Linking Education, Unemployment, and Poverty*

Insights from California's CalEnviroScreen Data

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We investigate the relationship between educational attainment and poverty rates in California using CalEnviroScreen 4.0 census-tract data compiled by the Office of Environmental Health Hazard Assessment (OEHHA). A simple linear regression of poverty rates on the percentage of adults without a high school diploma, shows that each one-percent increase in low educational attainment is associated with an average 0.98-percentage point poverty level increase. A supplemental model including unemployment shows only a minimal improvement in explanatory power, with education remaining the highest predictor that we explored. While diagnostic tests suggest violations of normality and variance constancy, the results can highlight the role that education plays in shaping socioeconomic vulnerability. These findings emphasizes the potential for targeted education policies to reduce poverty disparities across California communities.

1 Introduction

The link between educational attainment to socioeconomic well-being has been widely documented in prior research (for example, Cutler and Lleras-Muney (2006) and Zajacova and Lawrence (2018)).

The persistent geographic inequities California faces highlights the importance of examining how educational outcomes relate to poverty across communities. Using the CalEnviroScreen 4.0 dataset (OEHHA 2021b), we explore the following question in this project: **To what extent is tract-level poverty associated with low levels of educational attainment in California?**

*Project repository available at: https://github.com/iterrall/MATH261A-project-1-martinez.

The CalEnviroScreen dataset was originally designed to identify communities facing disproportionate environmental burdens. However, it also holds valuable data that can inform broader analyses of community socioeconomic well-being (OEHHA 2021b). Using its wealth of geospatial data can help us explore factors that may influence poverty at the census tract level. Understanding these relationships helps advise equitable policy interventions since socioeconomic disadvantage has been associated with both environmental risk exposure and adverse health outcomes (OEHHA 2021a; Morello-Frosch and Shenassa 2006).

We address this question by fitting a simple linear regression by taking poverty rate as a function of percentage of adults lacking a high school diploma. We then extend the analysis by exploring the contribution of unemployment makes on the model and examining the robustness of linear regression model assumptions.

The remainder of this paper is structured as follows: Section 2 discusses the data, Section 3 the model and the methods we used, Section 4 presents the results, and Section 5 discusses the conclusions in addition to weaknesses with the conclusions from this model.

2 Data

We use **California census tracts** as our observational units. Census tracts are small, relatively stable geographic areas defined by the (U.S. Census Bureau 2025a). We used the data in the **CalEnviroScreen 4.0** (OEHHA 2021a), which is a statewide screening tool devloped by the California Office of Environmental Health Hazard Assessment (OEHHA). CalEnviroScreen compiles socioeconomic, environmental, and health indicators to support data-driven policy and business decisions.

From the CalEnviroScreen 4.0 that is based on 2015–2019 American Community Survey 5-year estimates (U.S. Census Bureau 2025a; OEHHA 2021b, 2021a), we focus on the following socioeconomic measures in our analyses:

- **Poverty** is defined in this project as the percent of the total tract population living below twice the federal poverty level (FPL). Using a 200% threshold adjusts for California's relatively high cost of living (OEHHA 2021a; U.S. Census Bureau 2025b).
- **Education** represents the percentage of adults age 25 years and older without a high school diploma. This is calculated as 100 minus the share of adults who have completed high school or higher education (U.S. Census Bureau 2025a, 2025b).
- **Unemployment** is the percentage of the labor force that is unemployed in the tract (OEHHA 2021a; U.S. Census Bureau 2025b).

All three variables are percentages in between 0 and 100, so we interpret coefficients as percentage-point changes. This means they represent expected changes in poverty rate per one-point percentage change. For example, a one-point increase in the share of adults without a high school diploma corresponds to an expected change in the poverty rate by the estimated coefficient (Wickham, Hester, and François 2023).

We imported with the readr package (Wickham, Hester, and François 2023; R Core Team 2024) and cleaned the CalEnviroScreen 4.0 dataset to include only reliable and complete records. OEHHA flags tracts with high sampling uncertainty based on ACS standard error thresholds, and we excluded these along with any observations missing socioeconomic data. Using the dplyr package (Wickham et al. 2025; R Core Team 2024), we converted all variables to numeric form and dropped missing values for consistency. Then we created two analysis samples: a primary dataset that contains 7906 tracts with valid data for poverty and education and a supplemental dataset including 7658 tracts with complete data for poverty, education, and unemployment. This pre-processing ensured that our models were based on as complete and statistically reliable tract-level data as possible.

We note the **descriptive summaries** in the table Table 1 that we created using the dplyr, kableExtra, and knitr packages (Wickham et al. 2025; Xie 2015). Across 7658 tracts, the average poverty rate is 31.3%, ranging from 1.0% to 93.2%. The average share of adults (25+) without a high school diploma is 17.6%, with some tracts as high as 76.3%. The unemployment rate averages 6.3% and can reach 41.1%. These wide ranges highlight high variability across communities.

Table 1: Descriptive statistics for 7658 census tracts from the supplemental dataset including unemployment. Distributions represent tract-level rates (percentages) for each variable and summarize the mean, standard deviation, minimum, 25th percentile, median (50th percentile), 75th percentile, and maximum values.

	Distribution (percent)						
Variable	Mean	SD	Min	25th	Median	75th	Max
Poverty	31.3%	18.2%	1.0%	16.3%	27.8%	44.3%	93.2%
Low Education	17.6%	14.6%	0.0%	5.8%	12.7%	26.1%	76.3%
Unemployment	6.3%	3.8%	0.0%	3.6%	5.5%	8.0%	41.1%

We also calculated Pearson correlation coefficients among the key variables using stats::cor() (R Core Team 2024). Poverty is strongly correlated with low educational attainment (r $\approx$ 0.79), and moderately correlated with unemployment (r $\approx$ 0.55). The correlation between education and unemployment is weaker (r $\approx$ 0.39). These results reinforce our choice of education as the primary explanatory variable for modeling tract-level poverty. Although education shows the strongest correlation with poverty, we recognize that selecting explanatory variables solely based on bivariate correlations is not ideal statistical practice. Correlation does not imply causation, and such measures do not account for potential confounding or multicollinearity among predictors. However, our aim here is exploratory: to illustrate tract-level socioeconomic associations using a simple, interpretable model. Education was therefore selected as the primary explanatory variable because it provides a theoretically grounded and empirically strong relationship with poverty, while keeping the model parsimonious and transparent.

In our analysis, we include visualizations including a scatterplot of poverty versus education (Figure 1) that shows a positive linear trend. Additionally, we include a second plot coloring points by unemployment (Figure 5) that shows unemployment is also positively correlated with poverty, but with a weaker association than education (Figure 5) (Wickham 2016).

Finally, we note the **limitations** of our simple regression analysis. As with any ACS-derived data, estimates include sampling error, especially in smaller tracts. The variables have a bounded range between 0% and 100%, which could be introducing non-constant variance in regression models, and data clustering for percentage rounding. Additionally, the education measure applies only to adults 25+, while poverty covers all residents, so there is a variable denominator mismatch. Another limitation is the likely presence of geographic dependence because neighboring tracts could share similar socioeconomic conditions. This possible environmental clustering could bias standard errors and inference, which could suggest a need for spatial models or robust standard errors in future work.

3 Methods

To investigate the relationship between educational attainment and poverty, we adopt a simple linear regression model with poverty as the response and low-educational rate as the predictor. Let

- Y_i denote the percentage of the population living below 200% of the federal poverty line in tract i (poverty),
- X_i denote the percentage of adults age 25+ without a high-school diploma in tract i (education). We fit the following model:

  $$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i \text{ for } i = 1, ..., n$$

  where β_0 is the intercept (expected poverty rate if no adults lack a diploma), β_1 is the slope (expected change in poverty for one-percentage point increase in X_i), and ε_i is the error term that encapsulates unobserved factors that impact poverty rates not explained by low-educational attainment percentage (R Core Team 2024; Gelman, Hill, and Vehtari 2021; Kutner et al. 2005). As a robustness check of this model, we fit a supplemental multiple linear regression that adds tract unemployment rate U_i as a second explanatory variable:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 U_i + \varepsilon_i \text{ for } i = 1, ..., n$$

where β_2 is the slope on unemployment. This makes it possible for us to test whether unemployment explains variation in poverty beyond education.

We estimate the parameters of the model (β_0 and β_1) using ordinary least squares (OLS) in R with the `lm()` function (R Core Team 2024; Kutner et al. 2005). In our case, lm(pov ~ edu, data = to_analyze_df) regresses tract-level poverty rates in the percentage of adults without a high school diploma. The function outputs estimated coefficients, residuals, fitted values, and summary statistics that we accessed using functions like summary() and coef().

Model choice and considerations:

When choosing **explanatory variables**, we sought to identify which socioeconomic variables in CalEnviroScreen best explain variation in tract-level poverty. To guide this process, we initially ran simple regressions of poverty on each socioeconomic indicator and compared their R^2 values. Education (percent of adults without a high school diploma) exhibited the strongest association, with unemployment showing a moderate relationship. Although selecting variables based on bivariate relationships is not a best-practice approach to model building, we used this step as an exploratory tool to understand which indicators are most strongly associated with poverty. Based on this testing in addition to prior research linking low educational attainment to poverty in addition to poverty, we chose education as the primary explanatory variable and added unemployment in a secondary model to assess whether it improves explanatory power.

As discussed in Section 2, the variables are percentages (0–100%), so we interpret coefficients as percentage-point changes. We did not complete any **transformations** on them to preserve clarity of interpretations, though we note that bounded outcomes can produce non-normal residuals.

We completed **model validation** and fit by evaluating R^2, p-values, and diagnostic plots. We include the diagnostics we used to assess the validity of our standard linear regression **assumptions** using ggplot and R (Wickham 2016; R Core Team 2024):

1. **Linearity**: a straight line Figure 1 and Figure 2 suggest linearity between the predictor educational attainment and the outcome poverty.
2. **Independence of errors**: Figure 2 suggests independence if there is an even spread of points, while any clustering or patterns of the points would indicate a lack of independence between errors across census tracts.
3. **Constant variance**: consistent spread of points in Figure 2 provide evidence of constant variance of error terms across values of X_i, while any funneling of the points suggest a violation of this assumption.
4. **Normality of residuals** with mean zero: departures from the diagonal line the Q–Q plot (Figure 3) and skew in the residual histogram (Figure 4) indicate deviations from normality for the residuals.

Section 4 will show that while the simple model shows a relationship between the variables, our diagnostic checks suggest potential violations of error independence, variance constancy, and normality. Overall, the diagnostics provide evidence about the level of estimated coefficient reliability and inference validity from the model (Kutner et al. 2005), and Section 5 will highlight how assumption violations impact our model inductions.

Some of our possible pitfalls and **limitations** include spatial clustering of tracts (that would violate independence), measurement error from ACS survey margins, and mismatch in denominators (education measured for adults, and poverty measured for all residents).

In future work, we could address listed challenges with robust standard errors, variance-stabilizing transformations, or spatial models that explicitly account for geographic dependence. Additionally, like we inspect another factor on poverty rates in the dataset such as unemployment (Figure 5), we could explore other potential predictors of poverty by exploring more robust multiple linear regression models (Wickham 2016).

Together, these methods helped us create data cleaning, regression modeling, and visualization that can be reproducible.

4 Results

The simple linear regression of poverty level on education yields the following fitted model:

$\widehat{pov} = 14.255 + 0.979 \times (edu)$ with $R^2 = 0.616$ and number of tracts = 7906.

With a sample size of 7906 tracts, the intercept $\hat{\beta}_0 \approx 14.255$. Therefore, for a tract with 0% of its adults lacking at least a high school diploma, this model would predict an average tract poverty rate of 14.26%. The estimated slope $\hat{\beta}_1 \approx 0.979$, indicating a predicted average 0.98% increase in tract poverty rate for one-percent increase in adults without a high-school diploma in that tract. The model fit $R^2 = 0.62$, so about 61.59% of the variation in the poverty rate we are measuring is explained by low-education attainment percentage within a census-tract. The estimated effect of education appears to be statistically significant ($p < 0.001$), which provides evidence of a positive association between low education attainment and higher poverty rates.

To formally evaluate whether education is associated with poverty we conduct a t-test for the slope coefficient. Let our type I error rate be $\alpha = 0.05$. Let us test the following hypotheses: H_0: $\beta_1 = 0$ (no relationship between education and poverty) vs. H_a: $\beta_1 \neq 0$. The t-test for the education coefficient yields a large test statistic ($t \approx 113$) with a p-value <2e-16 ($p < 0.001$) (Robinson 2014). The p-value shows that the observed data is not more extreme than common rejection region thresholds like $< \alpha = 0.05$, we reject the null hypothesis and conclude that low educational attainment is associated with higher tract-level poverty rates.

From our model, we find that the 95% confidence interval (CI) for the education slope is approximately [0.96166, 0.99574]. This means that if we were to repeat this study many times using different random samples, about 95% of those intervals would contain the true value of the slope. In other words, we are 95% confident that for each percentage point increase in

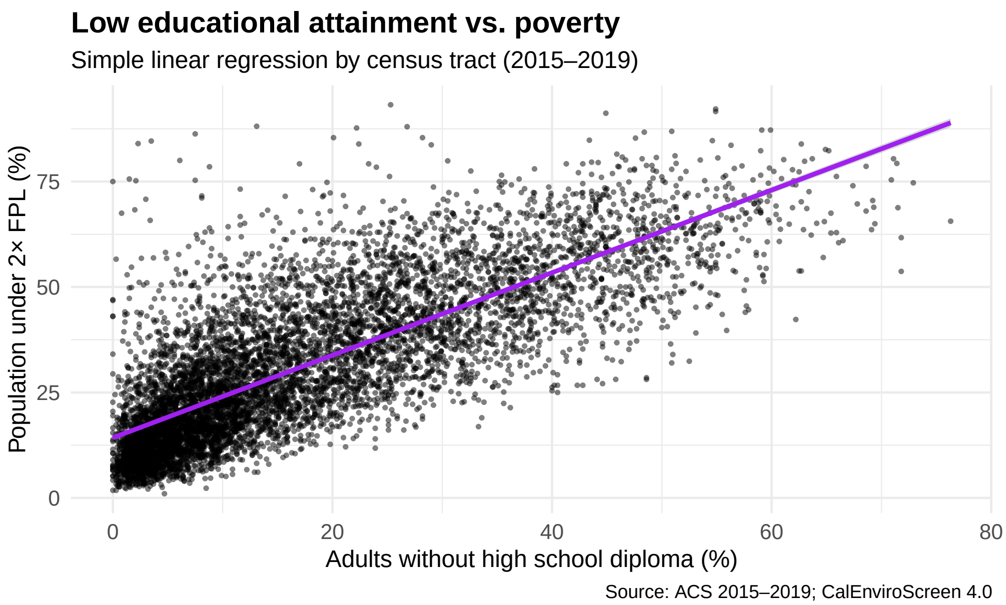

Figure 1: California census tracts (2015–2019): each +1 pp in adults without HS diploma is associated with 0.98 pp higher poverty (OLS). R^2 = 0.62.

adults without a high school diploma, the poverty rate of the same census tract will increase between approximately 0.9617 and 0.9957 percentage points.

We assess the reliability of our inferences for our primary simple regression with our diagnostic checks in Figure 1, Figure 2, Figure 4, and Figure 3. The residuals versus fitted plot shows curvature and clustering which indicates some unequal variances. The residuals histogram appears roughly bell-shaped, but its skew and the Q-Q plots's tail deviations indicate a deviation from error normality.

Additionally, we share a supplemental model with unemployment included to measure if another factor changes our results, which shows a similar effect ($\beta_1 = 0.838$) and a slightly higher $R^2 = 0.688$. Figure 5 visualizes this relationship by showing education remains a predictor of poverty even when controlling for unemployment. This suggests that differences in unemployment rates across tracts do not account for most of the variation in poverty once educational attainment is considered.

5 Discussion

Summary: The regression results (Section 4) show positive relationship between educational attainment and poverty. This model predicts that census tracts with higher percentages of

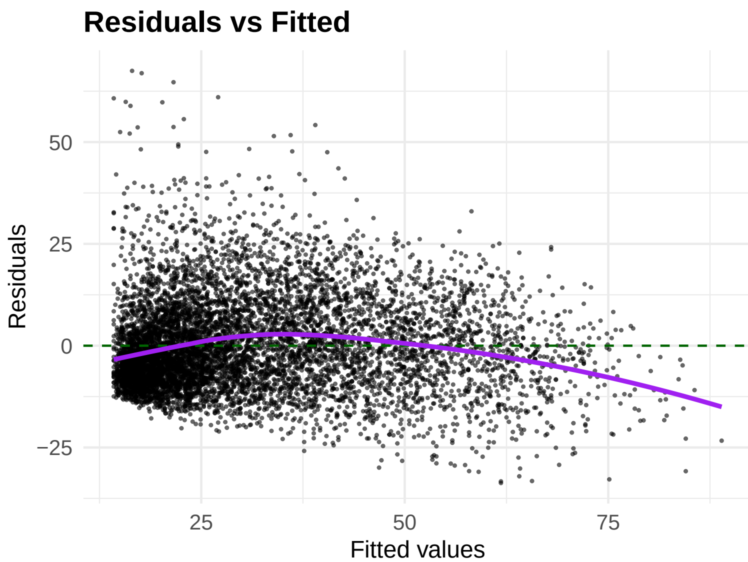

Figure 2: Residuals vs. fitted values for the simple OLS (poverty ~ education). Each point shows how much the model's prediction differs from the actual poverty rate for each census tract. The curved purple line shows the general trend in these residuals. While the points are mostly centered around zero, the curve bends upward and then downward, suggesting the model may not fit all values equally well and that the spread of errors changes across fitted values.

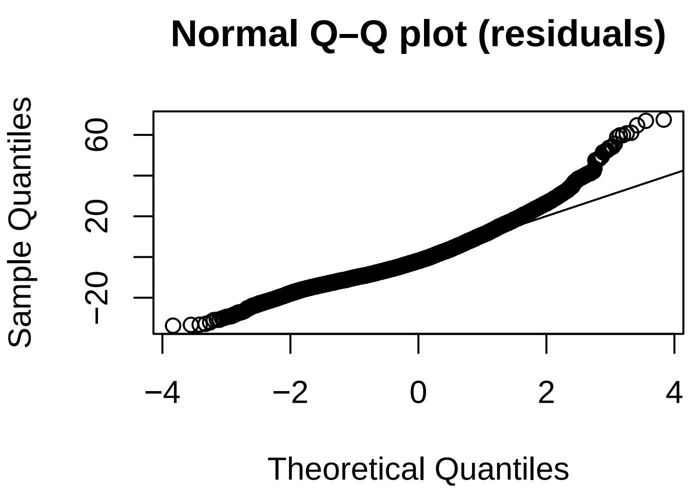

Figure 3: Normal Q–Q plot of residuals. Points near the line indicate approximate normality; curvature indicates deviations from normality.

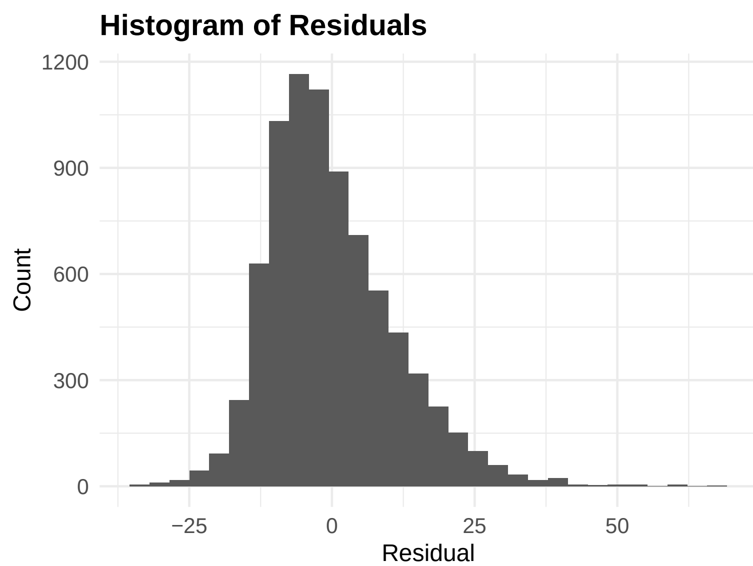

Figure 4: Histogram of residuals. A roughly bell-shaped, symmetric distribution supports the normal-errors assumption, skew indicates deviations from normality.

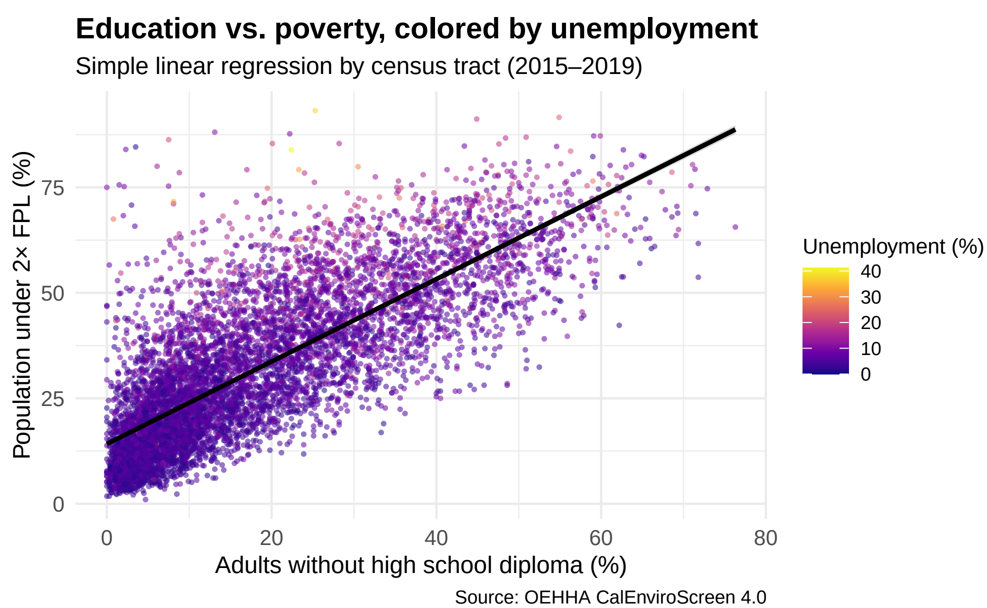

Figure 5: California census tracts (2015–2019). Poverty is higher where educational attainment is lower: each +1 % point in adults without a HS diploma is associated with 0.84 pp higher poverty (OLS), R^2 = 0.69.

adults without high school diplomas tend to experience higher rates of poverty. While unemployment is also positively correlated with poverty, its effect shows to be weaker than that of education. These findings share the importance of education as a key factor in community socioeconomic well-being.

Model assumptions: Our diagnostic plots show us several violations of the classical linear regression assumptions. Linearity appears reasonable from Figure 1, but independence of errors is unlikely given clustering in Figure 2, and the residuals show variability and non-normality in Figure 2 and Figure 3. If the residuals were approximately normal, the black dots would fall close to the straight diagonal line of the Q-Q plot. With thousands of tracts, coefficient estimates are stable, but standard errors may be understated under OLS assumptions. However, the plot bends upwards both in the lower and upper tails. Additionally, the histogram of residuals (Figure 4) appears approximately bell-shaped and centered near zero, which supports the assumption that the errors have mean zero. However, the distribution is not perfectly symmetric: the right tail is longer than the left, and there are some extreme positive residuals. This indicates mild right skew and the presence of high-poverty tracts where the model underpredicts. Overall, the violation of these assumptions do bring us to conclude our the inference from our confidence interval with caution. However, while the residuals do not follow a perfect normal distribution, the large sample size (n = 7906) reduces concerns about inference validity due to the Central Limit Theorem. Nevertheless, the skewness suggests that robust standard errors or a variance-stabilizing transformation (e.g., square-root of the response) might provide more reliable inference in future analyses. Overall though, the non-normality and changes in variance, our 95% confidence interval should only be drawn cautiously, so we might want to consider using more robust standard errors.

Comparing education and unemployment: When we added unemployment to the model, it did not meaningfully change the estimated effect of education. The unemployment has a weaker positive association with poverty, but the education coefficient remains consequential. This result challenges a possible assumption that unemployment is a primary driver of poverty. Figure 5 shows a high percentage of individuals are employed but remain below twice the federal poverty threshold OEHHA (2021a) set. This could indicate communities where individuals are working but still fall below the poverty threshold in our dataset. Comparatively, educational attainment shows a stronger relationship with poverty, which highlights its relevance as a relevant factor for socioeconomic well-being.

Generally speaking, the simple linear regression analysis for this research question can only draw questionable inferences, so the linear regression is likely not a full picture of the relationship between education and poverty. With that being said, we did see that the positive correlation in the linear regression model is likely statistically significant due to the p-value and R^2 value. Therefore, there is a positive relationship between low education attainment percentage and poverty rate percentage.

Limitations: We used cross-sectional, observational data, which limits our causal inferences. The nature of tract-level geographical dependence of the data likely violates the independence assumption. Additionally, the bounded percentage outcomes produce unequal variances. Finally the ACS sampling error introduces measurement error.

On a broader level, a limitation of our analysis is the definition of poverty. CalEnviroScreen uses 200% of the federal poverty level (FPL) to account for California's high cost of living. This is a more appropriate benchmark than the unadjusted FPL, it does not capture wide regional differences within the state. For example, housing costs in the Bay Area vs rural areas of California have a large range. Consequently, the same income threshold may reflect very different levels of economic hardship depending on location. This limitation means that the poverty measure could overstate poverty in some low-cost areas and understate it in high-cost regions. This could potentially introduce additional variation explained outside of education or unemployment.

Additionally, the education measure applies only to adults aged 25 and older, but the poverty measure covers the entire population. This mismatch means that our predictor and outcome are not measured on exactly the same group, thus introducing another limitation. For example, tracts with many children in poverty but relatively well-educated adults could weaken the observed association of our model. On the other side, tracts with low adult education may experience higher poverty rates even among children and elderly residents who are not part of the education measure. This difference in denominators introduces another possible measurement error into our regression.

Implications: The results we find from this paper suggest that low educational attainment is positively associated with poverty within California communities. This indicates interventions that expand access to high school completion programs or adult education initiatives could be tools for supporting economic well-being. Additionally, because CalEnviroScreen is used to guide environmental and equity-focused resource allotment, incorporating education as a socioeconomic vulnerability factor could help target resources more effectively and ensure that communities facing both environmental and socioeconomic burdens receive appropriate support.

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