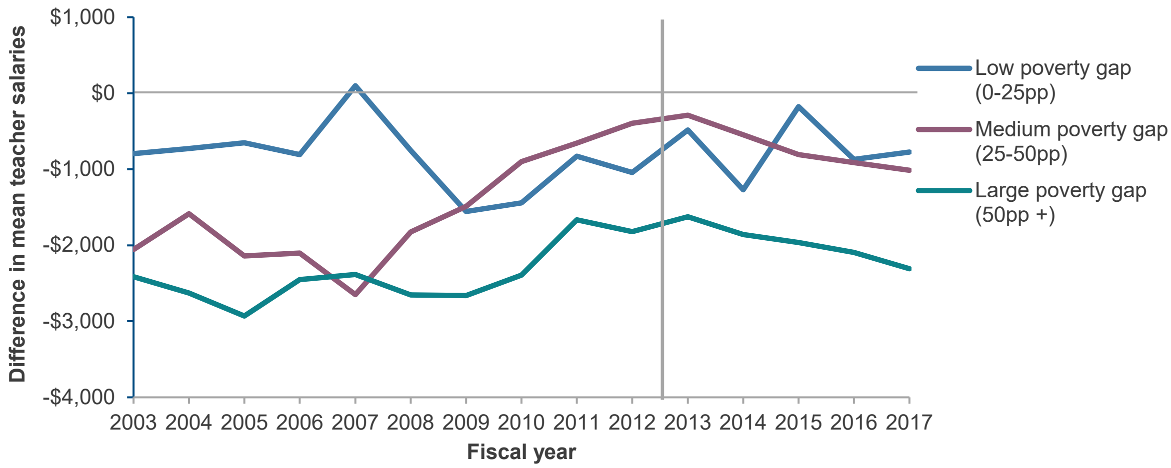
NOTES: Figure plots the difference in mean pupil-teacher ratios between the highest and lowest poverty quartile schools in a district, by district share high-need (top panel) or by district across-school poverty gap (bottom panel). Quartile means are weighted by enrollment. Mean district differences are weighted by ADA. Districts with fewer than 10 schools are excluded. Quartile gaps are only computed for the schools serving grades K-8 in a district. Districts with ADA less than 250 are excluded. Districts with greater than 500% or less than 20% of California mean spending per pupil are excluded. See Technical Appendix A for further detail on sample restrictions.

FIGURE D4

Within-district average teacher salary gaps over time, in high-need and non-high-need districts



Within-district average teacher salary gaps over time, in more and less segregated districts

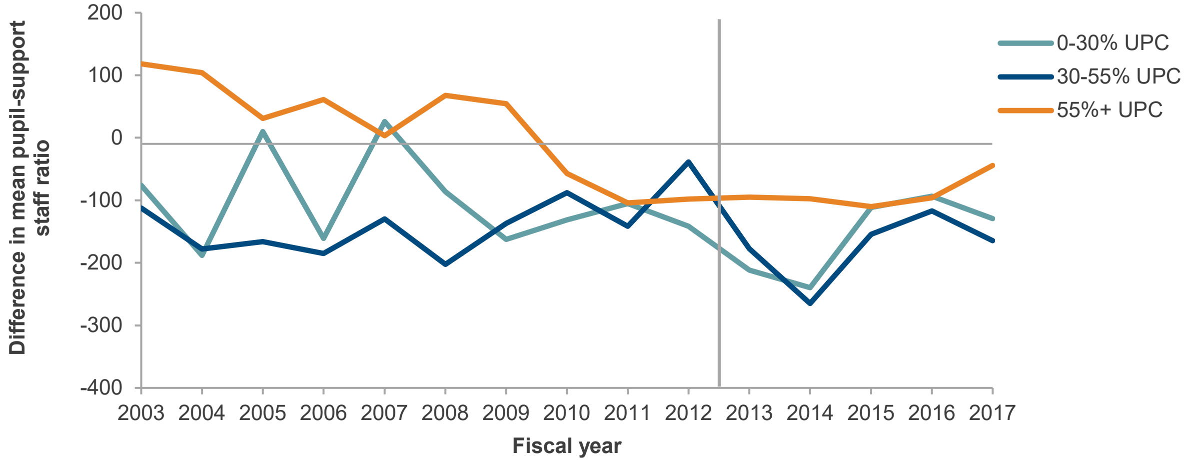


SOURCES: California Department of Education, staff demographics files, PAIF data files, student FRPM and UPC files, and J-90 files; Author's calculations.

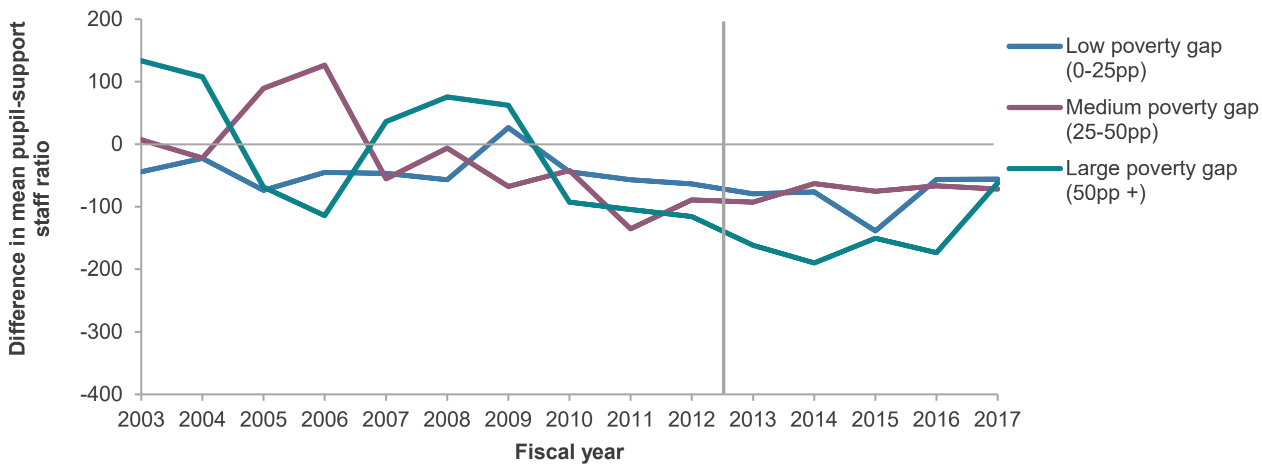
NOTES: Figure plots the difference in mean teacher salaries between the highest and lowest poverty quartile schools in a district, by district share high-need (top panel) or by district across-school poverty gap (bottom panel). Quartile means are weighted by enrollment. Mean district differences are weighted by ADA. Districts with fewer than 10 schools are excluded. Quartile gaps are only computed for the schools serving grades K-8 in a district. Districts with ADA less than 250 are excluded. Districts with greater than 500% or less than 20% of California mean spending per pupil are excluded. Districts with a salary match less than 95% are excluded. See Technical Appendix A for further detail on sample restrictions, and Technical Appendix B for detail on the estimation of teacher salaries.

FIGURE D5

Within-district support-staff ratio gaps over time, in high-need and non-high-need districts



Within-district support-staff ratio gaps over time, in more and less segregated districts

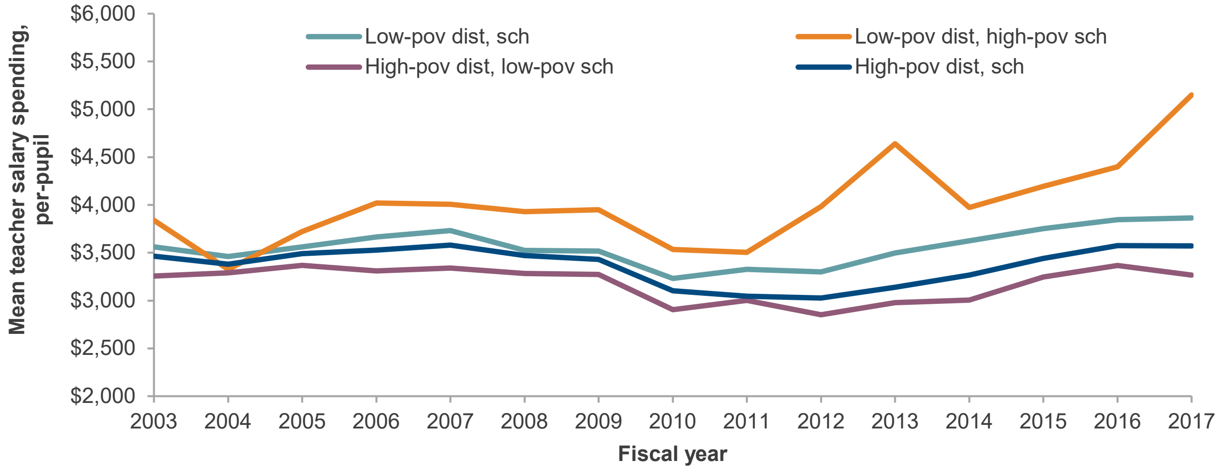


SOURCES California Department of Education, staff demographics files, PAIF data files, student FRPM and UPC files; Author's calculations.

NOTES: Figure plots the difference in mean pupil-support staff ratios between the highest and lowest poverty quartile schools in a district, by district share high-need (top panel) or by district across-school poverty gap (bottom panel). Quartile means are weighted by enrollment. Mean district differences are weighted by ADA. Districts with fewer than 10 schools are excluded. Quartile gaps are only computed for the schools serving grades K-8 in a district. Districts with ADA less than 250 are excluded. Districts with greater than 500% or less than 20% of California mean spending per pupil are excluded. See Technical Appendix A for further detail on sample restrictions.

FIGURE D6

Teacher salary spending is highest in high-poverty schools in low-poverty districts



SOURCES: California Department of Education, staff demographics files, PAIF data files, student FRPM and UPC files, and J-90 files; Author's calculations.

NOTES: Figure shows mean per pupil spending on teacher salaries, by school and district poverty. Districts with a salary match rate below 95% are excluded. Districts with ADA less than 250 are excluded. Districts with greater than 500% or less than 20% of California mean spending per pupil are excluded. See Technical Appendix A for further detail on sample restrictions, and Technical Appendix B for detail on the estimation of teacher salaries.

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