Analyzing the Effects of Student Spending on Academic Performance

Isamar Marte Nunez, Duru I. Unsal , and Jackline W. Wambua

Stanford University

Professor Guido Imbens and Professor Mary Wooters

ECON 115: Causality, Decision Making, and Data Science

December 11, 2024

Analyzing the Effects of Student Spending on Academic Performance

The allocation of financial resources within educational systems remains a critical topic in education policy. Debates persist regarding the extent to which increased funding influences student achievement. One perspective argues that enhanced financial resources enable schools to provide better educational services, therefore improving student performance. In contrast, some claim that simply increasing budgets does not necessarily lead to improved academic outcomes. This paper is an empirical study that aims to examine the causal relationship between per-pupil spending and student academic performance, focusing on students from low socioeconomic status (SES) in high schools in California.

In the academic year 2013-2014, California implemented the Local Control Funding Formula (LCFF) to subsidize public schools. In this setting, all schools receive a base funding determined by the number of students in their average daily attendance (ADA), and extra grants are available depending on the number of high-need students per school, which includes low-income students, participants in ESL programs, and children who receive foster care. One particular funding source is the Concentration Grant, which provides 65 percent of the adjusted base grant multiplied by ADA, and it is applicable when the percentage of targeted pupils exceeds 55 percent of a school district's enrollment. This specific cutoff makes this study a great candidate for regression discontinuity design (RDD), which we implement to analyze the data near the boundary and determine if increased funding influences student performance in English Language Arts (ELA) and Math assessments.

Data sources include the Census Day Enrollment Data, results from the California Assessment of Student Performance and Progress (CAASPP), California Basic Educational Data System (CBEDS) information on schools and districts, and the Current Expense of Education data to estimate per-student investment. Given that spending data is available at the district level, district averages are utilized as proxies for school-level spending.

Literature Review

Studies about the relationship between school funding and student achievement present varied and sometimes contradictory conclusions. However, research using causal inference methods is quite limited. Early publications, such as the Coleman Report in 1966, highlighted that the most important predictor of educational outcomes is socioeconomic status, pioneering discussions on resource allocation to mitigate these gaps and providing a reference for future research in the field of economics of education.

In How Money Matters: The Effect of School District Spending on Academic Achievement, Wenglinsky analyzed the effects of per-pupil spending on academic achievement, finding that increased spending on instruction and administration correlates with higher student performance, primarily because of reduced class sizes (1997). Wenglinsky used Structural Equation Modeling to demonstrate that financial resources significantly impact student outcomes, particularly in low SES areas.

In contrast, Hanushek (1986) argued that there is an inconsistent relationship between school resources and student achievement, suggesting that simply increasing funding does not guarantee improved outcomes. Hanushek's analysis emphasized the importance of how resources are utilized rather than the amount allocated.

More recent studies provide nuanced insights with the implementation of more rigorous causal methods. Jackson, Johnson, and Persico (2016) employed event study and instrumental variable models to show that a 10% increase in per-pupil spending each year for all 12 years of public school leads to 0.27 more completed years of education, approximately 7.25% higher wages, and a 3.67 percentage point reduction in adult poverty. These effects were more pronounced for children from low-income families, indicating that increased funding can have substantial long-term benefits for students.

In the context of California, a recent study on the LCFF shows that funding increases under this formula improved academic achievement across various grades and subjects, reduced grade repetition, lowered suspension rates, and enhanced high school graduation and college readiness rates (Johnson & Tanner, 2018). The impact was more significant with prolonged exposure to increased funding and higher funding amounts.

Collectively, the literature suggests that while increased school spending can positively affect student outcomes, the effectiveness of such investments depends on strategic allocation, with targeted funding for disadvantaged students yielding the most significant benefits. Given this context, our study breaks new ground by employing a regression discontinuity design to explore the effect of per-pupil spending on the academic performance of students from low SES backgrounds. We aim to understand whether higher per-student spending translates into improved 11th-grade CAASPP scores for economically disadvantaged students, while also examining how this spending effect differs between subject areas, such as Math and English Language Arts. To address these research objectives, we will use datasets containing information on district expenditures, student enrollment figures, and standardized test results.

Datasets

The first dataset in our study is the 2014-2015 CAASPP Smarter Balanced Assessments results. This dataset, aggregated by student groups, includes detailed performance metrics for socioeconomically disadvantaged students at the school level. Key variables include the mean scale score, the percentage of students meeting or exceeding standards, and other performance benchmarks. These metrics serve as the primary outcomes in our analysis and allow us to focus specifically on the target population of socioeconomically disadvantaged students. Although the policy change took effect in the 2013-2014 school year, the earliest available test score data is from 2014-2015, which we used for this analysis.

The second dataset is the 2014-2015 Current Expense of Education dataset, which reports the cost of education per average daily attendance (ADA) at the district level. Since spending data was not available at the school level, we assigned the district-level spending value to all high schools within the district.

While this approach is a limitation, it reflects the best available granularity for this analysis. Again, although the policy was affected in 2013, the earliest spending data available was for the following 2014-2014 school year.

The third dataset is the 2016-2017 Census Day Enrollment Data, which includes information on total school enrollment and the number of socioeconomically disadvantaged students. From this dataset, we calculated the ratio of socioeconomically disadvantaged students for each high school, which determined the treatment cutoff for the regression discontinuity design. Given that the enrollment data was collected in a year slightly offset from the other datasets, we proceeded with the assumption that the socioeconomic composition of schools remained relatively consistent during this short period, as significant variations in school demographics seemed improbable over such a brief interval. Similar to our other two datasets, this inconsistency in the school year for the data was due to a lack of published datasets; therefore, we used the earliest data available for the school year.

The datasets were merged using a combination of school and district identifiers. First, the CAASPP performance data was matched at the school level to the enrollment data, adding the calculated ratio of socioeconomically disadvantaged students. This school-level dataset was then merged with the district-level spending data using district identifiers. To ensure data quality, we cleaned the dataset by removing rows with missing or invalid values for key variables such as test scores, spending data, and the socioeconomic ratio. The resulting integrated dataset enables a nuanced analysis of how district spending potentially impacts academic outcomes for socioeconomically disadvantaged students.

Methods

We utilized a regression discontinuity design (RDD) to examine the impact of additional funding, defined as schools exceeding the 55% threshold of socioeconomically disadvantaged students (the treatment group). In the context of this study, the outcome of interest is the average test scores of low socio-economic status (SES) students in a school, specifically focusing on the score outcomes for the English Language Arts (ELA) and Math CAASPP tests.

Let Y_s represent the outcome (average test scores) for low SES students in school s. The potential outcomes for a school s are denoted as:

- $Y_s(0)$: The average test scores in the absence of the treatment (i.e., no additional spending on low SES students).
- $Y_s(1)$: The average test scores in the presence of the treatment (i.e., additional spending for low SES students).

The running variable X_s is defined as the share of low SES students in school s, and the treatment variable W_s is:

$$W_s = 1\{X_s \geq 55\%\}$$

where $W_s = 1$ indicates that the school's share of low SES students is at least 55%, and $W_s = 0$ otherwise. The 55% threshold represents the cutoff for receiving additional funding.

This RD design allows us to estimate the causal effect of additional funding (i.e., the treatment) on students' academic outcomes by comparing schools just below and just above the 55% threshold. Our approach involved three key steps: (1) an RD analysis without covariates and (2) an RD analysis controlling for school spending per Average Daily Attendance (ADA).

1. Regression Discontinuity Without Covariates

In the first stage, we performed RD analyses to estimate the effect of additional funding on mean scale scores in ELA and Math without controlling for any other variables. The threshold for treatment was defined as a school's socioeconomically disadvantaged student ratio meeting or exceeding 55%. To account for local effects near the cutoff, we restricted the analysis to a bandwidth of 5% around the 55% threshold.

The decision to use a 5% bandwidth was driven by the goal of balancing precision with potential bias. A smaller bandwidth (e.g., 5%) reduces the possibility of including observations that are too far from the cutoff, which might introduce greater variability and noise. It also allows us to focus on observations that are most relevant to the treatment effect—schools whose socioeconomically disadvantaged student ratios are very close to the 55% threshold. This choice ensures that we are capturing the causal effect of the treatment at the margin, where schools are most likely to be similar in all respects except for the funding differential.

For both ELA and Math, we created a binary treatment indicator (1 if the ratio of socioeconomically disadvantaged students was ≥55%, otherwise 0). The dependent variable in each regression was the mean scale score, and the independent variable was the treatment indicator. We applied Ordinary Least Squares (OLS) regression and visualized the results with scatterplots, indicating the cutoff and bandwidth limits. This initial RD analysis provided a baseline understanding of how mean scores differed across the funding threshold.

2. Controlling for School Spending per ADA

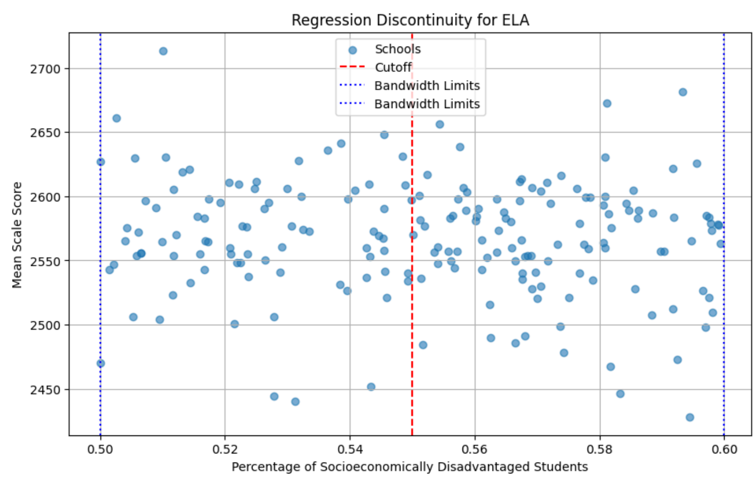
In the second stage, we incorporated schools' current spending per ADA as a control variable to isolate the effect of additional funding from potential confounding caused by variations in school expenditures. The analysis followed the same steps as in the first stage but included spending per ADA as an additional predictor in the regression model. For both ELA and Math, we regressed mean scale scores on the treatment indicator and school spending, using a wider bandwidth of 10% around the cutoff.

The decision to use a 10% bandwidth in this step allowed for a broader range of schools to be included in the analysis. The larger bandwidth helps to reduce the potential loss of statistical power that could result from limiting the analysis to a smaller range of observations. With the inclusion of spending per ADA as a control, the impact of the additional funding policy can be better isolated, allowing us to capture a more robust estimate of the treatment effect. This adjustment allowed us to estimate the treatment effect while accounting for differences in financial resources across schools.

Findings

Regression Discontinuity Without Covariates: English Language Arts

```
Regression Results for ELA:
                            OLS Regression Results
==============================================================================
Dep. Variable:       Mean Scale Score   R-squared:                       0.004
Model:                            OLS   Adj. R-squared:                 -0.001
Method:                 Least Squares   F-statistic:                    0.7348
Date:                Sat, 16 Nov 2024   Prob (F-statistic):              0.392
Time:                        12:29:18   Log-Likelihood:                -1018.8
No. Observations:                 195   AIC:                             2042.
Df Residuals:                     193   BIC:                             2048.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       2570.3459      4.902    524.322      0.000    2560.677    2580.015
Treatment     -5.5950      6.527     -0.857      0.392     -18.468       7.278
==============================================================================
Omnibus:                        8.832   Durbin-Watson:                   1.724
Prob(Omnibus):                  0.012   Jarque-Bera (JB):               10.735
Skew:                          -0.343   Prob(JB):                      0.00467
Kurtosis:                       3.922   Cond. No.                         2.80
==============================================================================
```

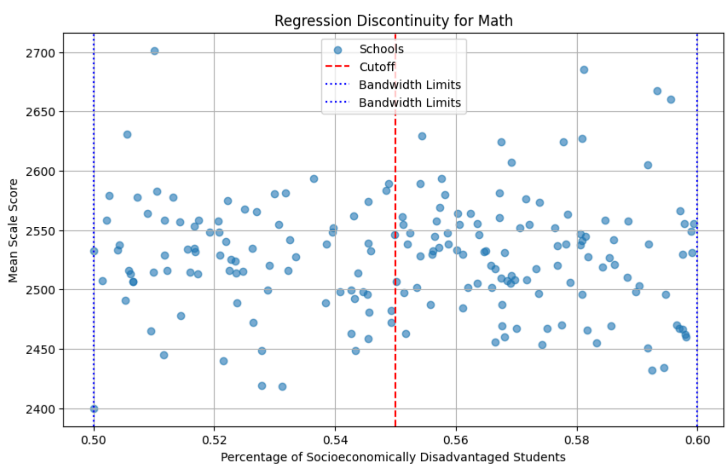


The regression discontinuity analysis without covariates assessed the causal effect of additional funding on mean scale scores in English Language Arts (ELA), using the socioeconomically disadvantaged student ratio as the treatment threshold. The treatment coefficient (-5.5950, $p > 0.1$), suggests that schools above the 55% threshold (eligible for additional funding) scored about 5.6 points lower on average than those below the threshold. However, this difference is not statistically significant ($p = 0.392$), providing insufficient evidence that additional funding influenced mean scale scores. The model has a poor fit, with an R-squared of 0.004, indicating that only 0.4% of the variation in mean scale scores is explained by the treatment indicator. The adjusted R-squared (-0.001) further confirms that the model explains virtually no variance.

The accompanying scatterplot visually supports these findings, showing substantial variation in mean scale scores around the 55% threshold without any clear discontinuity. The red vertical line represents the cutoff, and the blue dashed lines indicate the 5% bandwidth limits, revealing no apparent difference between schools above and below the threshold. In conclusion, this analysis indicates no statistically significant impact of additional funding (based on the ≥55% threshold) on mean scale scores in ELA within the 5% bandwidth. The weak model fit and insignificant treatment effect suggests that other factors may influence mean scale scores. Further analysis with covariates or alternative bandwidths could provide deeper insights.

Regression Discontinuity Without Covariates: Math

```
Regression Results for Math:
                            OLS Regression Results
==============================================================================
Dep. Variable:       Mean Scale Score   R-squared:                       0.002
Model:                            OLS   Adj. R-squared:                 -0.003
Method:                 Least Squares   F-statistic:                    0.4031
Date:                Sat, 16 Nov 2024   Prob (F-statistic):              0.526
Time:                        12:29:18   Log-Likelihood:                -1022.5
No. Observations:                 193   AIC:                             2049.
Df Residuals:                     191   BIC:                             2056.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       2525.2188      5.275    478.754      0.000    2514.815    2535.623
Treatment      4.4765      7.051      0.635      0.526      -9.431      18.384
==============================================================================
Omnibus:                       10.113   Durbin-Watson:                   1.760
Prob(Omnibus):                  0.006   Jarque-Bera (JB):               12.827
Skew:                           0.374   Prob(JB):                      0.00164
Kurtosis:                       4.017   Cond. No.                         2.78
==============================================================================
```

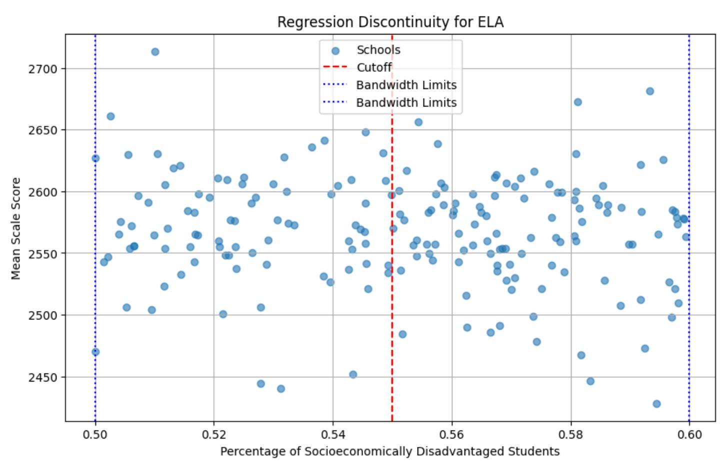


The regression discontinuity analysis without covariates for Math examined the effect of additional funding on mean scale scores, focusing on schools with a socioeconomically disadvantaged student ratio near the 55% threshold. The treatment coefficient (4.4765, $p > 0.1$) is positive but statistically insignificant, suggesting no evidence of a meaningful difference in mean Math scores for schools above versus below the 55% threshold. The R-squared value (0.002) indicates that only 0.2% of the variance in Math scores is explained by the treatment, with the adjusted R-squared (-0.003) further confirming the model's poor explanation.

The accompanying scatterplot provides a visual representation of mean Math scale scores relative to the percentage of socioeconomically disadvantaged students. The red vertical line marks the 55% cutoff, while the blue dashed lines represent the 5% bandwidth limits. The plot shows substantial variability in scores on both sides of the threshold, with no clear discontinuity at the cutoff, supporting the regression results. In summary, the analysis indicates no statistically significant impact of additional funding (based on the ≥55% threshold) on Math mean scale scores within the 5% bandwidth. The weak model fit and lack of significant treatment effects suggest other factors may influence Math scores, requiring further exploration with covariates or alternative methods.

Controlling for School Spending per ADA: ELA

```
Regression Results for ELA:
                            OLS Regression Results
==============================================================================
Dep. Variable:       Mean Scale Score   R-squared:                       0.011
Model:                            OLS   Adj. R-squared:                  0.000
Method:                 Least Squares   F-statistic:                     1.031
Date:                Sat, 16 Nov 2024   Prob (F-statistic):              0.359
Time:                        12:27:37   Log-Likelihood:                -1018.2
No. Observations:                 195   AIC:                             2042.
Df Residuals:                     192   BIC:                             2052.
Df Model:                           2
Covariance Type:            nonrobust
=============================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------
const                    2573.7586      5.725    449.584      0.000    2562.467    2585.050
Treatment                  -6.5908      6.579     -1.002      0.318     -19.566       6.385
Current Expense Per ADA    -0.0002      0.000     -1.152      0.251      -0.001       0.000
==============================================================================
Omnibus:                        8.651   Durbin-Watson:                   1.729
Prob(Omnibus):                  0.013   Jarque-Bera (JB):               10.392
Skew:                          -0.342   Prob(JB):                      0.00554
Kurtosis:                       3.901   Cond. No.                     5.42e+04
==============================================================================
```

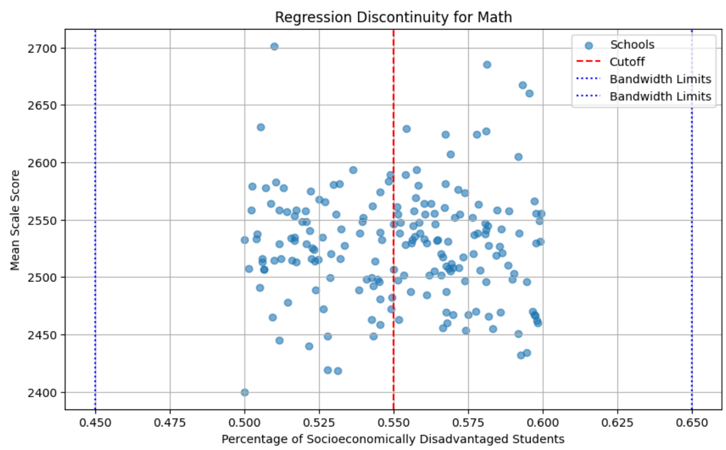


Incorporating school current spending per ADA as a control variable, the regression results for ELA indicate that the treatment indicator has a coefficient of -6.591 ($p > 0.1$), suggesting that schools above the threshold scored about 6.59 points lower than those below it. However, this difference is not statistically significant, providing no conclusive evidence of a treatment effect on ELA mean scale scores. Similarly, current spending per ADA has a coefficient of -0.0002 ($p > 0.1$), indicating no significant relationship between spending and scores. The model has a very low R^2 value of 0.011, showing that only 1.1% of the variation in scores is explained by the predictors, and an adjusted R^2 of 0.000, further underscoring its weak explanatory power.

Additionally, the scatterplot visually supports these findings, showing substantial variation in scores on both sides of the 55% cutoff with no clear discontinuity, even when considering the broader 10% bandwidth. Overall, the results indicate no significant effect of additional funding on ELA mean scale scores after controlling for spending per ADA, emphasizing the need for further analysis with additional covariates or alternative models

Controlling for School Spending per ADA: Math

```
Regression Results for Math:
                            OLS Regression Results
==============================================================================
Dep. Variable:       Mean Scale Score   R-squared:                       0.039
Model:                            OLS   Adj. R-squared:                  0.028
Method:                 Least Squares   F-statistic:                     3.813
Date:                Sat, 30 Nov 2024   Prob (F-statistic):             0.0238
Time:                        13:30:24   Log-Likelihood:                -1018.9
No. Observations:                 193   AIC:                             2044.
Df Residuals:                     190   BIC:                             2054.
Df Model:                           2
Covariance Type:            nonrobust
=============================================================================================
                              coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------
const                    2533.6520      6.067    417.609      0.000    2521.685    2545.619
Treatment                   2.0321      6.999      0.290      0.772     -11.773      15.837
Current Expense Per ADA    -0.0005      0.000     -2.685      0.008      -0.001      -0.000
==============================================================================
Omnibus:                       10.962   Durbin-Watson:                   1.795
Prob(Omnibus):                  0.004   Jarque-Bera (JB):               13.873
Skew:                           0.405   Prob(JB):                     0.000972
Kurtosis:                       4.033   Cond. No.                     5.42e+04
==============================================================================
```



Incorporating school current spending per ADA as a control variable, the regression results for Math scores showed nuanced findings. The treatment effect coefficient (2.0321, $p > 0.1$) is positive but statistically insignificant, indicating no robust evidence that schools above the 55% threshold (eligible for additional funding) scored differently from those below the threshold. However, the coefficient for current spending per ADA (-0.0005, $p < 0.01$) is negative and statistically significant, suggesting that higher spending per ADA is associated with slightly lower mean scale scores. The model's R-squared value (0.039) indicates that the included predictors explain only 3.9% of the variation in Math scores, reflecting a weak model fit. The adjusted R-squared (0.028) reinforces this, suggesting limited explanatory power. Visual inspection through the scatterplot similarly showed no apparent discontinuity in Math scores at the treatment threshold, supporting the statistical results. This analysis suggests that while spending per ADA may play a role, additional funding based on the ≥55% threshold does not significantly impact Math scores, and other unobserved factors may influence academic outcomes.

To visually support the regression findings, the scatterplot illustrates Math mean scale scores relative to the percentage of socioeconomically disadvantaged students. The red vertical line indicates the 55% cutoff for treatment, distinguishing schools above and below the funding threshold, while the blue dashed lines define the 10% bandwidth limits around the cutoff. The scatterplot reveals substantial variation in Math scores on both sides of the threshold, with no clear discontinuity at the cutoff. This visual evidence aligns with the regression results, confirming that additional funding based on the 55% threshold does not significantly affect Math scores.

Limitations

This analysis faced several limitations that could influence the findings and their interpretation. First, spending data was only available at the district level rather than the school level. As a result, spending was assumed to be uniform across all schools within a district, which may obscure variations in resource allocation among individual schools, reducing the precision of the analysis. Additionally, while the policy change took effect in the 2013-2014 school year, test score data was only available for the 2014-2015 school year, creating a temporal gap that may not capture the immediate effects of the policy. Similarly, enrollment data, used to calculate the socioeconomically disadvantaged student ratio, was from the 2016-2017 school year, slightly later than the other datasets. This mismatch could introduce inaccuracies if the socioeconomic composition of schools changed significantly over time.

Another limitation is that there was no data available for other covariates to control for beyond school spending per Average Daily Attendance (ADA), which restricted the ability to isolate the treatment effect from other influencing factors. Furthermore, the data cleaning process involved removing rows with missing or invalid values, which, while necessary for ensuring data quality, potentially reduced the sample size and may have affected the representativeness of the final dataset. Lastly, the reliance on datasets from different years, driven by data availability constraints, introduced potential inconsistencies during the merging process. This temporal misalignment, combined with the reduced sample size, may have limited the robustness of the analysis and the ability to draw precise conclusions about the relationship between spending and academic outcomes. Despite these limitations, the analysis provides valuable insights into the relationship between increased spending and academic outcomes for socioeconomically disadvantaged students.

Conclusion

Researching the effects of budget allocation is essential in determining the most cost-effective ways to impact educational experiences and the many benefits they have on students in the short and long term. This study aimed to contribute to the discussion by examining if increased school funding impacts student academic outcomes. Using a regression discontinuity design (RDD), we researched the causal effect of school funding by comparing schools that received additional funding through the Local Control Funding Formula (LCFF) to those within the 5% range of the eligibility cutoff.

Our analysis found null results, suggesting that increased funding did not lead to statistically significant changes in student performance as measured by 11th-grade scores on the CAASPP Smarter Balanced Assessments. These findings challenge the assumption that merely increasing financial resources automatically translates to better academic outcomes and highlight the need for further exploration into how and where funds are allocated. It also raises the question of analyzing if the funding provided is sufficient to produce the desired results.

However, it is crucial to consider that our study is limited in scope and focuses on average effects. For example, it is possible that increased funding benefits specific subgroups, such as economically disadvantaged students, or impacts non-academic outcomes like graduation rates, college readiness, or socio-emotional well-being, as other studies have found statistically significant evidence. These nuances could not be captured fully in our analysis and require further investigation.

Future research should build on this study by incorporating broader datasets, alternative measures of academic success, and diverse methodological approaches. Longitudinal studies or experimental designs that track individual students over time could provide deeper insights into the effects of school funding on academic and life outcomes. Similarly, exploring the interplay of funding with other variables, such as community resources, parental involvement, and school leadership, could enhance our understanding of what drives student success.

With this study in mind, policymakers should remain cautious in assuming that increased funding alone will close achievement gaps and should instead focus on optimizing resource allocation to address specific challenges and needs within schools. Constantly questioning and revising current policies allows governments to develop more effective strategies to create more efficient and equitable education systems.

References

Wenglinsky, H. (1997). How Money Matters: The Effect of School District Spending on Academic Achievement. *Sociology of Education*, *70*(3), 221–237. https://doi.org/10.2307/2673210

Hanushek, E. A. (1986). The economics of schooling: Production and efficiency in public schools. *Journal of Economic Literature*, 24(3), 1141–1177. https://www.jstor.org/stable/pdf/2725865.pdf

Jackson, C. K., Johnson, R., & Persico, C. (2016). The effects of school spending on educational and economic outcomes: Evidence from school finance reforms. *The Quarterly Journal of Economics*, 131(1), 157–218. https://gsppi.berkeley.edu/~ruckerj/QJE_resubmit_final_version.pdf

Johnson, R. C., & Tanner, S. (2018). Money and freedom: The impact of California's school finance reform on academic achievement and the composition of district spending. https://gettingdowntofacts.com/sites/default/files/2018-09/GDTFII_Report_Johnson.pdf