From Classrooms to Paychecks*

How Education Levels Shape Economic Outcomes Across Santa Clara County Neighborhoods

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This paper examines whether neighborhood-level differences in educational attainment are linked to household income across Santa Clara County. Using tract level data from the American Community Survey (ACS) provided by the City of San José (City of San José 2025). I apply a simple linear regression model with median household income as the response variable and the share of adults without a high school diploma as the predictor. The results show a strong negative relationship between tracts with lower educational attainment tend to have lower median household incomes. These finds highlight how educational disparities continue to shape local economic outcomes even within a wealthy region. The analysis suggests that improving education access may help reduce income inequality across neighborhoods.

Introduction

Education has long been recognized as one of the most important factors shaping peoples economic opportunities. Individuals who complete more schooling typically earn higher incomes, enjoy greater job stability and have access to a wider range of careers (Card 1999; Baum, Ma, and Payea 2003). On the other hand, communities where fewer adults complete high school often face long term challenges such as lower wages, reduced access to resources and fewer chance for upward mobility. These ideas motivates me to explore the link between education and income at the neighborhood level where disparities are often less visible but still meaningful.

Santa Clara County, the heart of Silicon Valley, provides an especially interesting setting for this question. The county is well known for its wealth and innovation, yet not all neighborhoods share equally in this prosperity. Some tracts benefit from high levels of education and the

*Project repository available at: https://github.com/arshekhada/Math-261A-Project-1.

rewards of the tech economy, while others lag behind in both schooling and earnings. Looking at these differences within a single county can reveal how local variations in education translate into differences in household income even in a region that is often considered wealthy overall.

Most research on this topic has focused on individuals or national trends leaving a gap in understanding how education and income interact across neighborhoods within the same county. This paper addresses that gap by asking: *Do census tracts with a higher share of adults lacking a high school diploma also report lower median household incomes?* To answer this question, I use tract-level data from the American Community Survey and apply a simple linear regression model with median household income as the outcome and the percent of adults without a high school diploma as the predictor.

The results show a strong negative relationship: as the share of adults without high school completion increases, the predicted median household income decreases. This finding is important because it highlights how educational inequality continues to shape economic outcomes even in one of the richest regions of the United States. Most studies on education and earnings focus on individuals or large scale national trends (Card, 1999; Baum, Ma, & Payea, 2003) but less is known about how these relationships play out across neighborhoods within a single county. This study helps fill that gap by examining local variations in education and income within Santa Clara County, providing a more detailed picture of inequality at the community level. The rest of this paper is organized as follows: the **Data** section describes the dataset and variables, the **Methods** section explains the regression model and its assumptions, the **Results** section presents the fitted model and interpretations, and the **References** section lists all sources used.

Data

The observational units in this study are **census tracts** within Santa Clara County, California. A census tract is a small, relatively stable subdivision created by the U.S. Census Bureau that is designed to capture population of roughly similar size and characteristics. Each row of the dataset corresponds to one tract and the cleaned dataset used in this analysis contains 150 tracts with complete information. Focusing on tracts rather than individuals allows for a neighborhood level view of the relationship between education and income.

The dataset is called *Equity Index Census Tracts* and was compiled by the City of San José using the **American Community Survey (ACS) 2021 5-year estimates** (City of San José 2025). While the full dataset includes many indicators of race, income, language and education. This project focuses on two main variables.

- The outcome variable is **Median Household Income (`INCMEDIANINCOME`)**, which measures the midpoint household income in U.S. dollars for each tract.

- The predictor variable is **Percent Without High School Education (`EDULESSTHANHS-RATIO`)** which captures the share of adults aged 25 or older in a tract who did not complete a high school diploma or equivalent.

Both variables are continuous: income is reported in dollars and the education variable is expressed as a proportion between 0 and 1. Some data preparation was needed before analysis. I removed columns that contained mostly missing values such as income broken down by race and I excluded derived equity score variables to avoid circularity, since some of them already combine education and income. I also dropped rows with missing values for the two main variables. After cleaning the dataset contained 150 complete tracts and 38 useful variables, although only two are used in the regression. Median household incomes in the cleaned data range from about $41,000 to $250,000 with some values top-coded at the ACS limit. The share of adults without a high school diploma ranges from close to 0% in some tracts to about 45% in others, showing substantial variation across neighborhoods.

The ACS is widely considered the most reliable source for tract level socioeconomic data but it is still based on surveys and therefore subject to sampling error and nonresponse bias. For example, smaller tracts may have less precise estimates and income is self reported, which can introduce measurement error. Alternative or additional sources could include California Open Data, San Francisco Open Data or the Harvard Dataverse, which also provide socioeconomic indicators at different geographic scales. However, the ACS remains the best choice for consistently measured data across all tracts in the county. To illustrate key characteristics of the data. I generated summary tables and visualizations such as histograms of income and education and a scatterplot of the two variables, which already suggested a strong negative association that motivated the regression analysis.

Methods

To examine the connection between education and income, I used a **simple linear regression** (SLR) model. This method estimates how changes in one explanatory variable are associated with changes in a response variable. In my case, the explanatory variable is the **percent of adults without a high school diploma** in each census tract and the response variable is the **median household income** of the tract.

Formally, the model can be written as:

$$\text{Income}_i = \beta_0 + \beta_1(\%\text{NoHS})_i + \varepsilon_i$$

where: -

- Income_i**:** The median household income in tract i (measured in U.S. dollars)

- $(\%\text{NoHS})_i$: The fraction of adults aged 25 or older without a high school diploma in tract i
- β_0: The intercept which represents the predicted income when the predictor equals zero
- β_1: The slope which shows the expected change in income when the predictor increases by one unit (interpreted as about $3,097 per one percentage point increase)
- ε_i: The error term, capturing unmeasured influences

Like all regression models, this one relies on several **assumptions**:

1. **Linearity** – the relationship between education and income is approximately linear.
2. **Independence** – the residuals (errors) for each tract are independent of one another.
3. **Constant variance (homoscedasticity)** – the spread of residuals is roughly the same across the range of the predictor.
4. **Normality** – the residuals are approximately normally distributed.

I checked these assumptions informally by looking at scatterplots and model output. While real-world data rarely fit perfectly, the model appeared reasonable for this tract-level analysis.

This study has several **limitations**. The model is bivariate meaning it only considers one predictor. Other important factors such as housing costs or employment sectors may also influence income but are not included here. In addition, the data are aggregated at the census tract level, so the results cannot be interpreted as applying to individual households. Finally, because the ACS is survey-based, there is some sampling error particularly in tracts with smaller populations.

All analyses were carried out in **R** (R Core Team 2025) (version 4.x) using the packages `readr` (Wickham, Hester, and Bryan 2024), `ggplot2` (Wickham 2016), `scales` (Wickham and Seidel 2022), `dplyr` (Wickham et al. 2023), and `broom` (Robinson and Hayes 2023). The workflow was designed to be reproducible: I cleaned the raw dataset, saved a cleaned version and then fit the regression model on this file. Although this model captures a clear relationship between education and income. It does not include other potential predictors such as housing costs, industry mix or demographic composition, which may also influence neighborhood income levels. Future extensions could incorporate these variables in a multiple regression framework to see whether the effect of education remains strong when controlling for other factors. Including additional predictors would also help address potential omitted variable bias and improve the models explanatory power.

All analyses were conducted in R (R Core Team, 2025) using the packages ggplot2 (Wickham, 2016), readr (Wickham, Hester, & Bryan, 2024), scales (Wickham & Seidel, 2022), dplyr (Wickham et al., 2023), and broom (Robinson & Hayes, 2023). I validated the model fit by reviewing standard regression diagnostics and confirming that the main conclusions remained stable.

Results

The fitted regression model shows a clear negative relationship between education and income at the neighborhood level. The estimated equation is:

$$\widehat{\text{Income}} = 183,922 - 309,721 \times (\%\text{NoHS})$$

Here, the intercept of about $183,922 represents the predicted median household income for a tract where all adults have at least a high school diploma. The slope coefficient is negative and large in magnitude. When interpreted on the percentage scale. It means that for every one percentage point increase in adults without a high school diploma. The median household income is predicted to decrease by about **$3,097**.

The model accounts for nearly half of the variation in tract level incomes with an R^2 of about 0.49. The slope coefficient is statistically significant ($p < .001$)and providing strong evidence that the relationship between education and income is not due to chance. Overall, the results confirm the main research question: neighborhoods with higher shares of adults lacking a high school diploma tend to have significantly lower median household incomes. This finding emphasizes the importance of educational attainment for local economic outcomes. However, it is important to interpret these results at the tract level rather than the individual level, since the analysis uses aggregated data. Future work could use more detailed data or additional variables to explore how specific community factors such as access to schools or employment opportunities influence these outcomes. This confirms the research question: tracts with lower levels of educational attainment also tend to have lower household incomes (Card 1999).

Parameter	Estimate	Std. Error	t-statistic	p-value
Intercept	183922	4431	41.51	2.01E-83
Percent without High School (ratio)	-309721	25995	-11.91	2.27E-23

Results from a simple linear regression predicting median household income from percent without high school diploma. The intercept is about $183,922, and the slope is –309,721 (p < .001) meaning income decreases by roughly $3,097 for every additional percentage point of adults without a high school diploma.

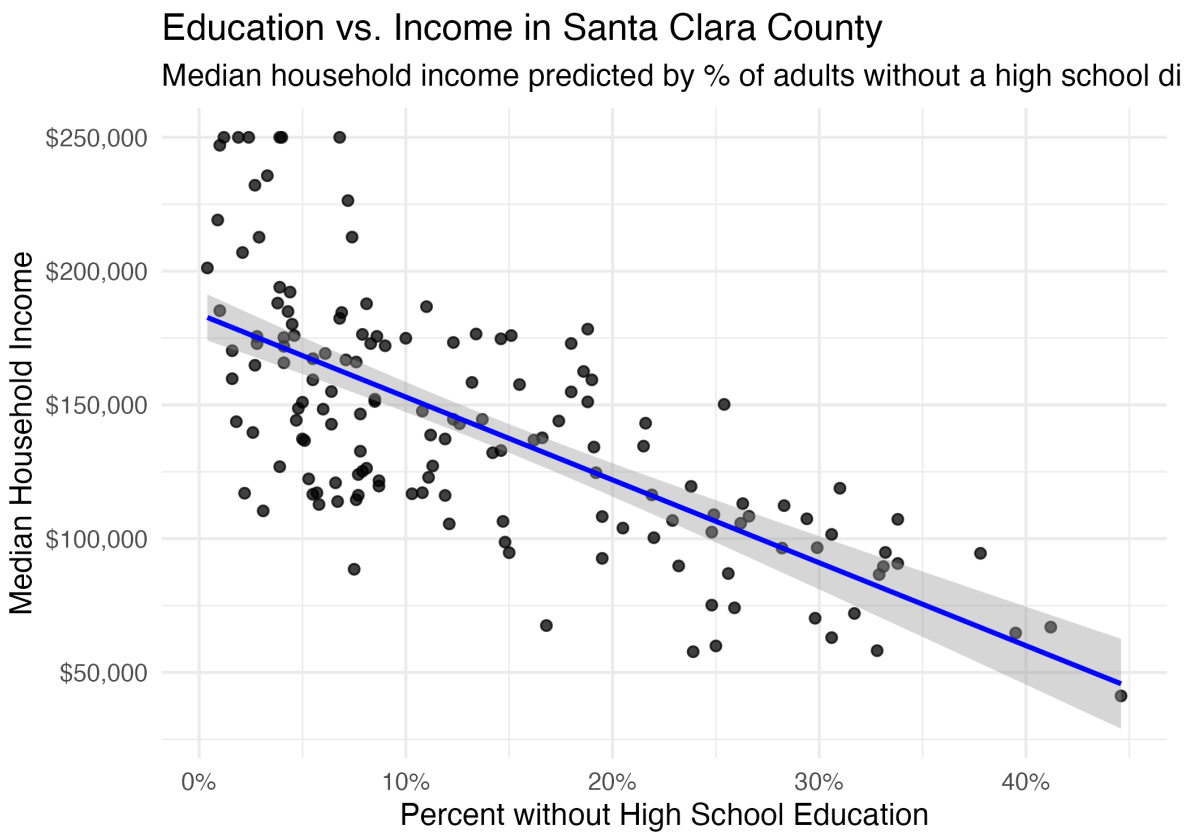

Figure 1: Education vs. Income in Santa Clara County. Relationship between educational attainment and median household income across Santa Clara County census tracts. Each point represents one census tract. The fitted regression line (blue) with a 95% confidence band shows that neighborhoods with a higher share of adults without a high school diploma tend to have lower median household incomes.

Discussion

The results from this analysis show a clear and statistically significant negative relationship between education and income across neighborhoods in Santa Clara County. In simple terms, areas with more adults who did not finish high school tend to have lower median household incomes. This directly answers the main research question and supports the idea that education plays a major role in shaping local economic outcomes. Even though Santa Clara County is known for being wealthy overall, the results show that not all communities share that prosperity equally.

I found it especially interesting how consistent the pattern was even small differences in education seemed to line up with noticeable changes in income. This suggests that improving education access and completion rates could be an effective way to reduce neighborhood level income inequality. These findings are also in line with earlier studies showing that education strongly influences earnings and job opportunities (Card 1999; Baum, Ma, and Payea 2003). In the context of a place like Silicon Valley, where most jobs require advanced skills these gaps in education can have even larger effects on local income differences.

Of course, this analysis has some limitations. The model only looks at one variable, so it doesn't consider other factors that might affect income like housing costs, job types or transportation access. Because the data come from the census tract level, the results describe neighborhood trends not individual outcomes. There is also some uncertainty in survey data like the American Community Survey, which can introduce small errors or sampling variation. Still, the relationship between education and income here is strong enough that these limitations are unlikely to change the main takeaway.

For future work, it would be useful to include more predictors in a multiple regression model to see how education interacts with other social or economic factors. It might also be interesting to look at how these patterns have changed over time. For example, whether the education income gap is getting smaller or larger across different parts of the county. Even though this project focuses on a simple regression, the results provide a clear and meaningful picture of how education continues to shape economic opportunity in local communities.

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