

# Do Lower Instructional Expenditures Lead to Higher 4-Year Public High School Graduation Rates in the U.S.?

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## Introduction

With the national public high school 4-year adjusted cohort graduation rate (ACGR) in the United States residing at 81.4%<sup>†</sup>, with the lowest rate of 71.7% held by Georgia and the highest rate of 89.7% claimed by Iowa, it is no surprise that many people would like to direct more money into the public education system. After all, it is commonly thought that more money in schools will translate into increased student achievement, and in particular more graduates. Educational expenses that are often first considered when utilizing this frame of thought are instructional supplies, instructional services, and teacher compensation, collectively known as instructional expenditures.

But does increased spending on instruction lead to higher 4-year public high school graduation rates? Some would argue yes. Instructional supplies and services are extremely important to student learning since they are part of the foundation of classroom education. More money for supplies and services would ensure that all students are set up for a successful learning experience. And perhaps paying teachers higher wages-or simply giving them annual bonuses for yielding higher standardized test scores-will increase their effectiveness as educators. A higher paid teacher could focus more on her curriculum instead of working a second, part-time job to make ends meet. While this theory seems plausible, the contrary theory seems reasonable too and is the hypothesis of this paper. Lower instructional expenditures per student may actually lead to higher 4-year ACGRs in U.S. public high school districts, because lower instructional expenditures would require schools to be innovative with their curricula in ways that promote student achievement and also require schools to employ the types of teachers who are willing to get paid lower salaries.

## Methods

In this investigation, we study the relationship between 4-year ACGR and instructional expenditures per student in public high school districts across forty eight of the fifty states, including the District of Columbia. We take into account demographic and financial variables related to education systems, including racial composition of a school, percentage of students identified as English language learners, and percentage of students receiving free or reduced lunch. Using a multiple linear regression analysis, we examine the aforementioned hypothesis that low instructional expenditures per student lead to higher 4-year ACGR in US public high schools.

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<sup>†</sup> Adjusted Cohort Graduation Rates quoted from the National Center for Education Statistics, Common Core of Data (CCD), for the 2012-2013 academic year.

## Data Sources

Data used in this study was obtained from the National Center for Education Statistics (NCES) and the U.S. Department of Education ED Facts Initiative (ED Facts) websites. All data reflect the 2012-2013 school year for school districts residing in the United States, including the District of Columbia, and are indexed with a unique Local Education Agency Identification (LEAID) number. The URLs of these data sources are provided in the Appendix at the end of this document.

## Variables of Interest

Since it is common for some students to change school districts throughout their high school experience, the 4-year adjusted cohort graduation rate (ACGR) is the version of high school graduation rate that is studied in this investigation. The ACGR accounts for student mobility, including transfers, emigration, and death during the 4-year academic period. ACGR is considered to be an accurate estimate of 4-year graduation rates. These data are found on the EdFacts website.

The primary predictor of interest in this investigation is Instructional Expenditure per Student. Instructional expenditures include costs for instructional supplies, instructional services, and teacher salaries and benefits. The data for this variable is provided by the Elementary / Secondary Information System (ElsI) tableGenerator tool on the National Center for Education Statistics website.

Other variables that are included in this investigation are: Urban Centric Locale; student-teacher ratio; number of students classified as English Language Learners (ELL); numbers of Hispanic, Asian / Pacific Islander, White, Black, and First Nations students; total student enrollment; and number of students eligible for free or reduced lunch (as a proxy measure for poverty), by school district. Urban Centric Locale indicates if a school district resides in a city (small, medium, or large), a suburb, a town, or rural area. These data are found on the NCES website using the Elsi tableGenerator.

It should be noted that the Idaho state education agency was not required to calculate or report the new four-year ACGR for academic year 2012-13. Therefore, data corresponding to districts residing in Idaho were not available and, consequently, those districts were excluded from this study.

## Data Cleaning

The aforementioned data were cleaned and transformed for analysis. Some ACGR data were provided in the form of a range, such as 60-69, or were anonymized as a code, such as "GT50", representing a value "greater than 50 percent". Records with ACGR values reported as a range greater than 5 (percent) were excluded in order to minimize the impact of these data on the final model since most ACGR values were greater than 60. The counts for each racial group were transformed to percentages of the student body, as were the counts for English Language Learners, and the counts for students in the reduced lunch program.

Only districts containing all of the desired predictors were included in the final analysis. Since the Alabama education agency did not report statistics on the number of English Language Learners for any of its school districts, all school districts residing in Alabama were incidentally omitted from this study.

## Statistical Techniques

A multiple linear regression (MLR) model was fit to the ACGR data while controlling for percentage of students eligible for free or reduced lunch, student-teacher ratio, percentage of English Language Learners, percentage of students from non-White, non-Asian racial backgrounds (i.e. Minority), and urban centric locale. The model is the following:

$$\text{ACGR} = \beta_0 + \beta_1 \cdot \text{InstructionalExpense} + \beta_2 \cdot \text{Lunch} + \beta_3 \cdot \text{StudentTeacherRatio} + \dots \\ \beta_4 \cdot \text{Minority} + \beta_5 \cdot \text{ELL} + \beta_6 \cdot \text{UrbanLocale}$$

The MLR model was chosen since these types of models generally perform reasonably well at capturing relationships between variables of interest, even those that are nonlinear, and are well-suited for interpretation, the primary goal of this work. The specific predictors chosen here were readily available and some have suspected to be related to high school graduation rates. The model was fit on a random 20% sample of the data set, and using this fit, the mean squared prediction error was calculated on the remaining 80% of the data. The model was also fit on California data and used to predict Wisconsin ACGR as a measure of robustness. Additionally, two standard diagnostic plots, the residuals versus fitted values and a Q-Q plot are provided.

A nonparametric bootstrap with 1,000 iterations was performed to estimate the coefficient for Instructional Expenditures per Student and the intercept term of the regression. This same bootstrap was used to obtain estimates for the standard deviations of these coefficients. The nonparametric version was utilized since the true underlying relationship between the predictors and outcome are likely not linear.

## Results

The summary of the estimated coefficients for this MLR model (Table 1) indicates p-values that are nearly zero for Instructional Expenditures and most of the other predictors, suggesting statistically significant relationships between these predictors and the outcome. The Adjusted R-squared value of 0.38 indicates that 38% of the variation is explained by the model. The estimated coefficient for the primary predictor, Instructional Expenditures, is -0.001 with a standard error of 1.18e-4, and a highly significant p-value smaller than 2e-16. The intercept, which describes the average graduation rate for White or Asian students from large cities is 115%, with a variance of 2.6%. This value for the intercept is clearly bogus and indicates problems with this model.

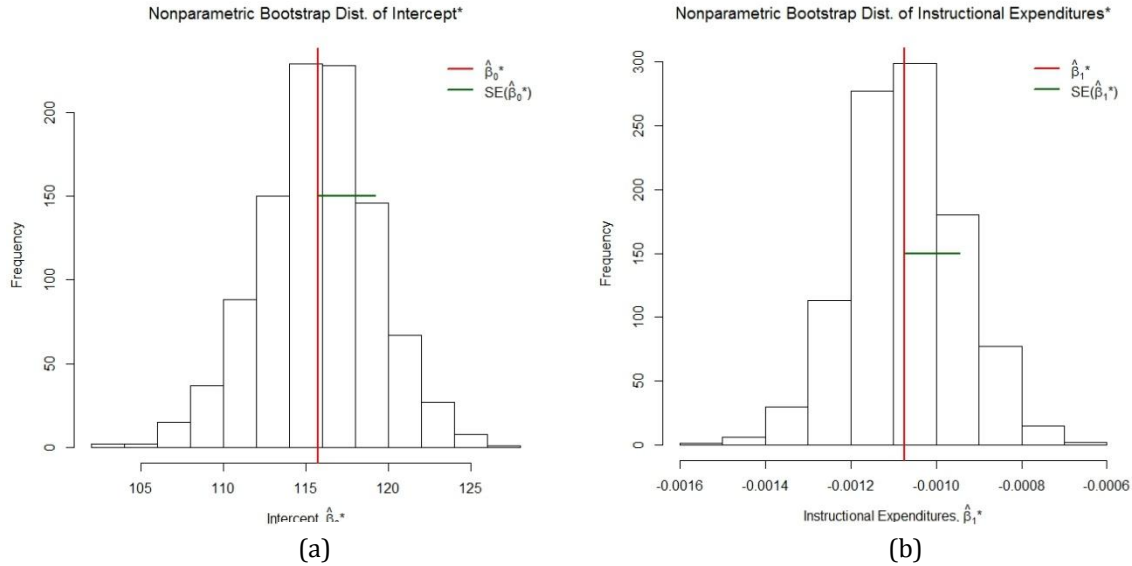
Table 1: Summary Statistics of the Multiple Linear Regression Model\*

Predictor	Estimate	Std. Error	p-value
Intercept	115.786039	2.577167	< 2e-16
InstrExpend	-0.001076	0.000118	< 2e-16
Lunch	-0.252791	0.015719	< 2e-16
StudentTeacher	-0.664773	0.083126	2.79e-15
Minority	-0.071632	0.013759	2.24e-07
ELL	0.276636	0.037017	1.43e-13
UrbanLocale12-City: Mid-size	-5.377098	2.218764	0.0155
UrbanLocale13-City: Small	-2.919518	1.892763	0.1232
UrbanLocale21-Suburb: Large	0.408248	1.675654	0.8076
UrbanLocale22-Suburb: Mid-size	0.510414	2.007054	0.7993
UrbanLocale23-Suburb: Small	1.725898	2.211794	0.4353
UrbanLocale31-Town: Fringe	0.190790	1.832274	0.9171
UrbanLocale32-Town: Distant	0.688573	1.740780	0.6925
UrbanLocale33-Town: Remote	-0.871989	1.783324	0.6249
UrbanLocale41-Rural: Fringe	1.120874	1.737001	0.5189
UrbanLocale42-Rural: Distant	1.797149	1.744921	0.3032
UrbanLocale43-Rural: Remote	1.843074	1.959563	0.3471

\*(1) Adjusted R-squared: 0.3798

(2) F-statistic: 51.52 on 16 & 1304 Degrees of Freedom (p-value: < 2.2e-16)

The nonparametric bootstrap (Figure 1a) yielded a value of -0.001075 for Instructional Expenditures, in agreement with the value reported in Table 1, and a standard deviation of 0.00013, which is smaller than that reported in Table 1. The p-value for this estimated coefficient was estimated to be nearly zero, which is consistent with the value reported in Table 1. The bootstrap estimates (Figure 1b) for the intercept term and standard deviation are 115 and 3.5, respectively. These are consistent with the value reported in Table 1. The associated p-value is again too small to measure and is consistent with the nearly-zero value reported in Table 1.

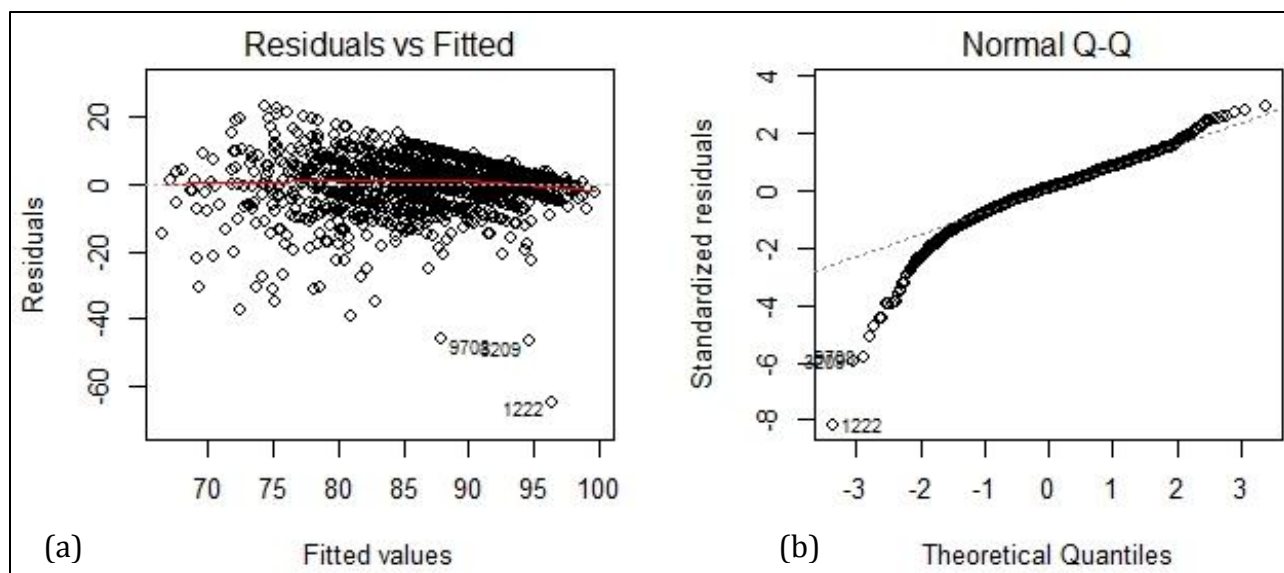


**Figure 1: Nonparametric bootstrap of (a) intercept and (b) Instructional Expenditure Per Student**

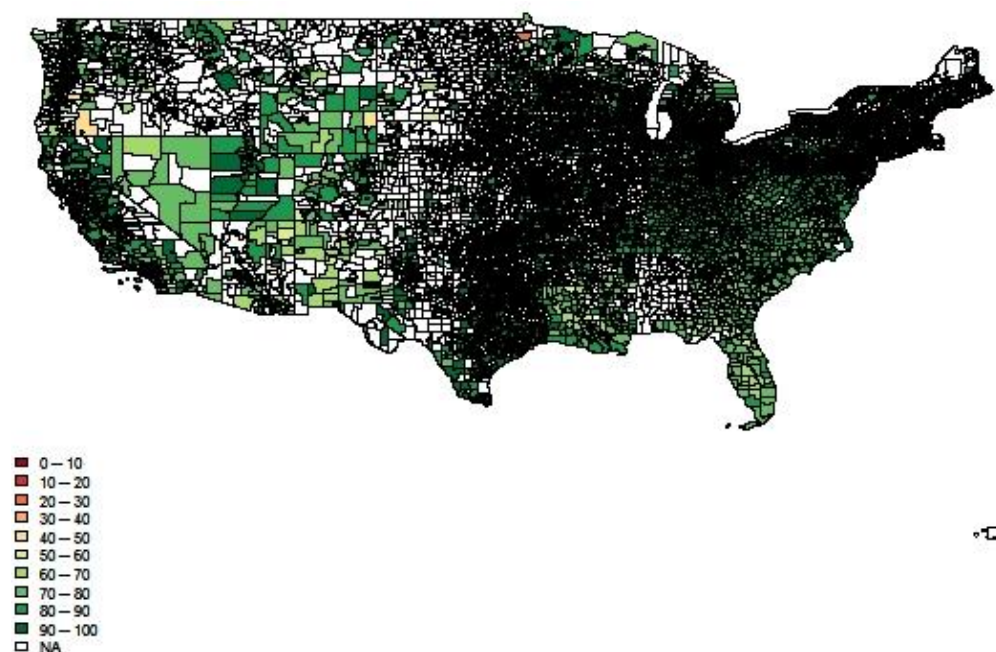
A plot of the Residuals vs Fitted ACGR Values (**Figure 2a**) reveals that the model suffers from non-constant variance since it contains a leftward-facing fan-shaped pattern. The Q-Q plot (**Figure 2b**) reveals violation of normality of the errors, since the data deviate from the straight line, particularly on the ends.

The mean squared prediction error when the model is run on the test set is 63%, which is substantially large. The mean squared prediction error was 29% for Wisconsin data when the model was fit using only the California data. This is a large error but not surprising considering the model has major problems.

Together, the spatial plots of the measured ACGR (Figure 3), predicted ACGR (Figure 4), and residuals (Figure 5) reveal problems with the MLR model as well as the technology used to visualize these data. The spatial plot of the predicted values for ACGR reveals problems with the model: most of the predicted values exceed 90% with hardly any values in the 50-70% range. This is unrealistic.

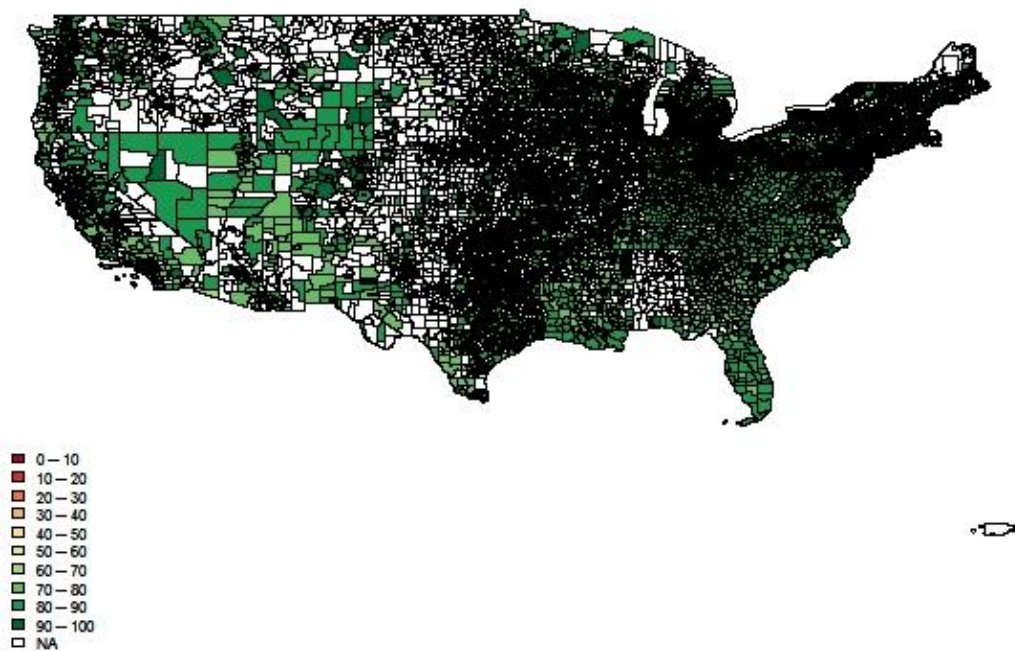


**Figure 2: Diagnostic plots for the MLR model (a) A leftward-facing fan may indicate non-constant variance (b) Normal Q-Q plot showing violation of the normality assumption.**

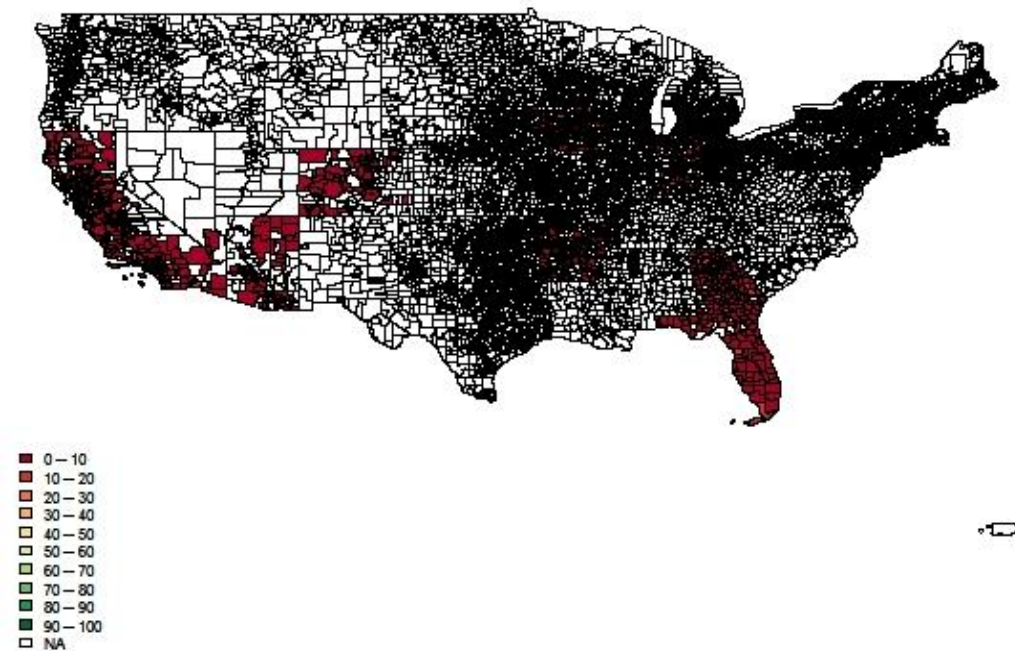


*Figure 3: Measured ACGR*





*Figure 4: Predicted ACGR*



*Figure 5: Residuals of the MLR*

## Conclusion

Unfortunately, the final model chosen for this data set suffered from high variance, as indicated by the funnel shape in **Figure 2a**, and leads to mean squared error of 63%. Despite efforts to transform several of the variables, including logarithmic transformations, square roots, reciprocal of the outcome, and several combinations of these transformations on the outcome and predictors of interest, the least unsatisfactory model obtained was the one provided here. Additionally, utilizing generalized additive models did not appear helpful. Additionally, technological issues related to mapping the data (with Shapefiles) made diagnosis challenging. Thus, with the modeling process still in need of refinement, no claim can be made at this time about the relationship between Instructional Expenditures per Student and ACGR. The hypothesis remains untested.

There were several limitations of this study which affect the results and analysis. A first limitation is the lack of potentially useful, confounding variables that could impact ACGR. Some of these variables are behavior and crime statistics in schools, attendance rates, availability of college-readiness programs such as Gear-Up, access to programs that help struggling students, participation in extracurricular activities, preparedness for high school upon completion of middle school or other measure of academic achievement at the start of 9th grade, educational attainment of parental guardian(s), to name a few. Many of these variables are available in the School Survey on Crime and Safety (SSOCS) for various years or the High School Longitudinal Study of 2009, but access to those data are excluded to qualified education researchers. A second limitation is the quality of the data used for the analysis. Data that is more complete or specific could lead to improved analysis. For example, one-third of the ACGR values were either completely anonymized or reported as a range of values (i.e, 60-69; 50+; 80+; below 50), where the reported ACGR ranges were largest for the smallest schools and visa-versa. Third, since these data were collected as part of a survey, there is randomness associated with reporting that include data entry errors, incorrectly quoted values due to misunderstanding survey questions, non-respondents (i.e. Idaho) or missing values for predictors used in this study (i.e. Alabama). Finally, had a more satisfactory model been found, inferences about individual students could not be made using the results provided by the model, as this would constitute ecological (inference) fallacy. Any correlations found using these aggregated data from school populations cannot be imposed upon any individual student.

Given additional variables and time to conduct the corresponding analysis, a better assessment of the relationship between ACGR and Instructional Expenditures per student could potentially be determined.

## Appendix

The following is a list of the data sources and corresponding URLs for the predictors used in this study.



[1] ACGR School Year 2012-2013 Data:

<http://www2.ed.gov/about/inits/ed/edfacts/data-files/acgr-lea-sy2012-13.csv>

[2] NCES 2013 Data for Income and Poverty:

<http://nces.ed.gov/programs/edge/tables.aspx?ds=acsProfile&y=2013>

[3] ELSi tableGenerator data:

<http://nces.ed.gov/ccd/elsi/tableGenerator.aspx?savedTableID=16594>

<http://nces.ed.gov/ccd/elsi/tableGenerator.aspx?savedTableID=36934>