My title*

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First author Another author

November 25, 2024

First sentence. Second sentence. Third sentence. Fourth sentence.

1 Introduction

Overview paragraph

Estimand paragraph

Results paragraph

Why it matters paragraph

Telegraphing paragraph: The remainder of this paper is structured as follows. Section 2….

2 Data

2.1 Data Overview

Our data (**shelter?**)….

We use the statistical programming language R (R Core Team 2023)….Our data (**shelter?**)….

The IPUMS USA database (Ruggles et al. 2024) is one of the largest collections of microdata from population censuses globally. Supported by organizations such as the National Institutes of Health and the University of Minnesota, it includes data from the American Community Survey (ACS) and other census programs. This resource provides detailed individual-level data, allowing researchers to address specific social, economic, and demographic questions. A

*Code and data are available at: https://github.com/RohanAlexander/starter_folder.

key feature of IPUMS USA is its capacity to create customized datasets by selecting variables based on research needs, minimizing the inclusion of irrelevant data.

For this study, data from the 2023 ACS sample in IPUMS USA were used. The selected variables include STATEFIP (state code), SEX (gender), AGE (age), RACE (race), EDUC (educational attainment), EMPSTAT (employment status), UHRSWORK (usual hours worked per week), and INCWAGE (wage and salary income). These variables cover geographic location, demographic characteristics, education, and employment conditions, providing a broad basis for examining factors influencing wage income.

Other databases, such as IPUMS CPS (Flood et al. 2024) and the National Longitudinal Surveys (Bureau of Labor Statistics 2023), were considered but deemed less suitable for this analysis. IPUMS CPS provides detailed labor market data but has a smaller sample size and limited geographic detail. The National Longitudinal Surveys track specific population groups over time but lack broad representation, making them less ideal for cross-sectional studies. In contrast, the 2023 ACS data in IPUMS USA offers larger population coverage and a diverse range of variables, making it a better choice for analyzing wage determinants.

2.2 Measurement

This study utilizes sample data from the 2023 ACS. The dataset is based on a 1% random national sample, ensuring broad representativeness. It includes individuals living in private households as well as those in group quarters, such as student dormitories and care facilities. Weights were applied to the data to account for potential biases introduced by the sampling design and nonresponse.

Data collection for the ACS involved structured questionnaires covering a wide range of topics, such as demographics, education, employment, and income. For example, UHRSWORK (usual hours worked per week) captures labor input based on respondents' reports of their average weekly work hours. The smallest geographic unit in the dataset is the Public Use Microdata Area (PUMA), which contains at least 100,000 residents and falls within state boundaries. This structure protects respondent privacy while supporting regional analysis.

While the ACS methodology ensures data reliability and extensive coverage, variables like income and work hours rely on self-reported responses, which may introduce minor inaccuracies. Nonetheless, the use of sampling weights and robust design make the dataset a reliable foundation for studying wage income and its associated factors. A detailed explanation of the survey methodology and sampling design is provided in the appendix.

2.3 Dataset Description

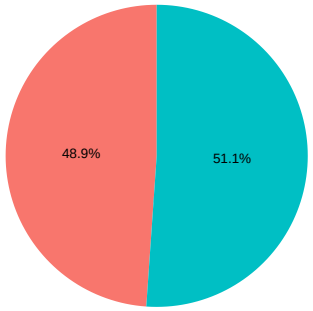
The sample of the cleaned dataset is shown in Table 1, including the following variables. UHRSWORK and INCWAGE are retained from the raw data, while the other variables are

Table 1: Cleaned Data Overview

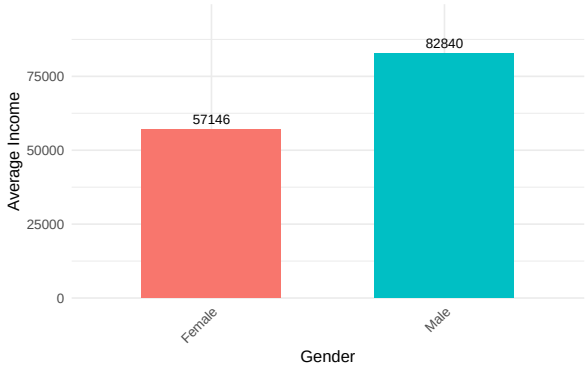
INCWAGE	UHRSWORK	education_level	region	age	gender	race_group
105000	40	Above_Bachelor	Northeast	49	Female	Asian
73000	40	Bachelor	South	29	Male	White
30000	45	Below_High_School	West	45	Female	Other
37000	40	High_School	West	27	Male	Other
1200	10	Some_College	South	22	Male	Black

newly constructed. During the data cleaning process, only individuals aged 18-65 and those with an employment status of "Employed" were included. This ensures the dataset focuses on studying the wage determinants of the employed labor force. Below is a description of each variable and how it was constructed:

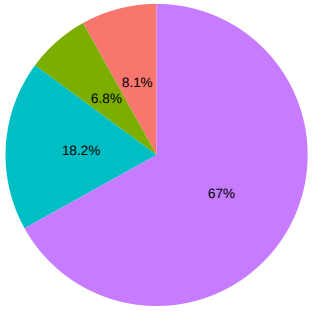
- **UHRSWORK**: Reports the number of hours per week the respondent usually worked if they were employed during the reference period.
- **INCWAGE**: Represents each respondent's total pre-tax wage and salary income earned as an employee during the previous year.
- **education_level**: Derived from the EDUC variable, which indicates respondents' educational attainment as measured by the highest year of school or degree completed. It is grouped into five categories: Below High School (includes all levels below high school), High School (completed grade 12), Some College (completed 1-2 years of college), Bachelor's Degree (completed 4 years of college), and Above Bachelor (more than 5 years of higher education).
- **age**: Filtered from the AGE variable to include only respondents aged 18 to 65. This variable records the respondent's age in years as of their last birthday.
- **region**: Constructed from the STATEFIP variable to represent geographic regions. Valid state codes (1–56) were grouped into four traditional U.S. regions: Northeast, Midwest, South, and West. Each state was assigned to its corresponding region for further regional analysis.
- **gender**: Based on the SEX variable, with original codes recoded as "Male" and "Female."
- **race_group**: Constructed from the RACE variable and grouped into four categories: White, Black, Asian, and Other. White and Black remain consistent with the original classifications. Asian includes Chinese, Japanese, and Other Asian categories, while Other includes all other races and mixed-race groups.



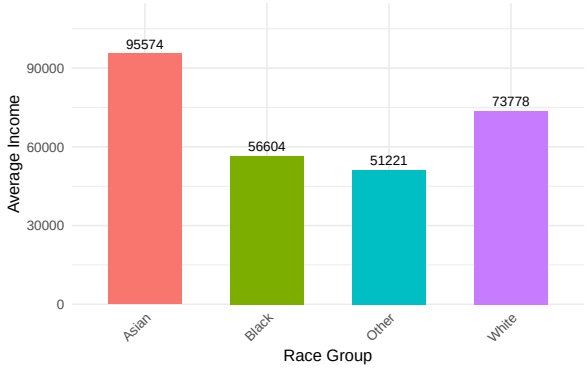
(a) Gender Proportion



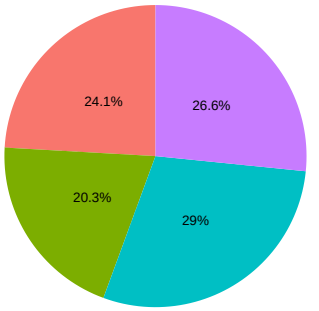
(b) Average Income by Gender



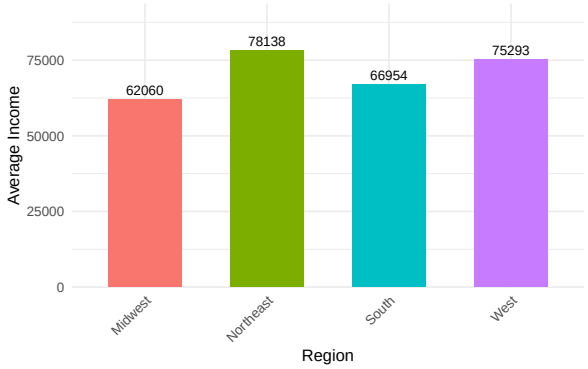
(c) Race Proportion



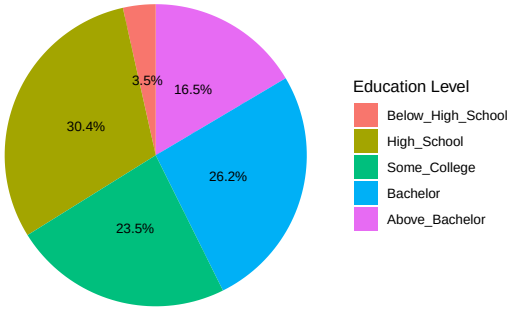
(d) Average Income by Race



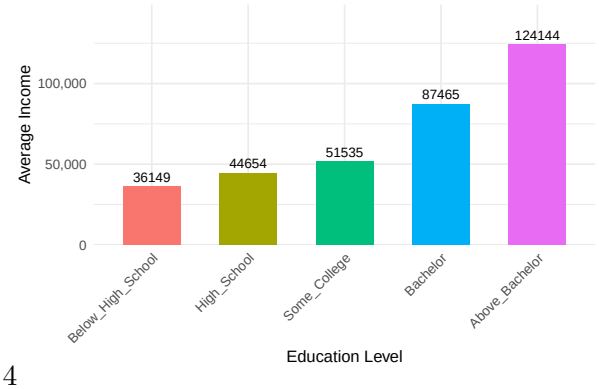
(e) Region Proportion



(f) Average Income by Region



(g) Education Proportion



(h) Average Income by Education Level

Figure 1: Demographics Distribution and Average Income by Group

2.4 Data Results

Figure 1 illustrates the distribution of demographic characteristics and their relationship with average income across gender, race, region, and education level. Pie charts display the proportional distribution of each group, while bar charts show corresponding average income levels, providing a straightforward depiction of these relationships.

Chart (a) shows the gender distribution: females account for 48.9% of the population, and males 51.1%, indicating a nearly equal split. Chart (b) shows that males earn an average income of $82,840, compared to $57,146 for females.

Chart (c) presents the racial composition, with White individuals forming the largest group at 67%, followed by Black individuals at 18.2%, Asians at 6.8%, and other racial groups at 8.1%. Chart (d) shows that Asians have the highest average income at $96,574, followed by White individuals at $73,778. Black individuals and other racial groups earn $51,221 and $56,604, respectively.

Chart (e) shows the regional distribution. The West represents the largest share at 29%, followed by the Northeast (26.6%), the South (24.1%), and the Midwest (20.3%). Chart (f) indicates that the Midwest has the lowest average income at $62,046, while the Northeast has the highest at $78,138. The South and West have average incomes of $66,954 and $75,293, respectively.

Chart (g) shows education levels: 16.5% of the population has less than a high school education, 30.4% has completed high school, 23.5% has some college education, 26.2% holds a bachelor's degree, and 9.5% has education beyond a bachelor's degree. Chart (h) highlights the connection between education and income. Those with less than a high school education earn $36,149 on average, while individuals with a bachelor's degree or higher earn $87,465 and $124,144, respectively. Income increases steadily with higher levels of education.

Figure 2 examines the relationship between income, work hours, and age, incorporating both individual-level data and aggregated trends.

Chart (a) is a scatter plot of work hours versus income, with each point representing an individual. The red quadratic regression line indicates a positive correlation between income and work hours, where longer hours generally lead to higher income. However, the regression line primarily reflects a linear trend, suggesting a stable relationship between income and work hours without significant signs of deceleration. Additionally, income variability increases with longer work hours, particularly beyond 50 hours per week, where fluctuations become more pronounced. Chart (b) illustrates the relationship between work hours and average income. While income generally increases with work hours, especially between 20 and 50 hours per week, it becomes unstable beyond 50 hours.

Chart (c) is a scatter plot of age versus income, with the red quadratic regression line showing that income increases with age before eventually declining. Chart (d) depicts the trend of average income by age. The line chart shows that average income steadily rises with age,

(a) Work Hours vs Income

(b) Average Income by Age

(c) Age vs Income

(d) Average Income by Work Hours

Figure 2: Income Trends by Age and Work Hours

peaking in the late 40s and early 50s, and gradually declines as individuals approach retirement age.

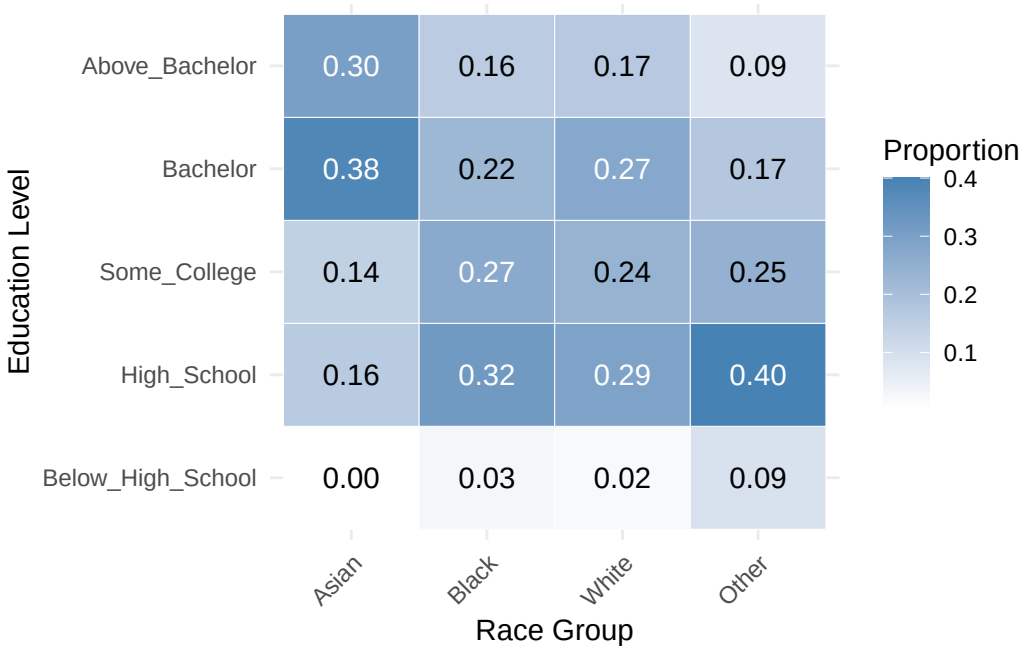


Figure 3: Proportion of Education Levels by Race Group

Figure 3 illustrates the proportion of different education levels across racial groups. The horizontal axis represents racial groups, including "Asian," "Black," "White," and "Other," while the vertical axis represents education levels, ranging from "Below High School" to "Above Bachelor." The intensity of blue indicates the proportion, with darker shades representing higher values.

Among Asians, the proportion of highly educated individuals is relatively high, with 38% holding a bachelor's degree and 30% having education beyond a bachelor's degree, while the proportion of those with "Below High School" education is 0%. In the Black group, "High School" accounts for the largest proportion at 32%, followed by "Some College" at 27%, while those with "Above Bachelor" degrees make up only 16%. In the White group, "High School" accounts for 29%, with 27% holding a bachelor's degree and 24% having "Some College" education, while 17% have "Above Bachelor" degrees. Among the "Other" group, 40% have a "High School" education, 25% have "Some College," 17% hold a bachelor's degree, and only 9% have "Above Bachelor" degrees.

Overall, the distribution of education levels varies across racial groups. Asians have a higher proportion of highly educated individuals compared to other groups, while "High School" education is more prevalent among Black and "Other" groups. This reflects the complex relationship between race and educational background.

3 Model

The goal of our modelling strategy is to quantify the contributions of key factors—such as weekly working hours, age (and its quadratic term), education level, region, gender, and race—to variations in income (log-transformed). By estimating the relative impact of these predictors, the model provides insights into potential social and demographic disparities in income.

Here we briefly describe the multiple linear regression model used to investigate these relationships. The model captures both linear and nonlinear effects (e.g., through the quadratic term for age), and all categorical variables are treated as factors to account for group-level differences. Background details, including diagnostics and model assumptions, are included in.

3.1 Model set-up

This study use Multiple Linear Regression (MLR) to model the relationship between income and various predictors, implemented using R's `lm` function. The dataset is divided into training and testing sets using the `createDataPartition` function from the `caret` package, with 60% allocated for model training and parameter estimation and 40% for testing to evaluate predictive performance.

Multiple regression models rely on several assumptions: linearity, meaning a linear relationship exists between independent and dependent variables; homoskedasticity, requiring constant error variance across predictors; independence of errors, meaning residuals are uncorrelated; normality, where residuals follow a normal distribution; and independence of independent variables, ensuring no significant multicollinearity. These assumptions are discussed in Section B and evaluated using the diagnostic plots shown in Figure 5.

The final model is displayed below:

$$\begin{aligned}\log(\text{INCWAGE}_i) = \beta_0 &+ \beta_1 \text{UHRSWORK}_i + \beta_2 \text{region}_i \\ &+ \beta_3 \text{education\_level}_i + \beta_4 \text{age}_i + \beta_5 \text{age}_i^2 \\ &+ \beta_6 \text{gender}_i + \beta_7 \text{race\_group}_i + \epsilon_i \end{aligned} \tag{1}$$

- β_0 is the coefficient for the intercept.
- β_1 is the coefficient for the continuous variable UHRSWORK_i, which measures weekly hours worked.
- β_2 is the coefficient corresponding to the categorical variable region_i, which includes the levels Midwest, Northeast, South, and West. Midwest is the reference level.

Table 2: Training and Testing Data Evaluation Results

Metric	Training	Testing
RMSE	0.773	0.786
MAE	0.543	0.568
R^2	0.488	0.468

- β_3 is the coefficient corresponding to the categorical variable education_level_i, which includes the levels Above Bachelor, Bachelor, Below High School, High School, and Some College. Above Bachelor is the reference level.

- β_4 and β_5 are the coefficients for the linear and quadratic terms of age_i, capturing the nonlinear relationship between age and income.

- β_6 is the coefficient for the binary variable gender_i, which includes the levels Male and Female. Female is the reference level.

- β_7 is the coefficient corresponding to the categorical variable race_group_i, which includes the levels Asian, Black, Other, and White. Asian is the reference level.

- ϵ_i is the error term, capturing the deviation of the observed value from the predicted value due to unobserved factors.

3.1.1 Model justification

The selection of variables and model structure was based on theory and data characteristics. Given the right-skewed nature of the income distribution in Figure 4, the dependent variable is log-transformed (`log(INCWAGE)`) to improve model fit. Furthermore, to capture the nonlinear relationship between age and income evident in Figure 2, a quadratic term for age (`age^2`) is included in the model. Categorical variables, such as region, education level, race group, and gender, are represented using dummy variables. Each category is compared to a reference category, allowing the regression model to capture and interpret group-level differences.

During the model selection process, an initial model included an interaction term between education level and race group (education_level:race_group), based on the association observed in Figure 3, while other variables remained unchanged. This interaction term aimed to evaluate income differences across racial groups at the same education level. However, most interaction terms were not statistically significant and provided minimal improvement to model fit metrics, such as adjusted R^2 and AIC. To simplify the model and enhance interpretability, this interaction term was excluded from the final specification.

Table 3: Estimated coefficients of the final model

	Coefficients	Lower.CI	Upper.CI
(Intercept)	6.1099	5.8478	6.3720
UHRSWORK	0.0400	0.0380	0.0421
regionNortheast	0.1287	0.0632	0.1941
regionSouth	-0.0192	-0.0794	0.0410
regionWest	0.1560	0.0927	0.2192
education_levelHigh_School	0.3352	0.2123	0.4581
education_levelSome_College	0.5094	0.3841	0.6347
education_levelBachelor	0.8713	0.7456	0.9970
education_levelAbove_Bachelor	1.0844	0.9537	1.2151
age	0.0985	0.0869	0.1101
I(age^2)	-0.0010	-0.0011	-0.0008
genderMale	0.2632	0.2186	0.3078
race_groupBlack	-0.1014	-0.2166	0.0137
race_groupWhite	-0.0007	-0.0834	0.0821
race_groupOther	-0.1290	-0.2230	-0.0350

The evaluation of the final model's performance was conducted on both training and testing datasets. As shown in tbl-test, the RMSE and MAE values are slightly higher for the testing data compared to the training data (0.786 vs. 0.773 for RMSE, and 0.568 vs. 0.543 for MAE), reflecting a modest decline in predictive accuracy when applied to unseen data. Similarly, the R^2 values are 0.488 for the training set and 0.468 for the testing set, indicating that the model captures a moderate proportion of the variability in the log-transformed income. Additionally, all variables included in the final model were statistically significant, with p-values below 0.05, further supporting the robustness of the selected predictors. Overall, the final model achieves a practical balance between complexity, interpretability, and predictive performance.

3.1.2 Model Results

Table 3 presents the effects of weekly working hours, age, region, education level, gender, and racial group on log income, along with their 95% confidence intervals. The estimated coefficients indicate varying degrees of influence among these factors.

Education level has the strongest impact on income. Compared to those with a high school education (the reference group), individuals with education beyond a bachelor's degree have a coefficient of 1.084, showing a significant increase in income. Similarly, those with a bachelor's degree and some college education have coefficients of 0.8713 and 0.5094, respectively, suggesting higher education correlates with higher income.

Age and its quadratic term reveal a nonlinear relationship. The positive coefficient for age (0.0985) indicates income increases with age. However, the negative coefficient for the quadratic term (-0.0010) shows this growth slows over time, eventually declining. This pattern reflects typical career income trajectories, with rapid growth early on, stability in middle age, and potential decreases later in life.

Gender also plays a significant role. Male income is significantly higher than female income, with a coefficient of 0.2632, even after controlling for other factors.

The effect of region varies. Compared to the Midwest (reference group), incomes in the West and Northeast are higher, with coefficients of 0.1560 and 0.1287. The coefficient for the South is -0.0192, close to zero, indicating little difference. This may relate to regional economic conditions and policies.

Weekly working hours show a modest effect on income, with a coefficient of 0.040. While longer hours increase income, the impact is relatively small, potentially due to wage structures and overtime policies.

The effects of racial group are more complex. Compared to Asian individuals (reference group), income for Black and "Other" racial groups is notably lower, with coefficients of -0.1014 and -0.1290. The coefficient for White individuals is nearly zero (-0.0007), indicating no significant difference. These patterns reflect complexities in racial income disparities.

In summary, education level has the largest influence on income, followed by age and gender. Region and racial group also play roles, while the effect of weekly working hours is smaller. These results provide a clear picture of how socioeconomic factors affect income and offer important context for further research and policymaking.

4 Discussion

4.1 First discussion point

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4.2 Second discussion point

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4.3 Third discussion point

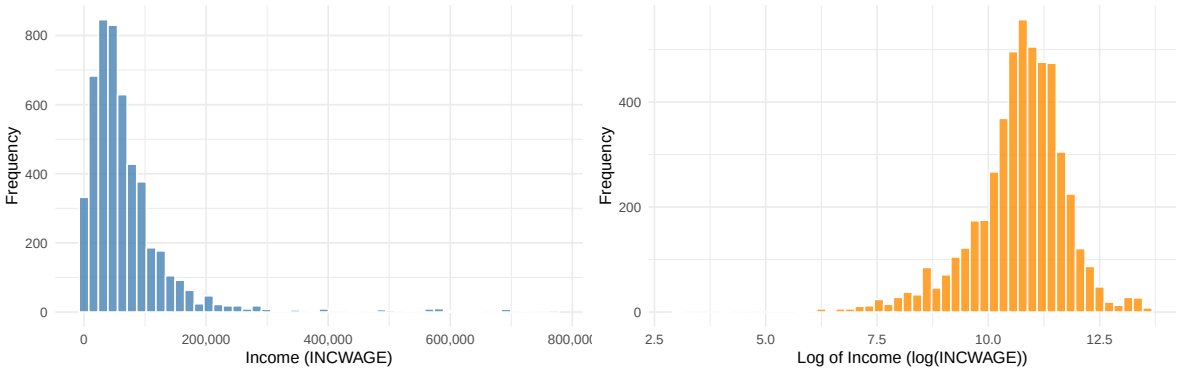
4.4 Weaknesses and next steps

Weaknesses and next steps should also be included.

Appendix

A Additional data details

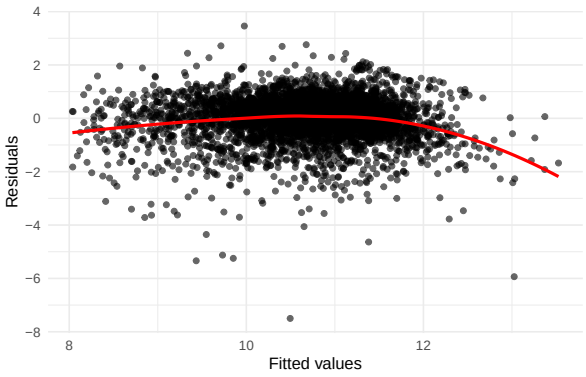
B Model details



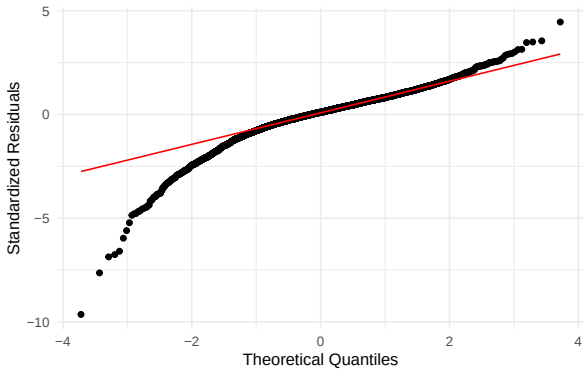
(a) Income Distribution (b) Log-transformed Income Distribution

Figure 4: Distribution of Income: Original vs Log-transformed

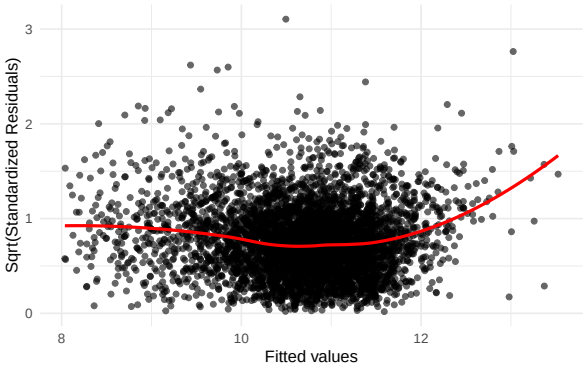
The model assumptions were checked using Figure 5. First, the Residuals vs Fitted plot tests the linearity assumption, showing that residuals are randomly scattered around the fitted values without any clear pattern, indicating that the linear relationship is valid. Second, the Normal Q-Q plot checks for the normality of residuals. Most points align closely with the diagonal line, suggesting the residuals are approximately normally distributed, with only slight deviations at the tails. Third, the Scale-Location plot evaluates homoskedasticity, and the red line remains mostly flat, suggesting that the variance of the residuals is fairly consistent. Finally, the Residuals vs Leverage plot identifies potential outliers or high-leverage points, indirectly testing the independence of errors and the independence of variables. Most points have low leverage, with only a few high-leverage points that may need attention. Overall, the assumptions are largely met, though there are some limitations that could be addressed with further refinements in the analysis.



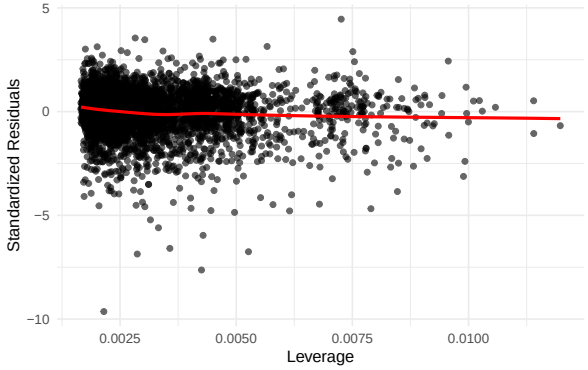
(a) Residuals vs Fitted



(b) Normal Q-Q Plot



(c) Scale-Location



(d) Residuals vs Leverage

Figure 5: Model Assumption Checks

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