Analysing the Factors Influencing the Wages of the US Workforce in 2023*

Higher Education and Male Gender as Key Determinants of Wage Increases Controlling for Region and Race

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This study uses a multiple linear regression model to analyze key factors influencing wages among the U.S. workforce, including education, age, gender, race, region, and hours worked. The results show that education is the strongest factor, with individuals holding a bachelor's degree earning over twice as much as those without a high school diploma, while men earn more than women, and Asian workers have the highest earnings among racial groups. The study also finds a nonlinear relationship between age and wages, with region and hours worked playing smaller but significant roles. By identifying these drivers, the research provides evidence to inform policies aimed at reducing wage gaps and promoting fairer economic outcomes.

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*Code and data are available at: https://github.com/JianingLi1225/Determinants-of-Wages.git

1 Introduction

Income inequality is a persistent social and economic problem with significant implications for individual well-being and societal stability. Understanding how personal characteristics and external factors shape income distribution is essential to addressing its underlying causes. While many studies have explored income inequality, few have systematically analyzed the interaction of these factors. Additionally, existing research often lacks recent data that are both nationally representative and adaptable for diverse analyses. This study addresses these gaps using the 2023 sample from the IPUMS database, which allows users to customize variables and provides high-quality, detailed data. Using this resource, the study identifies the main determinants of income inequality through a multiple linear regression model.

The estimand in this study is income. Specifically, it quantifies the effects of education, age, gender, race, region, and hours worked on income. By measuring these effects, the study seeks to uncover the mechanisms driving income inequality and provide a framework for understanding how personal characteristics and external conditions interact to influence income distribution.

The study finds that education is the strongest determinant of income. Higher levels of education lead to higher earnings, with individuals holding a college degree earning nearly 50% more than those without a high school diploma. The relationship between age and earnings is non-linear, with earnings peaking between the ages of 40 and 50 before declining, reflecting the impact of the occupational life cycle. In addition, gender and race show disparities, with men and Asians earning the highest average incomes, while women and certain minority groups earn less. Region and hours worked also affect earnings, but their effects are relatively small. Regional income differences reflect differences in economic development and policy environments, while hours worked show diminishing returns beyond a certain point. The findings are important because they reveal the role of education, gender, and race in driving income inequality and provide clear directions for policy interventions. They also provide empirical support for strategies to reduce income inequality, such as improving the allocation of educational resources, promoting gender equality, and increasing economic opportunities for minority groups.

This paper provides a thorough analysis of income inequality by examining its main factors and effects. Section 2 describes the dataset in detail, highlights its main features, and uses visualizations to present the analysis results. Section 3 focuses on the construction of the multiple linear regression model, validates its effectiveness, and presents the results of the analysis. Section 4 analyzes the research findings, explores the reasons behind the observed patterns, and offers policy recommendations to address income inequality. It also identifies the study's limitations and suggests directions for future research. Section A provides additional details on the model, and methods of survey and sampling, offering more detailed support for the study.

2 Data

2.1 Data Overview

We used data from the IPUMS USA database (Ruggles et al. 2024). All analyses were conducted in R (R Core Team 2023). Data simulation, testing, and cleaning were implemented using `tidyverse` (Wickham et al. 2019) and `testthat` (Wickham 2011), with specific tasks performed using `here` (Müller 2020), `arrow` (Richardson et al. 2024), and `readr` (Wickham, Hester, and Bryan 2024). Data manipulation was carried out with `dplyr` (Wickham et al. 2023) and `reshape2` (Wickham 2007), while data visualization was done using `ggplot2` (Wickham 2016), adjusted with `scales` (Wickham, Pedersen, and Seidel 2023). Model training and performance evaluation were supported by `caret` (Kuhn and Max 2008), with model testing and analysis conducted using `broom` (Robinson, Hayes, and Couch 2024). Model summaries were generated using the `modelsummary` package (Arel-Bundock 2022). Code style was standardized using `styler` (Müller and Walthert 2024). Code formatting and table presentation were handled by `knitr` (Xie 2024) and `kableExtra` (Zhu 2024), respectively, while regression diagnostics and additional analysis were performed with `car` (Fox and Weisberg 2019).

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 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. The cleaned dataset is presented in Table 2, along with detailed descriptions of variable definitions and construction methods, which are thoroughly explained in Section A.1.

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 uses sample data from the 2023 American Community Survey (ACS). The dataset is based on a 1% random national sample, ensuring broad representativeness. The sample includes individuals living in private households and those in group quarters, such as student dormitories, correctional facilities, and care homes. Weights are applied to reduce biases from the sampling design and nonresponse, enhancing result generalizability. The smallest geographic unit in the dataset is the Public Use Microdata Area (PUMA). Each PUMA includes at least 100,000 residents and is contained within state boundaries. This design anonymizes respondents' locations while enabling regional analysis.

The ACS collects data through mailed questionnaires, online submissions, and in-person or telephone interviews. The surveys cover a wide range of topics, such as demographics, education, employment, and income. For example, wage income is recorded by asking respondents to report their total pre-tax earnings from wages, salaries, tips, and other sources over the past 12 months. Similarly, the variable UHRSWORK (usual hours worked per week) measures labor input based on respondents' self-reported average weekly work hours during the survey.

Despite its robust sampling methodology and broad coverage, the ACS data has limitations. Variables such as income and work hours rely heavily on self-reported responses, introducing potential inaccuracies due to recall bias, rounding errors, or deliberate misreporting. For individuals with irregular or multiple income sources, questions about wages or hours worked may be interpreted variably, increasing measurement errors.

To address these issues, the ACS uses data validation checks and imputation techniques to handle incomplete or inconsistent responses. However, these methods cannot fully eliminate the risk of bias or error. Despite these limitations, the ACS dataset remains a reliable resource for analyzing wage income and related factors. Its combination of sampling weights, large sample size, and rigorous design framework supports robust analysis.

2.3 Data Results

Figure 1 illustrates the distribution of demographic characteristics and their relationship with average income across gender, race, region, and education level. Group proportions are shown alongside their corresponding average income levels, clearly illustrating these relationships.

Chart (a) illustrates gender distribution: females make up 48.9% and males 51.1% of the population, indicating a near-equal split. Chart (b) shows males with an average income of $82,840, compared to $57,146 for females.

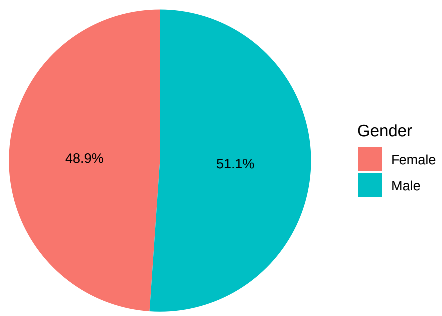
Chart (c) presents the racial composition, with White individuals forming the largest group at 67%, followed by Black individuals at 18.2%, Asians at 6.8%, and other racial groups at 8.1%. Chart (d) shows Asians with the highest average income at $96,574, followed by White individuals at $73,778. Black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

Chart (e) illustrates 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.

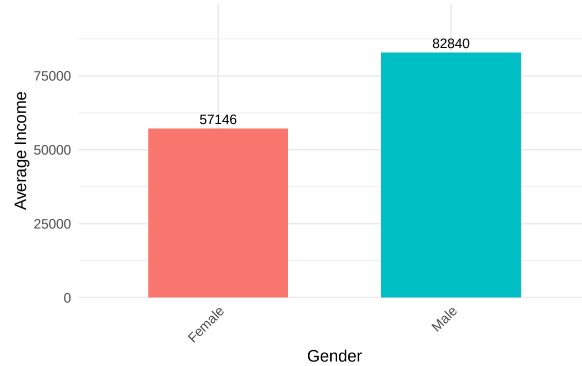
Chart (g) illustrates education levels: 16.5% have less than a high school education, 30.4% completed high school, 23.5% attended some college, 26.2% hold a bachelor's degree, and 9.5% pursued education beyond a bachelor's degree. Chart (h) highlights the strong relationship between education and income. Those with less than a high school education earn an average of $36,149, while individuals with a bachelor's degree earn $87,465, approximately 2.4 times higher. Income rises further for those with education beyond a bachelor's degree, averaging $124,144, highlighting the substantial impact of education on earnings.

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

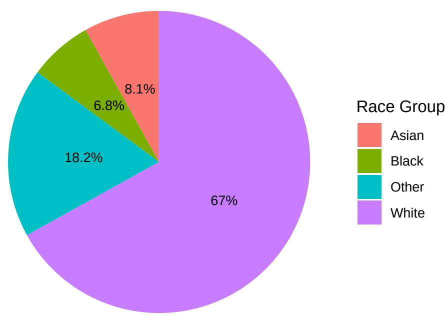
Chart (a) shows the relationship between work hours and income, with the red quadratic regression line indicating a positive correlation. Longer work hours generally correspond to higher income, with the regression line reflecting a stable linear trend without noticeable



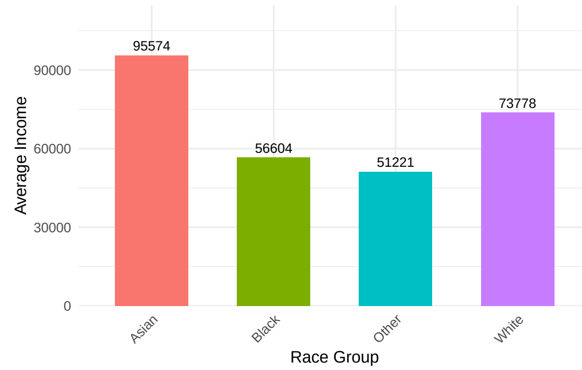
(a) Gender Proportion



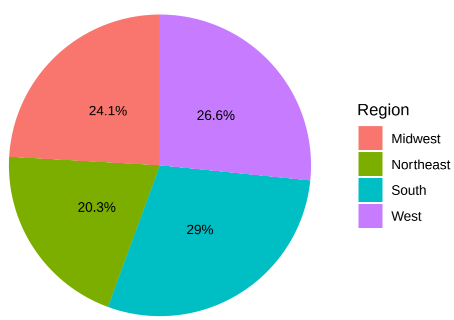
(b) Average Income by Gender



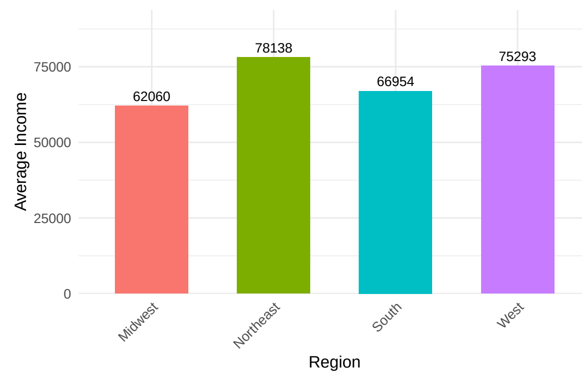
(c) Race Proportion



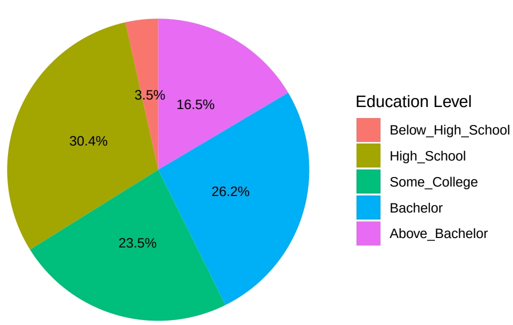
(d) Average Income by Race



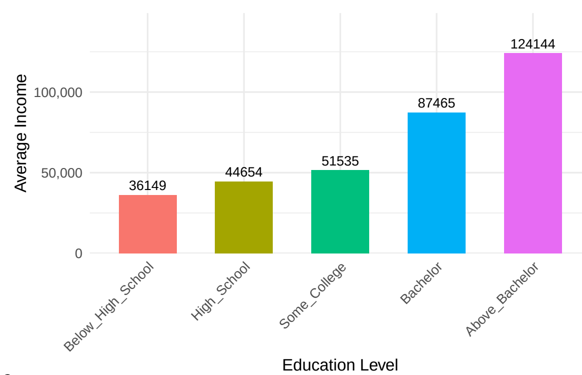
(e) Region Proportion



(f) Average Income by Region

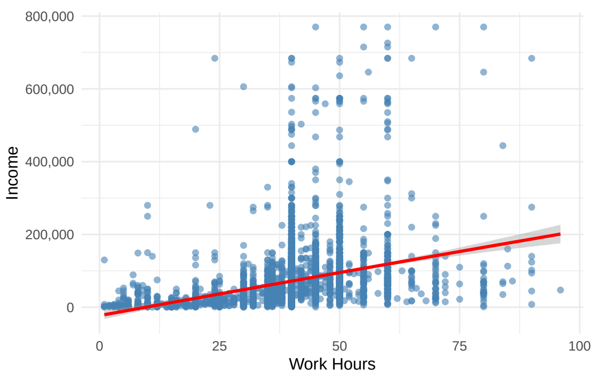


(g) Education Proportion

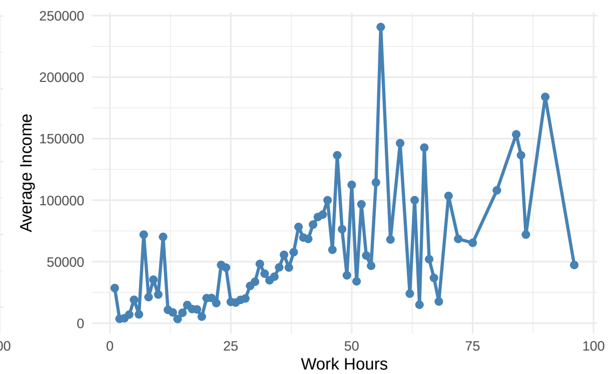


(h) Average Income by Education Level

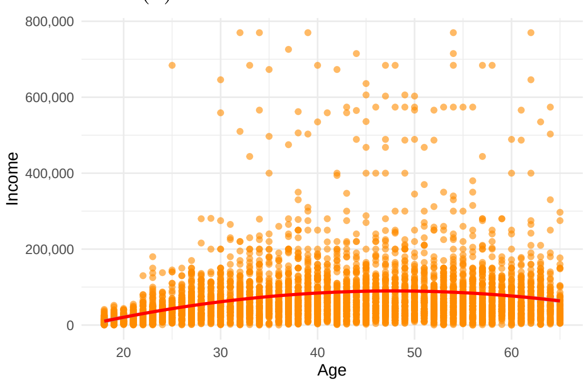
Figure 1: Demographics Distribution and Average Income by Group



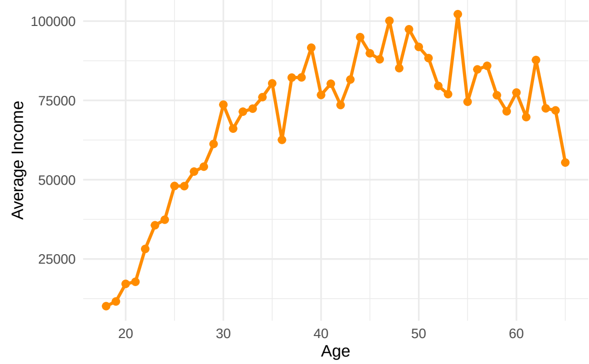
(a) Work Hours vs Income



(b) Average Income by Age



(c) Age vs Income



(d) Average Income by Work Hours

Figure 2: Income Trends by Age and Work Hours

deceleration. Income variability grows with longer work hours, especially beyond 50 hours per week, where fluctuations are more pronounced. Chart (b) depicts average income trends across work hours. Income steadily increases with work hours, especially between 20 and 50 hours per week, but becomes less consistent beyond 50 hours.

Chart (c) shows the relationship between age and income, with the red quadratic regression line revealing a rise in income with age before a gradual decline. Chart (d) shows average income by age as a line graph. It reveals that average income steadily increases with age, peaking in the late 40s and early 50s, followed by a gradual decline as individuals approach retirement age.

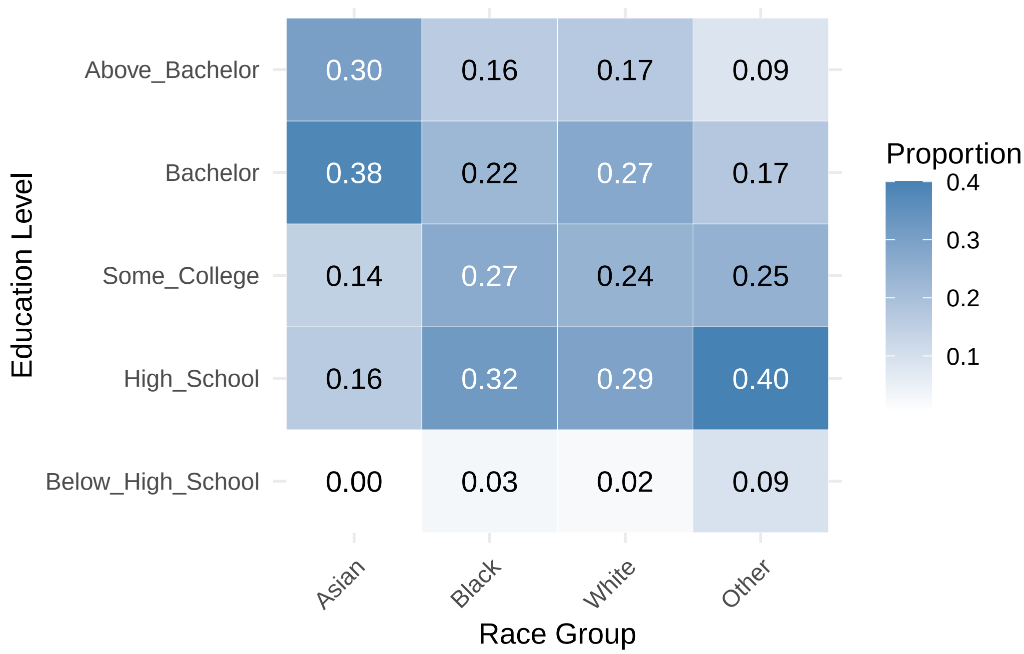


Figure 3: Proportion of Education Levels by Race Group

Figure 3 illustrates the proportion of different education levels across racial groups. Darker shades of blue indicate higher proportions.

Among Asians, 38% hold a bachelor's degree and 30% have education beyond it, while none fall under "Below High School." For Black individuals, "High School" is most common at 32%, followed by "Some College" at 27%, and "Above Bachelor" at 16%. In the White group, 29% have a "High School" education, 27% hold a bachelor's degree, 24% have "Some College" education, and 17% have "Above Bachelor" degrees. The "Other" category shows 40% with a "High School" education, 25% with "Some College," 17% with a bachelor's degree, and only 9% with "Above Bachelor" degrees.

Educational attainment varies significantly across racial groups, reflecting the nuanced relationship between race and education. Asians exhibit the highest levels of education, with strong representation in bachelor's and advanced degrees. In contrast, Black and White groups show broader distributions, with high school education being more common. The "Other" category, which includes smaller racial groups and mixed-race individuals, is concentrated at the high school level and underrepresented in higher education, indicating possible socio-economic and cultural disparities.

3 Model

The goal of this modelling strategy is to quantify the contributions of factors such as weekly working hours, age (including its quadratic term), education level, region, gender, and race to variations in log-transformed income. By estimating the relative impact of these predictors, the model examines 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.

3.1 Model Set-up

This study use Multiple Linear Regression (MLR) to model the relationship between income and various predictors, carried out with the `lm` function in R (R Core Team 2023). The dataset is divided into training and testing sets using the `createDataPartition` function from the `caret` package (Kuhn and Max 2008), 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, indicating a linear relationship between predictors and the dependent variable; homoskedasticity, requiring constant error variance across predictors; independence of errors, where residuals are uncorrelated; normality, where residuals follow a normal distribution; and low multicollinearity among predictors. These assumptions are discussed in Section A.2 and evaluated using the diagnostic plots shown in Figure 6.

The final model is displayed below:

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

Table 1: Training and Testing Data Evaluation Results

Metric	Training	Testing
RMSE	0.775	0.782
MAE	0.552	0.555
R^2	0.469	0.495

- 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.
- 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.

3.2 Model Justification

The selection of variables and model structure was based on theory and data characteristics. To address the right-skewed income distribution shown in Figure 5, the dependent variable is log-transformed (log(INCWAGE)) to improve model fit. Additionally, a quadratic term for age (age^2) is included to capture the nonlinear relationship between age and income observed in Figure 2. Categorical variables, such as region, education level, race group, and gender, are represented using dummy variables. Each category is compared to a reference group, enabling the model to 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 contributed minimally to metrics like adjusted R^2 and AIC. To simplify the model and enhance interpretability, this interaction term was excluded from the final specification.

The final model's performance was evaluated on both training and testing datasets. As shown in Table 1, 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 of 0.488 for the training set and 0.468 for the testing set indicate that the model captures a moderate share of the variability in log-transformed income. Additionally, all variables included in the final model were statistically significant, with p-values below 0.05, supporting the robustness of the selected predictors. Overall, the final model achieves a practical balance between complexity, interpretability, and predictive performance.

3.3 Model Results

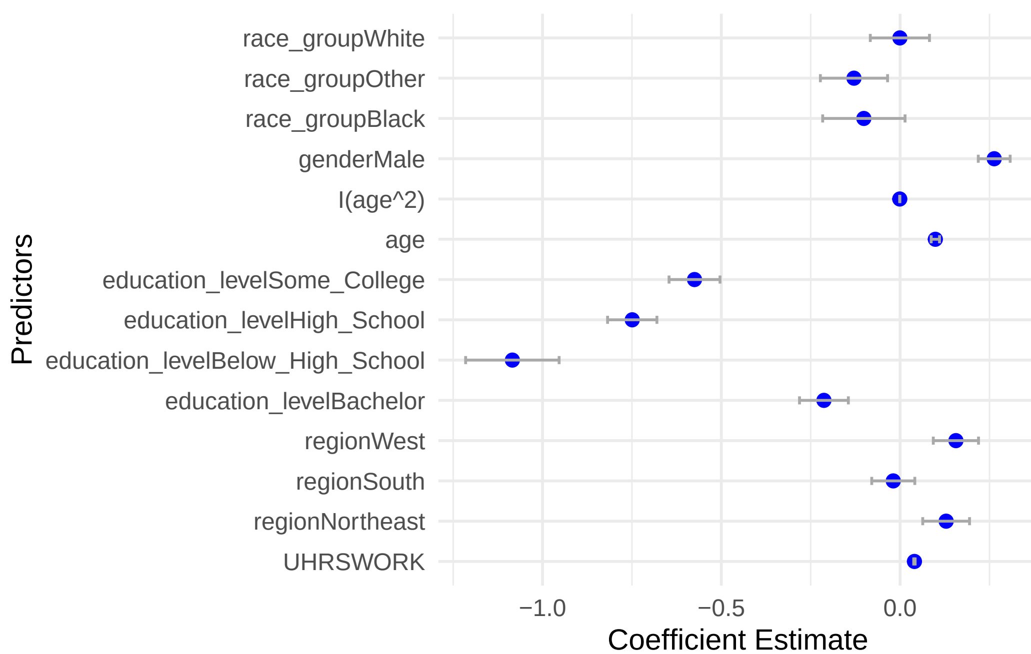


Figure 4: Predictor Coefficients with Confidence Intervals

Figure 4 shows the effects of weekly working hours, age, region, education level, gender, and racial group on income. The plot displays 95% confidence intervals for each coefficient, with detailed numerical values provided in Table 3 in Section A.2.

Education level is the most important factor. Individuals with lower education, such as "Below High School," have negative coefficients, while those with higher education, such as a "Bachelor's" degree, show positive coefficients. This underscores the economic advantages of higher education. However, the confidence intervals for education vary. For example, "Below High School" has a wider interval, indicating greater uncertainty in the estimate.

Age significantly influences income. The positive coefficient for age shows that income increases as people get older. However, the negative coefficient for age squared suggests that this growth slows over time and may decline later in life. The confidence interval for age is narrow, indicating a precise estimate. Gender differences are also evident. Male individuals have higher income, as shown by the positive coefficient for gender. The narrow confidence interval for gender confirms the reliability of this effect.

Racial factors present more complex dynamics. For example, "Black" and "Other" groups have negative coefficients and wider confidence intervals, reflecting greater uncertainty in their effects. In contrast, "White" individuals have coefficients close to zero and narrow intervals, showing minimal differences from the reference group. Regional effects are also notable. The "West" has positive coefficients compared to the reference region, while other regions show smaller or slightly negative effects. Some regional variables have confidence intervals that include zero, suggesting these effects may not be statistically significant.

Finally, the effect of weekly working hours on income is relatively small but still positive. Its narrow confidence interval indicates a stable and reliable estimate. Overall, these results clarify the socioeconomic factors influencing income and offer meaningful implications for future research and policy discussions.

4 Discussion

This paper uses a multiple linear regression model to analyze factors influencing income, including education, age, gender, race, region, and hours worked. This study uses data from the 2023 American Community Survey (ACS), which was cleaned and processed for analysis. The model quantifies the impact of these variables and explores their significance, showing how personal characteristics and external factors shape income distribution. Education, age, gender, and race are treated as endogenous variables, reflecting individual attributes, while region and work hours are considered exogenous, capturing the influence of external conditions on income. By analyzing these variables, the study provides evidence to inform policymaking and examines the roots of income inequality.

4.1 Education and Age: Primary Determinants of Income

Education strongly influences income, with a clear positive correlation between education level and earnings. Graduate degree holders earn significantly more, while a bachelor's degree also boosts income. However, those with only 1-2 years of college earn similar incomes to high school graduates, underscoring the importance of completing college. Higher education enhances economic potential and secures high-paying jobs. Most income differences stem from variations in bachelor's, graduate, and doctoral education levels, while pre-college education has a smaller impact.

Age significantly affects income. The model indicates that income peaks between ages 40 and 50 before gradually declining. The quadratic term captures this trend, reflecting how career stages impact earnings. Early in their careers, individuals see rapid income growth with experience and promotions. In later stages, productivity declines, and income typically decreases as retirement approaches.

Education and age shape an individual's earning potential. These findings inform career planning and provide guidance for policymakers. Individuals can enhance their competitiveness in the job market by pursuing a bachelor's degree or higher. Governments can increase education funding and provide financial aid to expand access to higher education. Additionally, support programs for those nearing retirement can help mitigate the impact of declining wages on their quality of life.

4.2 Gender and Race: Social Inequalities in Income Distribution

Income distribution shows clear gender inequality. Studies show that men earn significantly more than women, even when controlling for education, age, and other factors. This disparity may stem from gender bias and occupational segregation. Women are often expected to take on more family responsibilities and face potential career interruptions due to childbirth (Francine D. Blau and Kahn 2017). Additionally, men are overrepresented in many high-paying professions, contributing to lower average wages for women (Francine D. Blau, Brummund, and Liu 2013).

Racial disparities underscore another form of structural inequality. Research indicates that Asians earn the highest incomes, followed by Whites, while Black individuals and those from "other" racial groups earn the least. These differences can be attributed to historical and systemic factors, such as racial discrimination in the labor market and the underrepresentation of minorities in high-paying industries (Queneau 2009). Educational disparities between racial groups, as shown in Figure 3, also contribute to these income gaps.

Gender and race are exogenous factors beyond individual control. Addressing the gender pay gap requires targeted policies, such as promoting pay transparency and increasing women's participation in high-paying industries. To reduce racial income disparities, policymakers can implement measures like providing education and employment support for minority groups, encouraging diversity hiring, and strictly enforcing anti-discrimination laws. Cultural change is also crucial; reducing biases against women and racial groups can help narrow wage gaps and promote fairness.

4.3 Region and Working Hours: External Environmental Impact on Income

Region affects income. Studies show that incomes are higher in the Northeast and West and lowest in the Midwest. This may be due to differences in economic development and industry structures. Developed regions offer more high-paying jobs, while less developed areas have limited options. To reduce regional income gaps, the government can support industries in the Midwest and attract high-value sectors. Improving infrastructure and better allocating educational resources can also create more quality jobs in underdeveloped areas.

Income increases with work hours, but returns diminish. Beyond 50 hours per week, income becomes more unstable. This suggests that working longer hours does not always lead to higher pay. Policies like overtime pay rules or limits on work hours may play a role. The government should introduce better labor laws, such as capping excessive work hours. Encouraging businesses to innovate and improve efficiency can reduce reliance on long hours. These measures can protect workers' rights while promoting a fairer and healthier labor market.

4.4 Weaknesses and Next Steps

This study's data has certain limitations. It relies on survey responses, which can include self-reporting bias. For example, respondents may overestimate or underestimate their income or working hours. Additionally, the original data collection only classified gender as male or female. Non-binary and transgender groups were not included, leaving some populations unrepresented. Future research could incorporate more diverse datasets, such as administrative records or third-party data, to improve accuracy. Using more detailed classifications could also better reflect overlooked groups and enhance inclusivity.

Some important variables were not included in the analysis, such as industry classification. While industry significantly affects income, its complex structure and lack of standardized categories made it difficult to analyze. This exclusion might have introduced bias into the results. To simplify the model, smaller racial groups, such as Indigenous, and multiracial individuals, were categorized as "Other." While this approach simplified the analysis, it overlooked finer racial differences. Future studies could refine these categories and include more detailed variables when sample sizes allow.

The model also has limitations. With fewer variables, it cannot fully explain the complexities of income distribution. This study is based on U.S. data from 2023, so its findings may not apply to other countries or time periods. Future research could include more variables, such as industry, family background, and regional policies, to improve explanatory power. Combining time-series and cross-country data would also help study income trends and disparities on a broader scale.

Table 2: Cleaned Data Overview

INCWAGE	UHRSWORK	education_level	region	age	gender	race_group
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
73000	40	Bachelor	South	29	Male	White
105000	40	Above_Bachelor	Northeast	49	Female	Asian

A Appendix

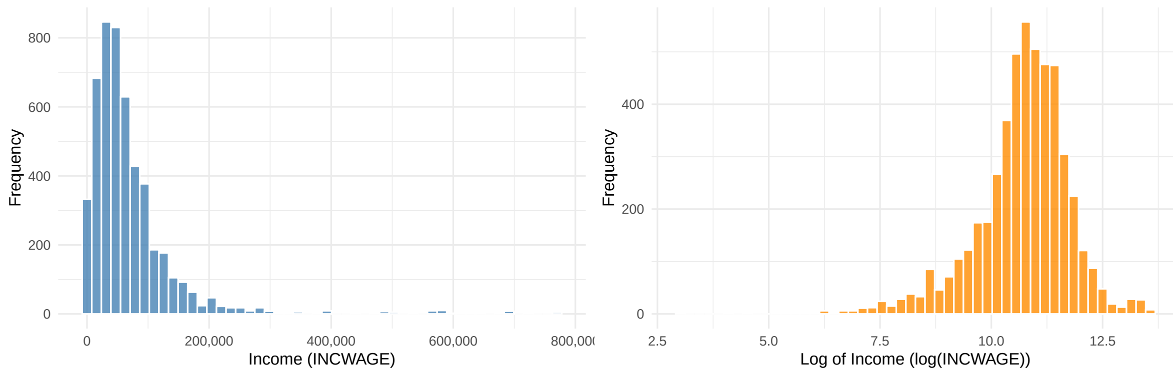
A.1 Dataset Description

The sample of the cleaned dataset is shown in Table 2, including the following variables. UHRSWORK and INCWAGE are retained from the raw data, while the other variables are 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.2 Model Details



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

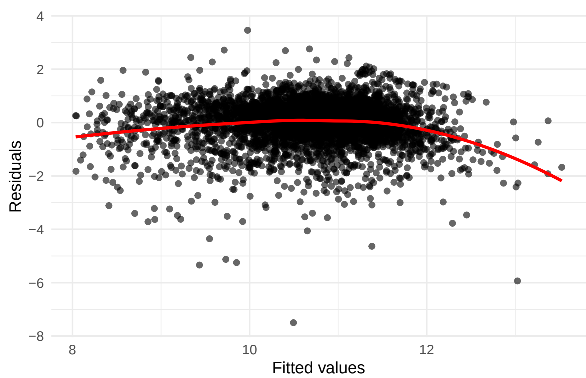
Figure 5: Distribution of Income: Original vs Log-transformed

The model assumptions were checked using Figure 6. 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.

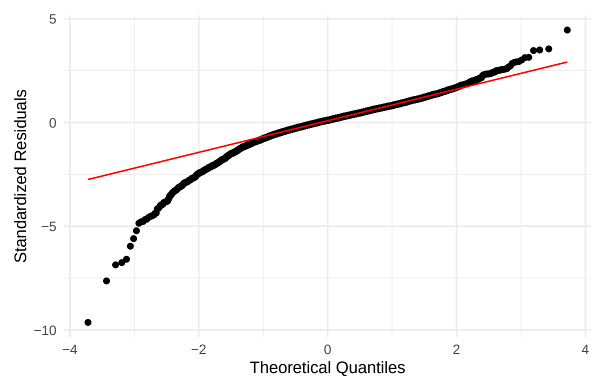
A.3 Idealized Methodology

A.3.1 Overview

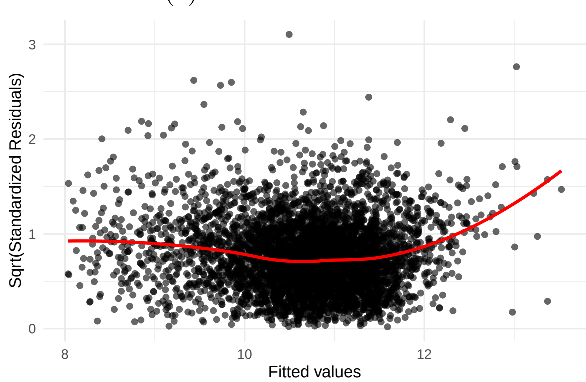
This survey is designed to collect data on factors influencing wages across the United States. The focus is on education, gender, race, region, and working hours. The budget is $100,000, covering sampling design, respondent recruitment, data collection, and quality control. The goal is to ensure high-quality, representative data. The results will help develop fair economic policies, reduce wage gaps, and promote equity.



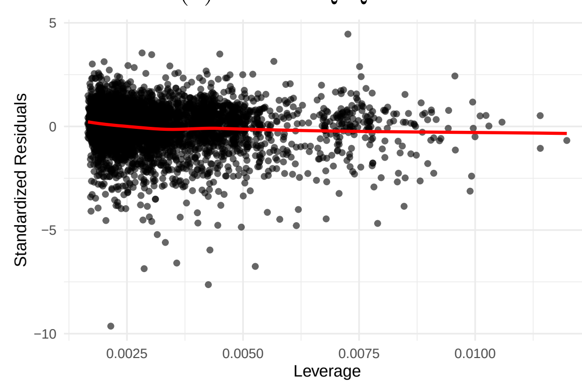
(a) Residuals vs Fitted



(b) Normal Q-Q Plot



(c) Scale-Location



(d) Residuals vs Leverage

Figure 6: Model Assumption Checks

Table 3: Estimated coefficients of the final model

	Coefficients	Lower.CI	Upper.CI
(Intercept)	7.1943	6.9446	7.4440
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_levelBachelor	-0.2131	-0.2814	-0.1448
education_levelBelow_High_School	-1.0844	-1.2151	-0.9537
education_levelHigh_School	-0.7492	-0.8182	-0.6802
education_levelSome_College	-0.5750	-0.6462	-0.5037
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_groupOther	-0.1290	-0.2230	-0.0350
race_groupWhite	-0.0007	-0.0834	0.0821

A.3.2 Sampling Approach

The survey uses stratified random sampling to ensure a comprehensive and representative sample. Respondents are grouped by gender, education, race, and geographic region. Gender categories include male, female, and non-binary/transgender. Education is grouped into high school or below, some college, and bachelor's degree or above. Race categories are White, Black, Asian, and Other (e.g., mixed or minority groups). Geographic regions include Northeast, Midwest, South, and West. Exact age is collected as a continuous variable. The total sample size is 5,000, with proportional representation for each group. This method ensures diversity and provides a strong foundation for analysis.

A.3.3 Recruitment

The survey combines online and offline recruitment methods to reach diverse participants. Online ads are placed on platforms like Google, Facebook, and LinkedIn. These ads target individuals based on occupation and location. The content emphasizes privacy and the importance of participation, with messages like, "Take 3 minutes to help uncover the key drivers of wage differences." This approach is effective for urban residents, younger people, and those with higher education levels.

For groups less likely to respond to online ads, such as older adults and rural residents, Random Digit Dialing (RDD) is used. Trained interviewers make calls across all states and record responses directly. This ensures inclusivity by reaching populations underrepresented in online recruitment.

To encourage participation, respondents are offered incentives. For every 100 surveys completed, one respondent is randomly chosen to receive a \$5-\$10 gift card. This incentive is explained at the start of the survey to motivate completion.

A.3.4 Data Collection and Survey Design

Data is collected primarily through Google Forms. Respondents can complete the survey on a computer or mobile device. Each Google account is limited to one submission to prevent duplicates. Responses from RDD participants are manually entered into the same system for consistency.

The survey includes attention check questions to ensure valid responses. For example, a question may ask respondents to "Select 'Other' to confirm you are paying attention." Responses failing these checks are marked invalid. This improves data quality without adding extra burden to respondents.

A.3.5 Data Validation and Quality Control

The survey implements several measures to ensure data accuracy and representativeness. Post-stratification weighting adjusts the sample to align with U.S. population characteristics. Logical checks identify and remove inconsistent responses, such as reports of zero work hours with high income. Duplicate submissions are identified and removed using account and IP address information. Missing data for open-ended questions, such as income, is handled using imputation. These steps improve the reliability and quality of the data.

A.3.6 Multi-Wave Data Collection and Aggregation

To capture changes in the labor market, the survey is conducted in three waves, two months apart. This approach tracks trends and seasonal variations. After each round, data is reviewed and aggregated using weighted averages. This reduces random fluctuations and provides more accurate results for analysis.

A.3.7 Budget Allocation

The budget is allocated based on the importance of each task. Approximately \$40,000 is spent on online ads to reach a wide audience. Another \$20,000 is used for RDD to connect with groups less accessible online, such as older adults and rural residents. An additional \$15,000 is set aside for incentives to increase completion rates. The remaining \$25,000 is allocated for data cleaning, validation, and multi-wave integration. This ensures efficient resource use and reliable survey outcomes.

A.4 Idealized Survey

The idealized survey questionnaire can be accessed via the following link https://forms.gle/Aw9cjdqL9tB9bNHr8

A.4.1 Survey Questions

Thank you for participating in this survey! This study aims to understand the factors influencing wages in the United States. Your responses will remain strictly confidential and will only be used for research purposes. The survey takes approximately 3-5 minutes to complete.

As a token of appreciation, participants who complete the survey will have the chance to win a $5-$10 gift card. One respondent out of every 100 will be randomly selected to receive this reward.

For Questions or Concerns, Please Contact:

Jianing Li
Email: lijianing.li@mail.utoronto.ca

1. What is your age?
    - Open-ended (numeric input)
2. What is your gender?
    - Male
    - Female
    - Non-binary/Transgender
    - Prefer not to say
    - Other
3. What is your highest level of education?
    - High school or below
    - Some college

- Bachelor's degree
- Master's degree or above

4. What is your race or ethnicity?
   - White
   - Black
   - Asian
   - Other (please specify): ____________

5. Which U.S. state do you currently reside in?
   - Dropdown list of all 50 states

6. To confirm you are paying attention, please select "Other" as your answer.
   - Male
   - Female
   - Other
   - Prefer not to say

7. What is your primary employment status?
   - Full-time
   - Part-time
   - Self-employed
   - Unemployed
   - Retired
   - Student

8. How many hours do you typically work per week?
   - Open-ended (numeric input)

9. What is your annual pre-tax wage or salary income?
   - Open-ended (numeric input)

10. How many years have you been working in your current field or profession?

- Open-ended (numeric input)

11. What is the primary reason you chose your current occupation?

- Interest/passion
- Financial stability
- Family influence
- Availability of jobs in the area
- Other (please specify): ____________

If you would like to participate in the reward draw, please provide your email address.
- Open-ended

Thank You!
Thank you for your time and participation in this survey. Your responses are valuable to our research.

Good luck with the reward draw!

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