Equity in School Funding: An Analysis of California’s Local Control Funding Formula’s Concentration Grant

A Capstone Research Project Presented for the degree of Master of Public Policy to the School of Public Policy, University of California, Riverside

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Introduction

In response to the well-understood effects of socioeconomic disadvantage on long-term academic performance and by extension, lifetime opportunity and outcomes of California's students, the state of California enacted major public school finance reform in the form of SB-97, known as the Local Control Funding Formula (LCFF), which was signed by Governor Jerry Brown and codified into law on September 26, 2013. LCFF sought to simplify the state funding mechanism, increase accountability, and most importantly, realign school financing to focus on *equity* by directing more funding to the students who stand to benefit the most from more educational resources: low-income students, English Learners, and foster youth. This groundbreaking school finance model seeks to ameliorate the achievement gaps and low educational outcomes associated with those disadvantaged student groups in order to uplift whole communities and foster true social and economic mobility. After six years of implementation amid a shift in curricula and testing, and after only being fully funded just last school year (2018-2019), policymakers and education advocates nationwide are eager to understand the impact of LCFF on student outcomes. A better understanding of the formula's effectiveness will determine whether California should stay the course and if the state's innovative funding scheme can serve as a model for other states. Due to the importance of length of exposure in analyzing the effectiveness of policy interventions on student outcomes, this study is one of the first and few of its kind. This study examines the link between increased funding and academic performance by synthesizing a novel dataset using data from the California Department of Education (CDE) and performing regression analyses. More specifically, we focus our analysis on the *concentration grant*, one of three major components of the LCFF, which directs additional funding to school districts with high concentrations of disadvantaged students. We find statistically significant, if small, increases in academic performance among student groups directly targeted by the LCFF. Given that this study uses data from the only academic year available in which LCFF has been fully funded, our findings suggest that the formula's *concentration grant* is having positive effects on targeted groups' academic achievement.

I. History of School Funding in California

Before the Local Control Funding Formula was adopted, K-12 schools in California were funded disproportionally due to the use of property taxes. Over time the dependence on property taxes was largely abandoned but funding remained unequal, and even when it became equal in many respects, policymakers recognized that it was inequitable. For most of California's history, school funding and oversight was hyper-localized with a majority of funding coming from property taxes and school boards holding significant power. Given the disparities in property value and ability to raise revenue via passage of local measures, low-income school districts often spent less on public education than wealthier districts.

One facet of the Civil Rights Movement of the 1960s was to begin to question the inequitable ways in which public schools were locally financed. The decision in *Brown V. Board of Education* (1954) set forth an ideal for equal educational opportunity by determining separate schooling was unequal. For many education advocates this ruling implied more than racial desegregation, it implied that disparate funding based on wealth could also be considered a violation of the equal protection clause under the Fourteenth Amendment. The argument was that as long as schools were funded primarily from local property taxes, students living in areas of high property values would have greater access to educational resources than their peers in areas with low property values. By the end of the 1960s, civil rights attorneys across several states began to challenge this school financing scheme. (Martin, 2006)

California's Supreme Court case, Serrano *v. Priest* was the first to succeed in its efforts. The California Supreme Court heard *Serrano V. Priest* in 1971 and determined that California's substantial dependence on local property taxes and resulting wide disparities in school revenue, violated the equal protection clause of the Fourteenth Amendment. Justice Sullivan stated in his opinion: "We have determined that this funding scheme invidiously discriminates against the poor because it makes the quality of a child's education a function of the wealth of his parents and neighbors". (Serrano v. Priest, 1971) The state's first response to this legal opinion was to enact revenue limits for "high spending districts'', *Serrano V. Priest II* determined this action still did not address unequal funding. Under legal pressure, the state legislature in 1977 devised a funding formula that enacted revenue caps and put state aid in place as a means to equalize funding across districts. Thus, the funding was equalized across districts in many respects, but was not made more equitable. The passage of Proposition 13 the following year is often credited as being the linchpin of what is commonly referred to as the "property tax revolt". Proposition 13 established a 1% limit on the property tax rate and a 2% limit on the annual increase in the assessed taxable value of an individual property, essentially protecting property owners from tax increases indefinitely. (Martin, 2006) Academics and economists have characterized the "property tax revolt" as a movement by the wealthy in opposition to the court ordered and state mandated school financial equalization efforts, but recently scholars such as Martin have refuted this assertion. (Martin, 2006) Nevertheless, Proposition 13 stood to significantly reduce the amount of local property tax contributions to public schools, leading to a shift in funding responsibility and oversight to the state.

The next major shift in school funding policy occurred in 1988 when voters passed Proposition 98 which created a minimum funding requirement for public schools. Under Proposition 98, the state is required to spend roughly 40 percent of General Fund revenues on its public schools. Most school district funding came through Prop 98 in the form of "revenue limits" in which base funding per pupil was provided and then school districts with revenues falling short of the limit received state funding to make up the difference. This was supplemented with state and federal categorical funding programs that placed restrictions on how the money was spent (Lafortune, 2019).

II. The Local Control Funding Formula

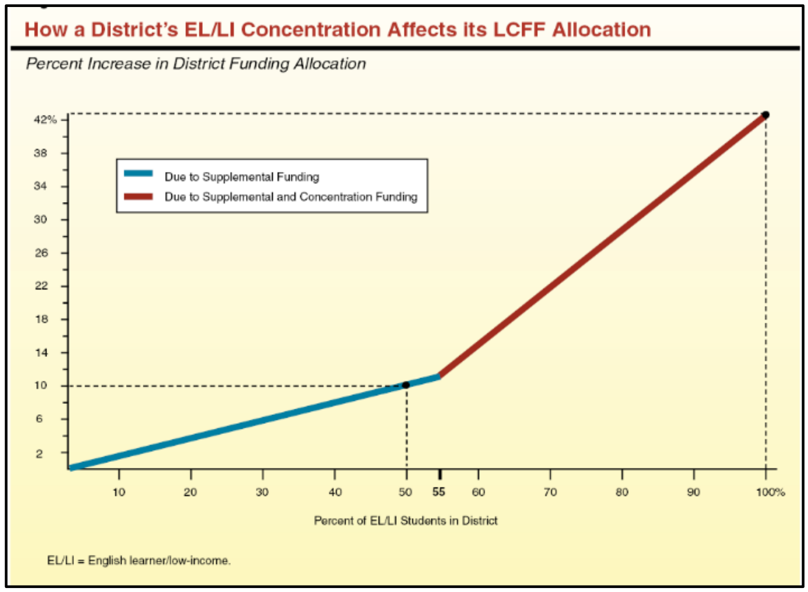
In 2013-2014 the state of California adopted the Local Control Funding Formula (LCFF). This new formula sought to simplify school finance and provide local flexibility and increased accountability that was previously absent with categorical funding programs. The new formula also focused on *equity* rather than *equality* by directing funding towards the students determined to be "high-needs", these students typically have lower academic achievement and stand to benefit the most from an increase in educational resources.

The LCFF formula is divided into three grants; the base grant, supplemental grant and concentration grant. The *base grant* varies by grade level but is tied to a school district's Average Daily Attendance (ADA), providing an equal base amount of funding per student across school districts. K-3 students receive slightly more money from the base grant to support smaller class sizes and 9-12 students receive slightly more funding to support Career Technical Education (CTE).

The *supplemental grant* provides supplemental funding to a school district equal to 20 percent of the base grant for each high-needs student in the school district. The three student groups identified as high needs by the formula are English Language Learners (EL), low-income students (LI), and foster youth. Students are classified as EL based on a home language survey and the California English Language Development Test (CELDT). Once they are determined to be Fluent English Proficient (FEP) they are no longer counted towards the supplemental grant part of the formula. Students are classified as "low-income" based on if they qualify for free or reduced-price meals (FRPM). In many cases, students are determined FRPM-eligible through an application process sent to students' households. If a household's income is below 185 percent of the federal poverty line ($43,568 for a family of four), the student is eligible for FRPM. In other cases, students are directly certified as FRPM-eligible due to participation in other social service programs, such as the California Work Opportunity and Responsibility to Kids program. Foster youth automatically are eligible for FRPM; therefore, the foster family's income has no bearing on the foster student's FRPM eligibility. (Taylor, 2013) If a student falls into more than one high-needs category, if they are both low-income and an English Language Learner for example, they are only counted once in the formula to create the *unduplicated pupil count*. For context, more than half of public-school students in California are economically disadvantaged (low-income), and about a third are English Language Learners (Murphy & Paluch, 2018).

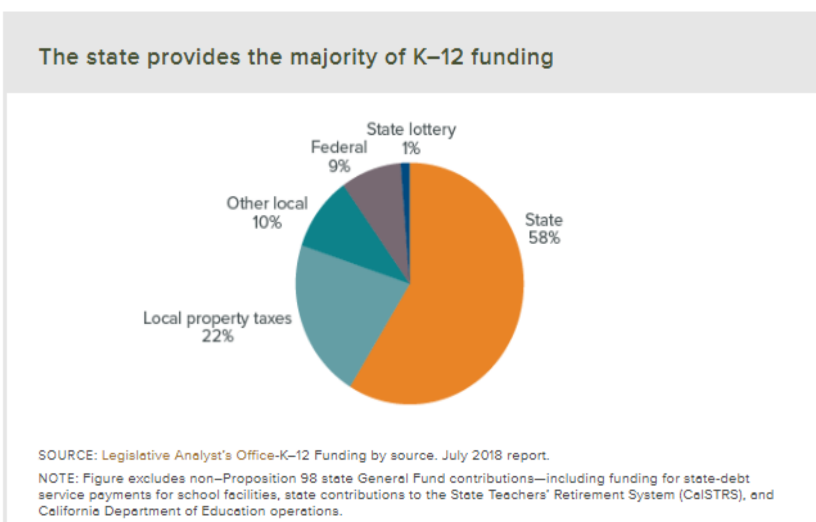
The *concentration* grant part of the formula is then awarded to those school districts in which 55 percent or more of the student population are high needs. For each student above the 55 percent threshold, districts receive additional funding equal to 50 percent of the base grant. (Hill and Ugo, 2015) This three-grant system can create large differences in per pupil funding. In 2018, base LCFF funding was $48 billion and additional funding for high-need students totaled $9.5 billion. Concerns about how districts are distributing supplemental funds have generated proposals for tighter rules on spending. (Murphy and Paluch, 2018) This sliding scale for funding is believed to be more equitable because high-needs students and districts receive more funding than their peers. The concentration grant in particular recognizes that producing better educational outcomes for high-needs students is more challenging in districts where this population is extremely concentrated.

LCFF allows funds to be spent for any educational purpose but requires districts to develop Local Control and Accountability Plans (LCAPs) that detail district goals and document how districts plan to measure their progress toward those goals. School districts must improve or increase services for high-need students in proportion to the increased funding they receive, but they may spend supplemental and concentration grants on district- and school-wide programs.(Taylor, 2013)



Source: California Department of Education

In 2018–19, California public schools received a total of $97.2 billion in funding from three sources: the state (58%), property taxes and other local sources (32%), and the federal government (9%) (Murphy & Paluch, 2018). The state of California is unique in the amount of funding it provides at the state level. California's proportions differ from many other states that have substantial local property tax revenue that is utilized to cover a larger share of school funding. Unlike most states, California's State Constitution, due to the passage of Proposition 13, limits local property tax rates (Taylor, 2018). Of the 6.2 million K–12 students in California, about nine out of ten attend one of the nearly 9,000 regular schools in 1,026 school districts while the other 11% of students attend about 1,228 charter schools—which are publicly funded but not subject to some state regulations.

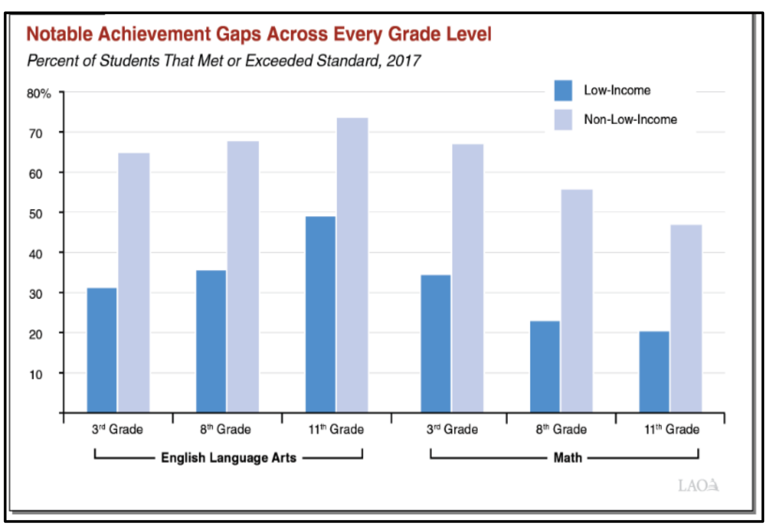


(Murphy & Paluch, 2018)

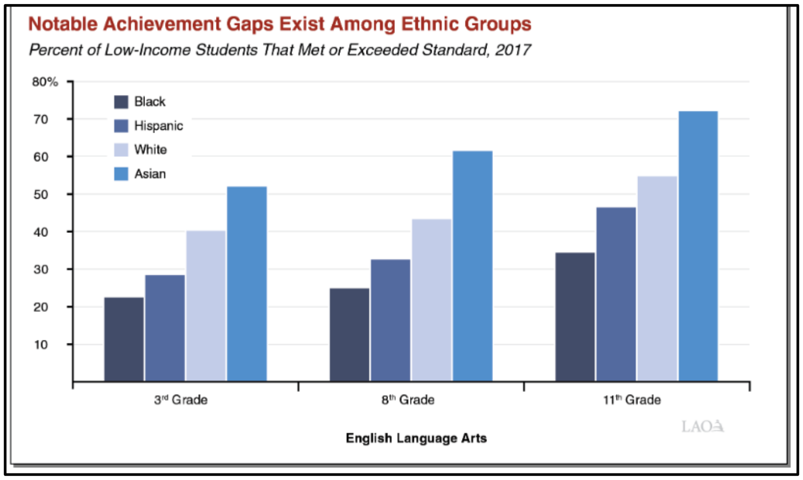
III. Disparities in Academic Performance and Educational Outcomes

Researchers, policy makers and advocates in education have long espoused issues related to equity, particularly as it relates to race, gender, and socioeconomic status. The Equality of Educational Opportunity report, commonly referred to as the “Coleman Report” published in 1966, set the standard for studying public education. It was initially a study commissioned by the U.S Department of Health, Education and Welfare to understand where the nation stood in terms of desegregation of public schools. The extensive report found that a student’s family background (their socioeconomic status) paired with the diversity of socioeconomic backgrounds of their peers in the classroom, was the biggest determinant of educational success. Coleman also found that a substantial achievement gap existed between African-Americans and their White peers, in which African-American students were often several grade levels behind in comparison (Coleman et al. 1966). Since then, a myriad of studies across several decades have confirmed Coleman’s findings to posit that inequalities in opportunity and outcomes along race and socioeconomic lines begin before a child enters school, persists throughout their education and on to the rest of their life. Moreover, these inequalities are more stark in the United States than they are in comparable countries (Bradbury et al. 2015). Poverty is associated with many conditions such as low educational attainment of one’s parents, poor nutrition and healthcare, fewer educational resources at home, weaker preschool education, more exposure to violence and abuse, lack of availability of resources among other characteristics that lead to lower educational outcomes for low-income students (Newberger et al. 2011).

The disparity in educational outcomes along socioeconomic and racial lines is still present today in the state of California. A 2018 LAO report found a stark disparity in test scores amongst student groups. A comparison between low-income and non-low-income students found that only 36 percent of low-income students met or exceeded the state standards in eighth grade English language arts, while 68 percent of non-low-income students met or exceeded standards in comparison. The gaps between students are similar in other grade levels and for math scores as well. Results on statewide exams show significant achievement gaps among California’s four largest ethnic groups. These gaps persist even after controlling for income. As the figure shows, low-income Black and Hispanic students have lower proficiency rates on eighth grade English language arts exams (25 percent and 33 percent) than low-income White and Asian students (44 percent and 62 percent). Similar differences among groups exist in third and eleventh grade (Taylor, 2018). When the scores for low-income students



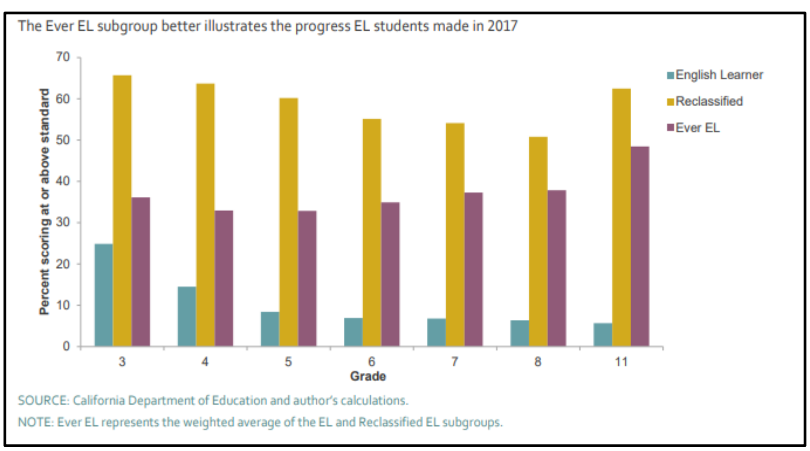
Source: California Legislative Analyst’s Office are broken down by ethnic groups, we see a compounding effect in which Black and Hispanic students are performing even worse than their other low-income peers. Race and ethnicity is notably not one of the high-need student categories identified by the LCFF formula to receive more funding, but race and ethnicity are certainly a consideration for the state and for districts when evaluating achievement gaps and developing LCAPs to produce better student outcomes . These low-income, low performing students are captured by the *unduplicated pupil count*, but the compounding effect of race and ethnicity and income is not captured by the formula. In addition to low-income students, the LCFF also determines English Language Learners to be high-needs students due to the additional barrier of language they must overcome in order to learn. As mentioned previously, once English Language Learners are determined to be "fluent proficient" they are no longer counted in the LCFF's unduplicated pupil count. For the majority of grade levels depicted, less than 10 percent of English Learners are scoring at or above standard on standardized tests, justifying the LCFF's prioritization of this group to receive additional funding to procure more educational resources.



Source: California Leglislative Analyst's Office

IV. Role of Increasing Inequality and Segregation

Schools with high concentrations of students in poverty tend to have less experienced teachers, higher teacher and staff turnover, more remedial and special education classes, fewer honors and AP classes, lower graduation rates, weak connections to college etc., further exacerbating the inequalities that exist before a student enters the classroom (Rothstein, 2004). As mentioned previously, over half of California's K-12 students are low-income, and a rising trend of income inequality in recent decades suggests poverty and concentration/segregation of those living in poverty are expected to increase. The very high level of student poverty is in part a reflection of the intense polarization and inequality of



incomes in the U.S (Noah, 2012). This signals that worsening student outcomes are to come, as the Coleman report and numerous studies posit, students' own socioeconomic background is related to their achievement, but the average socioeconomic background of their peers in school had an equal effect and sometimes even greater effect on academic achievement and educational outcomes than their own individual background (Rumberger & Palardy, 2005). The increased concentration of low-income students disproportionately affects Black and Latino students, creating "double segregation" of race and poverty. An analysis of school composition trends found the following:

> *The typical Black or Latino today attends school with almost double the share of low-income students in their schools than the typical White or Asian student. In the early 1990s, the average Latino and Black student attended a school where roughly a third of students were low-income (as measured by free and reduced-price lunch eligibility), but now attend schools where low income students account for nearly two-thirds of their classmates. There is a very strong relationship between the percent of Latino students in a school and the percent of low-income students. On a scale in which 1.0 would be a perfect relationship, the correlation is a high .71. The same figure is lower, but still high, for Black students (.53). Many minority-segregated schools serve both Black and Latino students. The correlation between the combined percentages of these underserved two groups and the percent of poor children is a dismaying .85.*
>
> -(Orfield et al. 2012)

The effect of "double segregation" is demonstrated previously in California test scores, with the disparate achievement scores of low-income students along racial/ethnic lines. Thus, we can expect that targeting school funds and educational resources to these poverty concentrated school districts via policy interventions like the *concentration grant* of the LCFF will become more paramount in addressing student inequities in educational outcomes.

V. Effects of funding interventions and the LCFF on student outcomes

With that understanding, policymakers have sought policy interventions to ameliorate the inequalities and disparities in success that exist amongst student groups. The LCFF developed and adopted by the California state legislature takes a funding approach to address these inequities by targeting funds to high-needs students. A meta-analysis of the effects of differential school inputs on student outcomes found that resource inputs of teacher education, teacher salary, pupil/teacher ratio, and administrative inputs (which can be facilitated by increased funding) found evidence of statistically significant relationships between those resource inputs and student outcomes (Hedges, Laine, & Greenwald, 1994).

With LCFF not being fully funded until 2018 (an increased K-12 commitment of $18 billion), and the adoption of Common Core standards in 2015 (and subsequent change in state testing from the STAR to SBAC test), conducting a quality longitudinal analysis of LCFF's impact on student performance has been a challenge for policy analysts. Johnson and Tanner's 2018 study is among the first to assess LCFF's impacts on student outcomes. In regards to the aforementioned challenges, they take into account years of exposure and changes in testing procedures, isolate the impact of LCFF funding increases from pre-existing trends and other coincidental changes, and "norm" both the STAR and SBAC tests to the National Assessment of Educational Progress (NAEP), which over this time period, had not changed. The results of their analysis showed average gains in mathematics and, to a smaller extent, in reading for all students. They found effects for high school math scores are particularly strong for students from low-income families (Johnson and Tanner, 2018).

More specifically, Johnson and Tanner find that a $1,000 increase in the average per-pupil spending during 8th through 11th grades leads to a 0.19 standard deviation increase in math and a 0.08 standard deviation increase in reading for poor children. A one standard deviation increase in the proportion of revenue that is unrestricted is roughly 4 percentage points. The same increase leads to a 0.08 standard deviations in reading for non-poor children, for whom no impact on math achievement is detectable. Only 5.8% of California's public school children are Black, so they were unable to break down the results on school-level test scores separately for Black students due to missing reported information in public data when small numbers of Black children are in a school. However, they do find that among Hispanic children, a $1,000 increase in per-pupil spending during 8th through 11th grades leads to an increase of 0.19 standard deviations in math, and 0.11 standard deviations in reading. No statistically significant effects were detectable for White students. The overall positive effects evaluated in their study increase in tandem with the amount of spending increases and the number of school-age years of exposure (Johnson & Tanner, 2018). We take a more simplified approach to our analysis of the *concentration grant* by analyzing the interaction effect between the increase in per-pupil spending that comes with the *concentration grant* and test scores. We come up with similar results in our analysis when utilizing this method.

One of the most glaring challenges with analyzing public school finance is the lack of comprehensive school-level financial data, making it difficult to determine spending *within* a district and whether the *supplemental* and *concentration grants* are reaching the students and schools with the highest need. As a result, analysts rely heavily on teacher pay and experience data to evaluate whether funding is reaching the groups that LCFF targets, but this paints a limited framework of understanding. Nevertheless, Johnson and Tanner posit that LCFF-induced increases when utilized for teacher salaries per pupil (which include both increases in the number of teachers hired and increases in teacher salary) have a positive statistically significant effect on student achievement for low-income and Hispanic students (Johnson & Tanner, 2018). Their findings in this regard are supported by Julien Lafortune's analysis of whether the increased funding from LCFF is reaching high-need students. Lafortune finds that the increase in funding from LCFF was spent on salaries and benefits for teachers and staff. Between the 2013–14 and 2017–18 school years, student spending in high-need districts rose by over $500 more per pupil than in low-need districts. Class sizes during this period decreased in high-need districts more so than in low-need districts. Lafortune's findings for the most part indicate that LCFF funding is reaching the high-need students for whom it was intended. However, high-need districts have a greater reliance on novice and less-qualified staff, suggesting it may take time for gains from LCFF to manifest in high-need schools and districts. Lafortune recommends that ensuring the equitable distribution of LCFF funding will require policies that track funding within districts better, therefore allowing for better accountability of school districts and their use of funds for high-needs students (Lafortune, 2019).

VI. Analysis

Our study aims to determine if the three-tiered grant structure of the LCFF is achieving its intended purpose of funneling money equitably to high needs students. This analysis was performed using a jupyter notebook, which is an editor that allows the integration of the python programming language and markdown language into a single readable notebook. The original data sources, data cleaning merging process and documentation, all regression models, and additional supporting documentation for this project are available to view at https://github.com/fiendskrah/finalcapstone.

Data Sources

In order to conduct our analyses, we first synthesized several datasets. These datasets are 1) student performance data, represented by scores on the Smarter Balanced Assessments (SBAC) in both English language arts (ELA) and math, 2) LCFF funding by district, and 3) eligibility data for FRPM. All data sets provide data for academic year 2018-2019, which is the focal time period of our study. The number of districts varied across datasets: (ELA: 921, math: 920, LCFF: 944, and FRPM: 978). All of these data sets, with the exception of the LCFF dataset, have school-level data, while the LCFF dataset is limited to the district level. Because the LCFF is our primary interest, we opted to aggregate the other datasets to the district level, which allowed us to use school districts as our unit of analysis. Ideally, our analysis would be performed using individual schools as units of analysis. However, as found in previous studies, financial data that is school specific is not readily available.

Methods

To answer our research question, we performed regression analyses to determine if a district receiving a concentration grant had any effect on a student group's scores on the SBAC tests. The SBAC data contains scores for each of the seventeen student groups within each district, but some student groups were missing from certain districts. A school district could conceivably not contain enough students of a particular group to report their scores, but this likely is indicative of at least slightly imperfect SBAC data. As a result, the number of observations varied from model to model depending on which student group was being examined. The seventeen student groups are: all students, African American, American Indian, Alaska Native, Asian, Filipino, Hispanic, Pacific Islander, White, multiple races, English Language Learner, English Learners only (anachronistic group indicating no additional learning barrier such as low-income), RFP (English learners who have achieved proficiency), English only, socioeconomically disadvantaged, students with disabilities, foster youth, and homeless youth. Due to redundancies in student group classifications, we chose to only examine seven of the groups: 1) English Learner and 2) SES disadvantaged, because they are student classifications targeted by the formula; 3) African American, due to continuing disparities in outcomes along racial and ethnic lines resulting from historical racism and segregation; 4) Hispanic, for the same reasons as African American but also because of their large share of the state's population; 5) Asian, who have the highest statewide average scores, and 6) White, to serve as a group not widely adversely affected by structural inequalities as their other student peers. Additionally, we examined the 7) "all student" group to observe any potential district-wide effect on SBAC scores.

Dependent variables

The SBAC data contains two potential indicators to serve as our dependent variable: 'currstatus', or the scores for that particular student group for the given year, or 'change', which indicates the difference between this year's scores and last year's score. While we built models utilizing both options, we decided to discard the models utilizing the change variable, despite returning significant coefficients, due to an understanding that the recency of the implementation of Common Core curricula in academic years 2014-2015 resulted in an overall drop in performance, but scores are expected to increase annually as teachers and students adjust to the new curricula, standards, and new testing model. This expected increase could potentially confound any model with the 'change' indicator as it's dependent variable.

Independent variables

To distinguish districts that receive a concentration grant from those that do not, we create a binary dummy variable called 'treatment'. Districts where treatment = 1 are districts that have an *unduplicated pupil count* comprising of at least 55% of the district's student body, as determined by the LCFF data. The LCFF data contains separate columns itemizing each of the three grants. While our interest is in the effectiveness of the *concentration grant*, regressing only the funds from the *concentration grant* would leave out the districts with less than 55% of high needs students, which serve as a control group for our analysis. To include the control group, we needed to use the total amount of grant funding. However, district funding from all three grants varies due to variations across districts in the number of students they have and the number of students determined to be high-needs. Therefore, regressing the total funding from LCFF without accounting for the size of the district in some way would result in a wide variation, creating too much noise in the coefficients to be interpreted meaningfully. While the LCFF data does not contain information on enrollment numbers, the FPRM data contains enrollment numbers by individual schools, which, after aggregating to the district-level, can be matched to the LCFF data districts and then divided by total funding to infer a 'per_capita_spending' variable. After these inferences and merges, we have our synthesized dataset which includes district identifiers, per-capita grants allotted to those districts, and performance indicators of each student group in each district. We can now slice this data by selecting student groups, which allow us to construct regression models for each student group across the state. Our regression formula is:

Performance indicator = a + per-capita funding + treatment + (per-capita funding x treatment) + e

The interaction effect of (per-capita funding x treatment) allows us to account for the size of each district while still capturing the increased funding from the concentration grant.

Primary Findings

We performed fourteen regression analyses (seven student groups x two performance indicators) and found three statistically significant interaction coefficients across three student groups. Table 1 displays the regression output for our model of English scores for the English Language Learner group. This model is of particular significance due to the disadvantages experienced by the English Language Learner group described in Section III. We find a very small,

```
In [97]: results = smf.ols(formula='ela_currstatus ~ per_capita_funds*treatment', data=el_df,).fit()
         # english learners
         print(results.summary())

                                    OLS Regression Results
         ==============================================================================
         Dep. Variable:         ela_currstatus   R-squared:                       0.231
         Model:                            OLS   Adj. R-squared:                  0.227
         Method:                 Least Squares   F-statistic:                     76.48
         Date:                Fri, 12 Jun 2020   Prob (F-statistic):           2.79e-43
         Time:                        14:01:50   Log-Likelihood:                -3689.9
         No. Observations:                 770   AIC:                             7388.
         Df Residuals:                     766   BIC:                             7406.
         Df Model:                           3
         Covariance Type:            nonrobust
         ==============================================================================================
                                          coef    std err          t      P>|t|      [0.025      0.975]
         ----------------------------------------------------------------------------------------------
         Intercept                      9.3239      9.592      0.972      0.331      -9.506      28.154
         per_capita_funds              -0.0038      0.001     -3.320      0.001      -0.006      -0.002
         treatment                    -58.0248     11.124     -5.216      0.000     -79.861     -36.188
         per_capita_funds:treatment     0.0032      0.001      2.520      0.012       0.001       0.006
```

Table 1: Regression output: English scores, English learner student group

but statistically significant coefficient of 0.0032 for our interaction effect, indicating that the extra funding allotted by the concentration grant to the treatment districts are having a positive effect on english SBAC scores for the English Language Learner group.

Table 2 displays the regression output for our model of math scores for the SES disadvantaged group. This finding is also relevant to policy makers due to LCFF's stated intention of assisting low-income students. Again, the coefficient of 0.0023 is very small, but statistically significant, indicating a positive effect of the *concentration grant* on the scores of low-income students.

```
In [109]: results = smf.ols(formula='m_currstatus ~ per_capita_funds*treatment', data=low_ses_df,).fit()
          # low ses
          print(results.summary())

                            OLS Regression Results
          ==============================================================================
          Dep. Variable:           m_currstatus   R-squared:                       0.190
          Model:                            OLS   Adj. R-squared:                  0.187
          Method:                 Least Squares   F-statistic:                     69.98
          Date:                Fri, 12 Jun 2020   Prob (F-statistic):           1.16e-40
          Time:                        14:01:53   Log-Likelihood:                -4287.1
          No. Observations:                 899   AIC:                             8582.
          Df Residuals:                     895   BIC:                             8601.
          Df Model:                           3
          Covariance Type:            nonrobust
          ==============================================================================================
                                       coef    std err          t      P>|t|      [0.025      0.975]
          ----------------------------------------------------------------------------------------------
          Intercept                  -18.0204      7.089     -2.542      0.011     -31.932      -4.108
          per_capita_funds            -0.0028      0.001     -3.384      0.001      -0.004      -0.001
          treatment                  -45.5084      8.572     -5.309      0.000     -62.333     -28.684
          per_capita_funds:treatment   0.0023      0.001      2.371      0.018       0.000       0.004
```

Table 2: Regression output: math scores, SES disadvantaged student group

Lastly, table 3 presents the regression output for our model of math scores for the Hispanic student group. An initial concern of this finding is that there could be some overlap between student groups. A student could conceivably belong to both the English learner group and the Hispanic group (or the low-income group and the Hispanic group). However, due to the larger proportion of Hispanic students in California compared to other states, and the understanding that they perform lower than their White and Asian peers, we include this model in our findings.

While individual ethnic groups are not targeted by the LCFF, this finding indicates that there can be beneficial effects to groups beyond those targeted. The 2018 LAO report cited in Section III indicates that achievement gaps exist between ethnic groups, even when controlling for factors understood to impact academic performance such as income. However, the fact that we did not find significant coefficients in any other ethnic group model urges caution when interpreting these benefits to be widely applicable.

```
In [125]: results = smf.ols(formula='m_currstatus ~ per_capita_funds*treatment', data=hisp_df,).fit()
          # hispanic
          print(results.summary())

                                OLS Regression Results
          ==============================================================================
          Dep. Variable:           m_currstatus   R-squared:                       0.262
          Model:                            OLS   Adj. R-squared:                  0.260
          Method:                 Least Squares   F-statistic:                     100.4
          Date:                Fri, 12 Jun 2020   Prob (F-statistic):           1.41e-55
          Time:                        14:01:56   Log-Likelihood:                -4065.6
          No. Observations:                 850   AIC:                             8139.
          Df Residuals:                     846   BIC:                             8158.
          Df Model:                           3
          Covariance Type:            nonrobust
          ==============================================================================================
                                         coef    std err          t      P>|t|      [0.025      0.975]
          ----------------------------------------------------------------------------------------------
          Intercept                    3.8486      8.101      0.475      0.635     -12.053      19.750
          per_capita_funds            -0.0047      0.001     -4.951      0.000      -0.007      -0.003
          treatment                  -67.1237      9.758     -6.879      0.000     -86.276     -47.972
          per_capita_funds:treatment   0.0041      0.001      3.734      0.000       0.002       0.006
```

Table 3: Regression output: math scores, Hispanic student group

VII. Discussion

We interpret the statistically significant large negative coefficient for 'treatment' across each of these models to be endogenous to those districts. The treatment districts are those districts that have a majority (<55%) share of high-needs students. Due to the lower achievement scores of high-needs students, these districts are extremely likely to have lower scores just by virtue of the composition of their student body. Furthermore, 'assignment' of the treatment in this case is not random due to being specifically targeted by LCFF, which violates OLS assumptions. The large size of the 'treatment' coefficients make sense when considering that some of these districts have *unduplicated pupil count* shares as large as 100% and that concentrated poverty has a negative effect on academic achievement, as described in Section III. The 'per_capita_funds' variable does not encompass anything beyond the amount of money granted to a district on a per student basis, and includes all districts in the synthesized dataset. We therefore conclude that neither the 'treatment' variable nor the 'per_capita_funding' variable can be interpreted with much meaning by themselves.

Limitations

One major limitation lies in the incompleteness of the data. Each of the datasets used in this study contained fewer districts than the 1,037 districts listed on the California Department of Education's website. Additionally, the differences in the number of districts across our datasets creates problems in matching districts. While it is troubling to note that the state lacks complete data on institutions receiving taxpayer money, the number of school districts is subject to change based on districts being created, merged, or dissolved as a county's need arises. This is simply indicative of the fact that data collection and management in this area needs to be improved. It is not uncommon for studies regarding education policy to drop districts due to matching errors or outliers. In our case, districts are dropped in the process of slicing student groups from the synthesized dataset based on if those groups' scores are collected by that district.

Another limitation is the recency with which the LCFF has been fully funded by the state legislature. As discussed in Section V, the 2018-2019 academic year is the first year that LCFF was fully funded. While this study produced optimistic results, we will need to see more data years of academic performance with full LCFF funding to have a comprehensive understanding of the effects of the *concentration grant* on student performance.

Policy Recommendations

As discussed in Section IV, the disadvantages associated with low-income students is further compounded by race and ethnicity. Poor Black and Latino students perform lower than their other low-income peers, creating impacts of "double segregation," a phenomenon that is projected to worsen as these students attend schools whose student body is becoming increasingly poorer and more segregated. State legislators should consider expanding the criteria for *concentration grants* to include extra funding to students affected by double segregation. One way to address this could be to create another funding layer to the LCFF - in the same way that the *concentration grant* targets high-needs students, a fourth *'double segregation'* grant could trigger under certain conditions that would allow it to target high-needs districts with high Black and Latino populations.

The issues with incompleteness and inconsistency in education data hamper the efforts of policy analysts to improve California's education systems, including both the current study and several studies in our literature review. The California Department of Education should perform a full review of data collection methods and storage practices to ensure the completeness and accuracy of data for future studies. The previously cited differences in district numbers between datasets (and the lack of explanation or notation from CDE) are glaring examples. Other issues include the use of 14-digit CDS (county, district, school) codes, which are designed to make matching operations between datasets easier. However, in practice, the CDS codes are constructed differently across datasets: some datasets contain one column with the entire CDS code, while others split the code into three columns (one for county, district, and school, respectively). CDS codes are particularly important when one needs to distinguish between districts or schools that have the same name. Finally, as described in Section V, the complete inaccessibility of school level financial data hampers policy analyst's ability to determine whether funds are actually being directed to high need students and schools within a district. Requiring funding reporting at the individual school level would allow for a more thorough analysis of the impact and implementation of the formula, as well as facilitate better school district accountability and transparency.

While the incompleteness of data could be indicative of a lack of systematic oversight in data control, the issue of inconsistency could potentially be addressed by the development of an application programming interface (API). APIs allow any user who has acquired approval to interface directly with the agency's data via a coding language to download only requested data in a format specified by the user. APIs are common at companies that make data available for users, but are increasingly being used at federal agencies such as the Bureau for Economic Analysis to allow for transparency and accountability. If CDE were to develop an API, it could potentially facilitate more precise analysis of education policy. Generally speaking, all local and federal government agencies that deal with public-facing data should work towards developing an API. Ideally, there would be national guidance from congress in terms of storage practices to allow better comparison of data across states.

Items for further research

As alluded to in the previous section, this analysis relies on only one data year of full funding for the LCFF. Further iterations of this study as data years become available could yield a more complete understanding of the dynamics of concentration funding on high-needs school districts. Another dimension to this iteration could be differentiation of district types. According to CDE's website, there are 345 unified school districts, 528 elementary school districts, 76 high school districts, and 88 'other' districts, each with a different base grant formulation, as discussed in Section II. Differentiating models by district type could reveal varying effects of the *concentration grant.*

An alternate iteration of this research could be to incorporate regression discontinuity designs. The sample of districts could be narrowed down and 'paired' for treatment and control in a number of ways. Scholars can utilize geographic data, income data, and demographic data from the census to match districts that are most alike in household income, ethnic group makeup, or are within a certain distance from each other to better isolate the effects of the *concentration grant.*

Importantly, the major barrier to understanding the link between funding and student performance, as discussed throughout this report, is the lack of comprehensive school-level funding data. We have relatively good school-level data for performance indicators and FRPM eligibility, but without untangling the complex web of funding mechanisms that power individual schools, policy makers will always lack a complete understanding of the impacts of increased funding on academic outcomes.

Conclusion

This study contributes to the collective body of research of policy makers and education policy scholars by examining the link between increased per-capita funding via the LCFF *concentration grant* and academic performance for disadvantaged student groups. Our findings indicate that LCFF is having a beneficial effect for these student groups, but we emphasize that incomplete data continues to be a major impediment to a comprehensive understanding of these effects. Moreover, LCFF is still in its infancy: more years of being fully funded, increased length of exposure to LCFF, and allowing time for students and teachers to adjust to new curricula and testing is crucial to understanding the full effects of this policy. Unfortunately, due to the volatility of California's revenue base due to a heavy reliance on personal income taxes, funding LCFF stands to be impacted by dramatic fluctuations in the economy, such as the economic recession we are currently experiencing due to COVID-19. Nevertheless, LCFF is a groundbreaking policy intervention that very early on is showing promising returns. Further analyses of the formula stand to assist the state with adjusting the formula for better optimization, and informing school finance reform efforts in other states.

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