How are wages affected by different demographic groups?

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I. Introduction

Throughout the United States disparities exist between diverse groups of people when it comes to things like housing, quality of life and much more. A major cause for many of these socioeconomic differences is disparities in how these groups are paid for their labor that have their own long lasting societal causes.

These inequalities in pay have been around for decades, with differences in pay between men and women and how much Black and Hispanic race groups earn compared to White individuals becoming part of broader conversation about inequality in the United States more recently. Despite the increased focus on these wage gaps and legislation aimed at reducing these disparities, they still exist today.

That said, the COVID-19 pandemic created another layer of economic distress, which may have worsened the existing wage gaps. Job losses during this time were aimed towards lower-paying jobs, typically occupied by women or minority groups. We want to understand the full extent of how the pandemic changed the wage gaps among different demographics (Hann 2024).

To illustrate how extensive these disparities are and to show how they impact people all around the country, we will see if our key variables such as age, gender, race, and educational attainment have had a different impact on wage in the height of the pandemic, and the significance of these relationships.

We used publicly available data from the 2020 IPUMS data to find the difference in pay. In our research, we found that wage disparities are not fully explained by certain factors such as education or experience. Research by Patten (2016) and Wisniewski (2022) support this claim that wage gaps still exist in different racial and gender groups when controlling education or experience. Allen (2019) and Van & Stoeldraijer (2010) highlight how intricate the relationship between age and wage is, that there are other key factors to dig into to fully explain this relationship such as productivity, pay, and experience.

II. Literature Review

The COVID-19 pandemic has increased the existing wage gaps, particularly among women, age levels, and people of color. It is a common assumption that more women are hired for roles requiring social skills such as relationship-building or managing interpersonal tasks (Hann 2024). As workers age, their productivity may decline in physical strength, but experience and cognitive abilities can offset this in other areas. In examining these issues, previous studies consistently show that demographic factors like age, race, and gender play significant roles in determining wages, with variations across industries and sectors. For example, research by Patten (2016) and Allen (2019) finds that Black and Hispanic workers earn less than their White counterparts, despite similar education and experience levels. We want to dig into this by analyzing wage trends in 2020 to see the bigger picture. We aim to explore how wage changes impact different demographic groups, identifying who benefits from these changes and who faces disadvantages.

When considering the economy, the U.S. Bureau of Labor Statistics found that the onset of the pandemic eliminated 20.9 million jobs in the private sector, primarily low-paying jobs. This is vital to note as low paying jobs are mostly occupied by women. This may impact our analysis when comparing hourly wages based on gender. Further, hourly earnings showed little to no change from February 2020 to February 2024 (U.S. Bureau of Labor Statistics). The wages were more heavily influenced by one's industry of work. While our research does not take occupation into consideration, it is a good factor to note.

A common theme in existing literature is the role of demographic factors in wage disparities. Patten (2016) and Wisniewski (2022), for example, find that racial and gender wage gaps persist even when controlling education and experience. Similarly, Allen (2019) and Van & Stoeldraijer (2010) have documented how age influences wage disparities, with older workers sometimes earning less due to declines in physical productivity, though experience and cognitive abilities can mitigate this. De LaPena and Mincer (1974) found compelling evidence to conclude that there is a positive relationship between years of schooling and overall wage. Our study is positioned to expand on these findings by using the most recent 2020 data, allowing us to examine whether the COVID-19 pandemic has had a disproportionate impact on certain demographic groups.

According to the U.S. Bureau of Labor Statistics (2021), Whites make up 70% of the workforce, followed by Hispanics/Latinos at 18%, Blacks at 13%, and Asians at 13%. These groups display median weekly earnings of $1,003, $758, $749, and $1,310, respectively. The Bureau's report also highlights labor force participation and unemployment rate differences: Hispanics had the highest participation at 79.1%, while Blacks had the lowest at 65.6%, and unemployment rates were highest among Black workers at 11.4%. These findings reflect broader patterns noted in the literature, where racial wage gaps are not only tied to education and experience but also to systemic factors like discrimination, occupational segregation, and access to networks and opportunities. Patten's (2016) study indicates that, in 2015, Black and Hispanic men earned significantly less than White men, with Black men earning just 75% and Hispanic men earning only 67% of their White counterparts' wages. Wilson and Darity (2022) saw that while net productivity has grown 68% since 1979, median wages have only grown by 14%, and wages for Black workers only grew by 5%. Additionally, Asian men out-earn White men on average ($24 per hour vs. $21), reflecting how race intersects with labor market outcomes. Our paper aims to re-examine these racial disparities with 2020 data to see how trends have shifted in the wake of the pandemic.

While much of the existing literature, including Patten (2016), uses data from the mid-2010s, our study provides a contemporary analysis by focusing on data from 2020, a period marked by significant economic disruption due to the COVID-19 pandemic. This shift allows us to analyze whether the pandemic exacerbated existing wage gaps, or whether current trends have emerged, making our research uniquely positioned to offer fresh insights into the ongoing issue of wage inequality. This paper looks at the effects of wages on race. It differs from that of Patten (2016) in that it uses the most recent data. While the previous authors use data from 2015, we are focusing on data from 2020.

When looking at the effect of wages on age, Allen (2019) and Van and Stoeldraijer (2010) both demonstrate that age and wage are positively related. As workers age, their physical productivity may decline, but experience and cognitive abilities can offset this. Studies have shown that older workers are often able to maintain competitive wages if their experience compensates for reduced physical strength, though this is not the case in all industries. However, in sectors where physical strength is important, aging could result in reduced wages due to lower productivity. Over the past few decades, there has been a growth in the labor force share of older workers- from 12% in 1998 to 23% in 2018. Firms are often concerned with whether to hire older workers because they are unsure of how long they will be with them, they insist on scheduled accommodation, and they might not understand modern technology. Firms typically sequence a worker's pay throughout their career- for instance paying them a smaller wage at the beginning of their career to ensure that they are both productive and responsive, and then once they have met expectations, they are compensated a larger sum. Firms hire more young workers when they are the most cost-effective option, and they hire more older workers if their productivity offsets their cost (Steven 2019).

Education attainment is another factor that significantly impacts wage levels. De LaPena and Mincer (1974) found that at any given age, the rate at which one makes money increases with schooling. This challenges the notion that age and wage are positively related, as it does not account for educational attainment. In other words, a younger worker with more education will make more than an older worker who completed less years of school. The U.S. Bureau of Labor Statistics states more educated individuals lead to less unemployment in the workforce. This is the case because the more education individuals have, the more skills they gain, and the more they offer employers. Our project will further test this claim and see how much explanatory power education has when looking at the topic of wages.

Finally, looking at the last factor in our research paper Census Bureau data show that pay gaps between genders are real and have persisted since the 1980s, even in the same field of work. Fry and Aragano (2025) note that the pay gap is smaller in younger individuals aged 25- 34, where women earn 95 cents for every dollar a man earns. This could be due to the lack of experience in the workforce when compared to older individuals. Hann (2024) states that women earn 16% less than men on average and only earn 84 cents for every dollar a man makes. Wisniewski (2022) on her research demonstrates that the gender wage gap in the U.S. is still a major issue. This gap is even wider for women of color. Black women earn around 70 cents, Hispanic women 65 cents, and Asian women about 90 cents for a dollar White men earn. These studies share a common theme of gender occupational segregation, with women disproportionately employed in lower-paying industries like education and healthcare, while men are overrepresented in higher-paying fields like finance and technology. Fry and Aragano (2025) contribute to that fact by stating that men are more likely to be a manager or boss when compared to women (28% vs. 21%). This aligns with our hypothesis that the gender wage gap is, in part, a result of sectoral disparities. Furthermore, caregiving responsibilities disproportionately placed on women often lead to fewer hours worked, compounding wage disparities. It is typically the case in these studies that having a child will increase men's salaries but decrease women's salaries. This paper builds on these findings by focusing on how these persistent disparities have been affected by the economic disruptions caused by the pandemic.

All these studies focus on the wage gap and labor market inequalities based on different demographic factors like race, sex, and age. Each study determines how these factors influence hourly wage, labor force participation, and employment. They all have a systematic pattern of inequality through the age wage gap (Allen 2019; Van & Stoeldraijer, 2010), racial wage gap (Patten, 2016), and sex wage gap (Hann, 2024; Wisniewski, 2022). Moreover, these studies provide insight into the underlying causes of these disparities, including occupational segregation and varying hours worked per week. Also, factors such as education and hours worked per week may play a role in wage determination, where these variables collectively impact remains a topic for our analysis.

Building on this foundation, our research will test whether demographic groups such as age, sex, race, and education will affect wages. The studies considered in this paper supported the fact that differing demographic groups do impact wages. While this is the case, we propose the following hypothesis to understand the impact that different demographic had on wages in the height of the pandemic:

- Null hypothesis: Wages are not affected by age level, sex, race, education, or the number of hours worked per week.
- Alternative hypothesis: Wages are affected by age level, sex, race, education, or the number of hours worked per week.

By using recent data from 2020, our research aims to see whether wage gaps still exist across different demographics and whether hourly wages are shaped more than just their performances. Through this, we aim to contribute new insights into the current state of wage inequality in the context of the COVID-19 pandemic.

III. Methodology

This study examines how wages differ across demographic groups by analyzing cross-sectional data from the 2020 IPUMS sample. The dataset contains 3,792 observations and eight key variables, focusing on individuals aged 16 to 64 who are employed. It offers a comprehensive snapshot of demographic and labor characteristics, allowing us to investigate wage disparities across sex, race, age, educational attainment, and hours worked per week.

The primary dependent variable is *hourly wage*, which is treated as a continuous variable after being transformed using the natural logarithm. This transformation helps address skewness in the wage distribution and allows coefficients in our models to be interpreted as approximate percentage changes.

Our main independent variables include sex, race, age, education level, and hours worked per week. Race is a categorical variable representing different racial groups. We decided to focus on the majority groups in the U.S. which are Black, White, Asian, and Hispanic.

Sex is also a categorical variable indicating gender (male, female, and others). While age is presented with numerical values it is a categorical value with the range 16-64 which is the legal age to work in the U.S. Employment status captures whether an individual is employed or unemployed and we focus on people who are employed as we are testing the effect of wages on different demographics. Full-time/Part-time status indicates employment type.

Finally, educational attainment categorizes individuals based on their level of education such as bachelor's, associate's, high school diploma, no school, master's degree, and doctor's degree rather than providing exact years of schooling.

The table below gives a comprehensive breakdown of the demographic characteristics of a sample population, segmented by race, sex, employment status, full time/part time status, and educational attainment. Each category is accompanied by the number of observations and their respective proportions, offering insight into the composition of the dataset.

Number of Observation and Proportion Table

Variable	Category	Number of Observation	Proportion
RACE	Asian	1586	5.25%
	Black	3619	11.97%
	Hispanic	3980	13.16%
	White	21050	69.62%
	TOTAL	30235	100%
SEX	Female	14061	46.51%
	Male	16174	53.49%
	TOTAL	30235	100%
EMPLOYMENT STATUS	Employed	30235	100%
PART-TIME/ FULL-TIME STATUS	Full Time	30235	100%
EDUCATINAL ATTAINMENT	No Schooling	78	0.26%
	High School Diploma	16530	54.67%
	Associate's Degree	3582	11.85%
	Bachelor's Degree	7877	26.05%
	Master's Degree	1910	6.32%
	Doctrate Degree	258	0.85%
	TOTAL	30235	100%

The largest demographic group within the dataset is White, comprising 69.62% of the sample, with 21,050 observations. This significant majority is followed by the Hispanic group, which accounts for 13.16% and Black group making up 11.97%. The smallest racial category is Asian, with 5.25%. Together, these four groups sum up to the total number of 30,235 observations confirming the diversity of the sample while highlighting a pronounced racial majority of White individuals.

The table indicates a balanced gender distribution, while male participants representing 53.49% and female accounting for 46.51%. This almost equal division suggest that gender-based analysis will not suffer from severe imbalances, allowing more equitable comparisons between male and female subgroups.

Educational attainment within the sample shows substantial diversity. The largest category is high school diploma holders, comprising 54.67%, followed by those with a bachelor's degree at 26.05%. Associate's degree holders make up 11.85%, while master's degree and Doctorate degree holders constitute smaller fractions, 6.32% and 0.85%, respectively. A notably small group 0.26% of individuals have No Schooling 78 observations. This distribution implies that most individuals in the sample possess at least a high school education, reflecting an educated workforce.

The entire sample consists of employed, full-time individuals, with the number of observations totaling 30,235 in both categories. This means that our analysis will reflect full-time workers, so our findings do not apply to part-time or unemployed populations.

The table below presents a descriptive statistic for the key variables used in our analysis. The sample's mean for age is 40.8, about 40 years old, with a range from 15 to 64, reflecting the working-age population. The mean hourly wage is $22, with a wide uncensored range from $1 to $100, indicating significant wage variation across individuals.

Table 1: Descriptive Statistics for Cleaned Dataset

Statistic	Min	Max	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
HOURWAGE	1.0	100.0	22.0	11.4	15.0	19.0	26.0
AGE	15	64	40.8	12.8	30	40	52

To build an empirical understanding of how demographic variables influence wages, we began with a linear regression, including our independent variables (e.g., age, sex, race, education). The model used *HOURWAGE* as the dependent variable, representing everyone who has reported hourly wage. The model is specified as follows:

$$\boldsymbol{HOURWAGE_i = B_o + B_1 RACE + B_2 AGE + B_3 SEX + B_4 EDUC + u_i}$$

The equation provides the foundation of our analysis, allowing us to test whether these factors affect wages. In this model, *Wage* represents the dependent variable or the outcome we are trying to explain. The intercept, B_0, is the baseline wage when age, sex, and race are at their reference values. The coefficients, B_1, B_2, and B_3, quantify the impact of each independent variable which are age, sex, and race on wages. Specifically, B_1 indicates the wage change associated with a one-unit increase in age, while B_2 and B_3 represent the wage differences between sexes and races, respectively. The error term, u, accounts for other unobserved factors influencing wages. This regression framework allows us to assess the individual contributions of age, sex, and race to wage variation and can be extended to explore.

After estimating the model, we applied the Breusch-Pagan test to assess heteroskedasticity. The models showed significant heteroskedasticity ($p < 0.05$), violating one of the key OLS assumptions. As a corrective, we re-estimated standard errors using robust variance estimators (HC0), which ensured more reliable inference.

Then, we transformed the hourly wage variable using a natural log to estimate an alternative model which is the natural log of HOURWAGE. This is a common approach in labor economics that helps stabilize variance, reduce outlier influence, and better satisfy ordinary least squares (OLS) assumptions like linearity and homoscedasticity. It also facilitates easier interpretation of coefficients: for instance, the estimated coefficient on race indicates the percentage difference in hourly wage between racial groups, all else equal.

Finally, to account for potential interactions between demographic variables, we included interaction terms in our multivariate models. Specifically, we tested for interactions between race and education, sex and education, and sex and race. These interaction terms let us examine whether one variable's effect on hourly wage differs depending on another's level. Including these terms helps capture more nuanced relationships that might otherwise be overlooked in a purely additive model.

IV. Results & Analysis

To see how hourly wages differ across demographic groups, we looked at detailed descriptive stats for people aged 16 to 64, grouped by race, sex, and age. We summarized the data in five tables showing the mean, median, interquartile range, standard deviation, and variance. These stats give an early look at the wage gaps that drive the rest of the regression analysis.

For workers between 16 and 25, Asian females earn the most on average at $20.90 an hour. Asian males come next at $18.90. White males make $17.10, and White females follow at $16.40. Black and Hispanic workers in this age group earn less—usually between $14 and $15.50—no matter the gender. Wages also vary a lot within groups, especially for Asian females, where the standard deviation is 10.4. That shows just how wide the pay range can be, even within the same demographic.

Demographic Group	N	Mean	Median	Q1	Q3	St. Dev.	Variance	Min	Max
Asian - 16-25 - Female	68	20.9	17.5	14	25	10.4	108	10	50
Asian - 16-25 - Male	71	18.9	17	14	21.5	7.6	58.3	2.1	43
Black - 16-25 - Female	210	15	14	10.3	17.4	8	64.7	2.1	87
Black - 16-25 - Male	244	14	13	10.5	15.8	4.8	23	6.8	42.2
Hispanic - 16-25 - Female	316	15.1	13.9	12	16	6.5	41.7	2.8	60
Hispanic - 16-25 - Male	431	15.5	15	12	17.6	4.8	23.5	1	41
White - 16-25 - Female	1194	16.4	15	12	18	7.2	52.1	1	55
White - 16-25 - Male	1653	17.1	15.4	13	20	7.1	49.7	4	100

In the 26–35 age group, wages start to rise as people get more experience. Asian males and females are still at the top, both averaging over $24 an hour. White males are close behind at around $22.50. Black and Hispanic women earn less, usually between $17.30 and $18.40. One thing that stands out is how the wage gap within each group grows with age like for Asian males, where the standard deviation jumps to 13.5, meaning their pay is spread out a lot more as careers move forward.

Demographic Group	N	Mean	Median	Q1	Q3	St. Dev.	Variance	Min	Max
Asian - 26-35 - Female	187	24.4	20	15	30	13.1	172.1	7.2	80
Asian - 26-35 - Male	230	24.2	20	15.5	28	13.5	182	5.5	99.8
Black - 26-35 - Female	481	17.3	16	13	20	7.5	56.5	1	67
Black - 26-35 - Male	427	18.1	17	14	21	6.5	42.7	5	50
Hispanic - 26-35 - Female	476	18.4	16.5	13.8	21	7.5	56.9	3	63
Hispanic - 26-35 - Male	669	19.7	18	15	23	7.6	57.7	7.2	80
White - 26-35 - Female	2398	20.8	18	14.5	25	9.4	88.6	2.1	99
White - 26-35 - Male	2916	22.5	20	16	26	10.6	112	1	99

By ages 36–45, most workers have built up a lot of experience, and the wage gaps between groups become even more noticeable. Asian males earn the most at $28.50 an hour, which is the highest across all age and race groups. White males are not far behind at $26, and Asian females also do well, averaging $27.30. But the gap's still there in Black and Hispanic women in this age range as they only make around $19 to $21 an hour. This group also shows the biggest spread in wages, especially among Asians, which could mean there is a wide range of jobs or pay levels within the same demographic.

Demographic Group	N	Mean	Median	Q1	Q3	St. Dev.	Variance	Min	Max
Asian - 36-45 - Female	185	27.3	22	16	35	15.1	227.3	5	76
Asian - 36-45 - Male	176	28.5	22	17	35.8	16.8	283.7	7.2	99
Black - 36-45 - Female	483	21.1	16.5	13	23.9	13.5	183.1	1	99
Black - 36-45 - Male	351	21.8	18	15	26.2	11.5	132.7	6.1	99
Hispanic - 36-45 - Female	375	19	16.8	13.5	22	9.1	82.6	1.4	76
Hispanic - 36-45 - Male	559	22	19	15	25.5	10.9	119.5	8	100
White - 36-45 - Female	1930	23.1	20	15.3	27.8	11.5	132	1	84.4
White - 36-45 - Male	2466	26	23	17.5	31	12.1	147.1	1	100

For workers aged 46–55, the same wage patterns continue. Asian males still lead with the highest average at $30.60 an hour, well above everyone else. White males come next at $26.20. Women across all races earn less, with White females making a bit more than Black or Hispanic females. Even after decades of working, Black women are still averaging just $20.10 an hour.

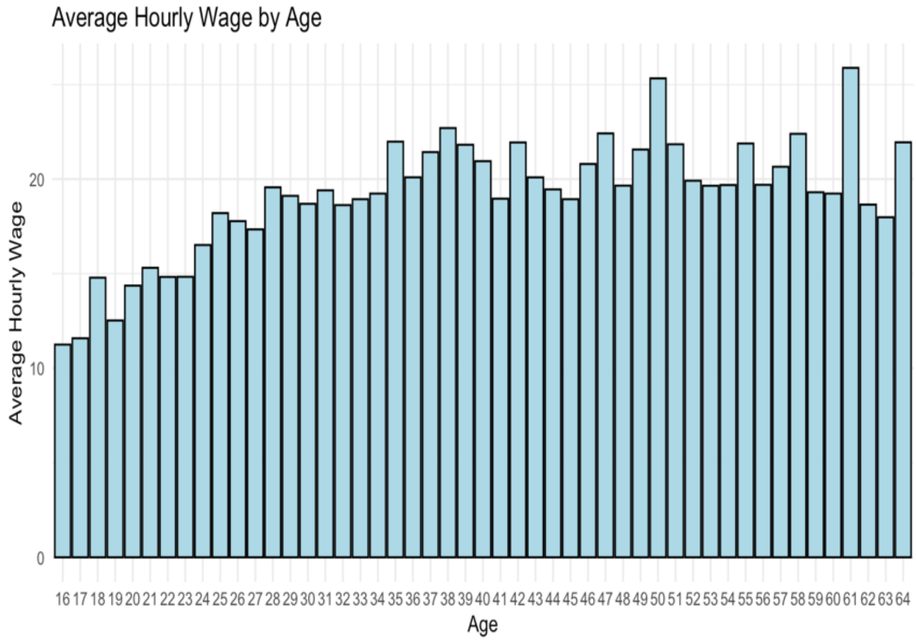
Demographic Group	N	Mean	Median	Q1	Q3	St. Dev.	Variance	Min	Max
Asian - 46-55 - Female	203	24.3	19.5	14	30	15.5	239.5	1	100
Asian - 46-55 - Male	193	30.6	26	17	40	17.2	294.9	5	100
Black - 46-55 - Female	439	20.1	16.9	13.8	22.5	11.6	134.1	1	99
Black - 46-55 - Male	367	21.1	18	14.5	25	10.3	105.5	1	72.1
Hispanic - 46-55 - Female	344	19.9	16.1	13	22	10.6	113.2	6	70
Hispanic - 46-55 - Male	443	22.8	20	15	27	11.1	123.1	8	80
White - 46-55 - Female	2208	22.6	19	15	26.9	11.7	136.4	1	100
White - 46-55 - Male	2358	26.2	23	17.8	31.5	12.4	154.9	1	99.6

In the final working years (ages 56–64), wage growth starts to level off a bit. White and Asian males still earn the most, averaging $25.80 and $25.50 an hour. For women, though, wage growth continues to lag. Black and Hispanic women are still making under $20 an hour on average. Even this close to retirement, the long-term effects of pay gaps are still clear. There is also a lot of variation in wages at this stage, which might be due to people switching to part-time, starting new careers, or shifting into distinct roles late in life.

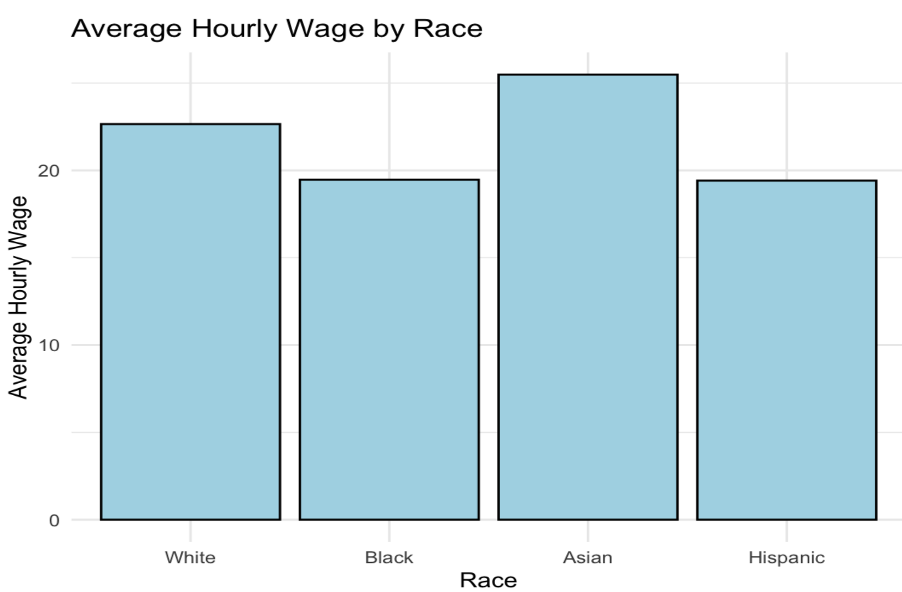
Demographic Group	N	Mean	Median	Q1	Q3	St. Dev.	Variance	Min	Max
Asian - 56-64 - Female	140	23.5	19	14	26.2	14.9	220.8	7.8	92
Asian - 56-64 - Male	131	25.5	21	15	30	15.9	254.2	8.2	100
Black - 56-64 - Female	340	20.2	18	13.4	25	10.6	111.5	7	80
Black - 56-64 - Male	275	23.6	19	16	28	11.9	142.4	9	77
Hispanic - 56-64 - Female	157	18.7	17	12.7	22	8.8	77.8	8.2	70
Hispanic - 56-64 - Male	210	22	18.5	15	25	10.9	119.5	7.2	68.5
White - 56-64 - Female	1926	22.4	19	15	25.8	11.7	138	1	100
White - 56-64 - Male	1994	25.8	22	17	30	13.1	172.5	1	100

Overall, the descriptive stats show consistent wage gaps across race, sex, and age. Asian and White males earn the most at every stage, while Black and Hispanic females earn the least. As people get older, the spread in wages within each group also gets bigger, pointing to more stratification in the labor market. These patterns help set the stage for the regression results and give important context for the policy takeaways discussed later.

To dig deeper into how age, sex, race, Hispanic origin, and education affect hourly wages, we moved from summary stats like the mean and median to visual tools. Bar graphs are especially helpful here; they make it easy to see how average wages differ across groups and highlight clear trends and gaps. With these graphs, we can see the wage differences play out across categories.

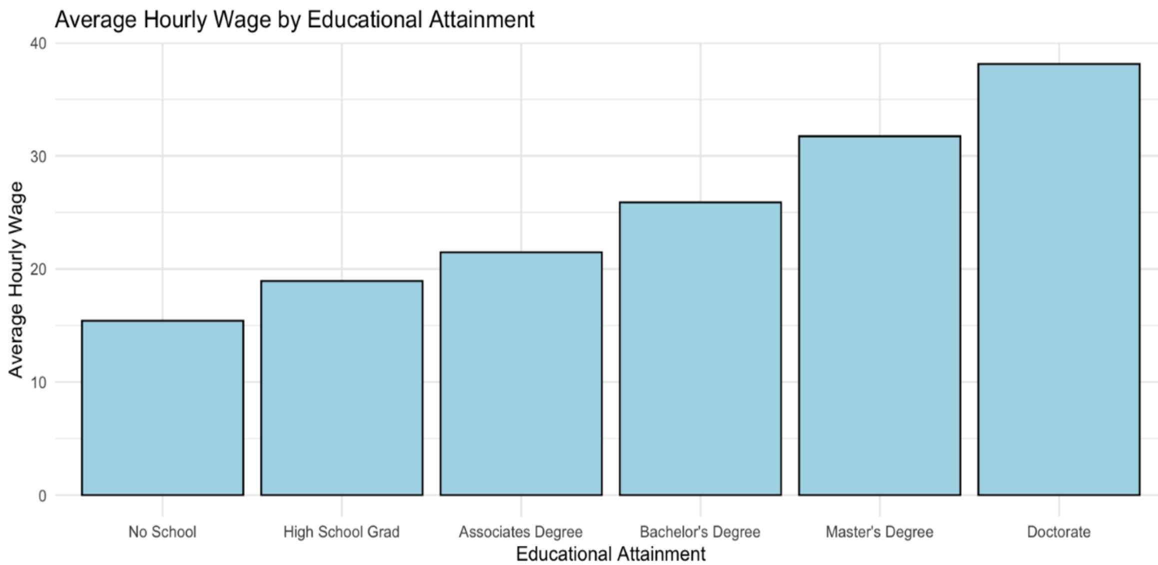


This bar graph looks at the categorical variable "age" and how it relates to average hourly wages. There is a clear positive trend; wages go up as age increases. The lowest average wage is at age 16, and the highest is at age 61. That makes sense since older workers usually have more experience and skills due to being in the workforce longer. The wage rate begins to level off once again after age 61, as more individuals are leaving the workforce.



Race was another key variable in our analysis. We looked at four main groups: White, Black, Asian, and Hispanic. The bar graph clearly shows that Asians have the highest average hourly wage, followed by Whites, then Blacks and Hispanics. This lines up with what we found in the literature, Black and Hispanic workers tend to earn less on average, while Asians and Whites earn more. The visual just helps reinforce those patterns.

In terms of gender, we looked at disparities between males and females. It is clear to see that between the two, men tend to make a greater hourly wage than women. This data is supported by many of our findings in our observations.



Our final variable was educational attainment, and it included no schooling, high school diploma, associate's degree, bachelor's degree, master's degree, and doctorate. Education and hourly wage have a positive relationship as well, since the more education one has, the greater their wage is on average.

Bar graphs are great for spotting patterns like how women and minority groups consistently earn less, but they do not tell us why these gaps exist. To dig deeper, we move to regression models. They let us control multiple factors at once and see how race, gender, and education interact to shape wages. This way, we are not just looking at differences—we are figuring out what is driving them.

Table 1: Regression Models: Hourly Wage by Demographic and Employment Variables

	Dependent variable:			
	Hourly Wage			
	(1)	(2)	(3)	(4)
Age	0.164^{***}			
	(0.005)			
Black		-3.264^{***}		
		(0.191)		
Asian		2.786^{***}		
		(0.386)		
Hispanic		-3.314^{***}		
		(0.166)		
Sex (Male)			-2.102^{***}	
			(0.130)	
Educ(High school Diploma)				3.235^{***}
				(0.705)
Educ(Associate)				5.778^{***}
				(0.719)
Educ(Bachelor's)				10.228^{***}
				(0.718)
Educ(Master's)				16.171^{***}
				(0.801)
Educ(Doctrate)				22.520^{***}
				(1.491)
Constant	15.342^{***}	22.728^{***}	23.025^{***}	15.716^{***}
	(0.187)	(0.079)	(0.092)	(0.702)
Observations	30,235	30,235	30,235	30,235
R^2	0.034	0.020	0.008	0.136
Adjusted R^2	0.034	0.020	0.008	0.136
Residual Std. Error	11.215 (df = 30233)	11.294 (df = 30231)	11.363 (df = 30233)	10.609 (df = 30229)
F Statistic	$1{,}065.143^{***}$ (df = 1; 30233)	210.474^{***} (df = 3; 30231)	257.363^{***} (df = 1; 30233)	950.450^{***} (df = 5; 30229)
Note:				*p<0.1; **p<0.05; ***p<0.01

To begin our analysis, we started with a simple linear regression to see how age affects hourly wage. The model came out as: **HOURWAGE = 15.34 + 0.164*AGE**. That means for every extra year of age, hourly wage goes up by about 16 cents, assuming everything else stays the same. The positive coefficient makes sense with human capital theory. People usually earn more as they get older because of experience, skills, and time in the workforce. To check if the model holds up, we ran a Breusch-Pagan test for heteroskedasticity. The p-value was closer to zero, so we reject the null of homoscedasticity. That means the OLS standard errors might be off. To fix this, we used robust standard errors with White's HC0 estimator to get more reliable results. The updated results show that the age coefficient is still statistically significant, even after adjusting for heteroskedasticity. This backs up the idea that there is a solid, positive link between age and hourly wage.

Next, to get a better look at wage differences across racial groups, we ran a regression using RACE1 as a categorical variable, with White as the reference group. The model looks like this: **HOURWAGE = 22.728 − 3.264*BLACK* + *2.786*ASIAN − 3.314*HISPANIC.** The intercept (22.73) is the average hourly wage for White workers. On average, Black workers earn $3.264 less, Asian workers earn $2.786 more, and Hispanic workers earn $3.314 less compared to Whites. All these coefficients are statistically significant at the 1% level. We also tested for heteroskedasticity using the Breusch-Pagan test, and the p-value was closer to zero. So, we reject the null hypothesis that states that there is no heteroskedasticity. Because of that, we used robust standard errors (White's HC0) to correct it. Even after correcting for heteroskedasticity, the results still show that racial wage gaps are strong and statistically significant.

Next, we ran a simple linear regression to look at how sex relates to hourly wage. The equation is: **HOURWAGE = 23.025 − 2.102*SEX.** The intercept (23.025) is the average wage for male workers. The coefficient on sex is -2.102, meaning female workers earn about $2.102 less per hour than males, on average. This gap is highly significant ($p < 0.001$), even without controlling for things like education or experience. To check the assumptions, we ran a Breusch-Pagan test for heteroskedasticity. The p-value was under 0.05, so we reject the null hypothesis. We used robust (HC0) standard errors to fix this. Even after the correction, the gender wage gap still holds up as statistically significant.

To see how education affects wages, we ran a simple linear regression with hourly wage as the dependent variable and education (EDUC) as the only predictor. EDUC is treated as a continuous variable that reflects years or levels of schooling. The estimated model is: **HOURWAGE = 15.716 + 3.235*high school diploma + 5.778*associate's degree + 10.228*bachelor's degree + 16.171*master's degree + 22.520*doctorate degree**. The intercept (15.716) shows the estimated wage for someone with the lowest level of education, no formal schooling. On average, individuals with high school diploma earn $3.235 more, individuals with associate’s degree earn $5.778 more, individuals who have their bachelor’s, master's and doctorates degree earn $10.228, $16.171, and $22.520 more, respectively. This result is highly significant ($p < 0.001$) and lines up with human capital theory: more schooling leads to higher pay. To check model assumptions, we used the Breusch-Pagan test for heteroskedasticity. The p-value was also closer to zero, so the null hypothesis does not hold. we corrected for that using robust (HC0) standard errors. The education coefficient stays positive and highly significant, even after correcting for heteroskedasticity. This just reinforces how strong the link is between education and higher wages.

To see how much age, race, and sex explain wage differences together, we ran a joint hypothesis test using the full model, which also controls for education and hours worked. The test was based on the following hypothesis:

- Null hypothesis: The new added variable will not support the base data
- Alternative hypothesis: The new added variable will not support the base data

This test checks whether age, race, and sex add any extra value in explaining hourly wages beyond what is already captured by education and hours worked. Using robust (HC0) standard errors, the F-test gave us: F = 702.36, with 3 degrees of freedom, 30,229 total observations and a p-value less than 2.2e-16. That is well below 0.001, so we reject the null. This means age, race, and sex do matter. They explain a significant part of the wage variation even after controlling for other factors. Leaving them out would lead to a mis-specified model and biased results.

Next, we estimate three linear regression models and one polynomial model to break down what drives hourly wages. Each model builds on the latter. Starting with basic demographics, then adding education, and finally including a polynomial factor AGE.

To get a clearer picture of wage inequality, we ran three step-by-step regression models, each adding more variables based on economic theory and labor market research. This approach helped show how adding factors like age and education changed the effects of race and sex on wages. We also used robust standard errors in all models to account for heteroskedasticity.

	Dependent variable:			
	HOURWAGE			
	(1)	(2)	(3)	(4)
AGE		0.161***	0.164***	0.793***
		(0.005)	(0.004)	(0.028)
Black	−3.094***	−3.074***	−2.550***	−2.648***
	(0.191)	(0.187)	(0.171)	(0.171)
Asian	2.859***	2.731***	0.452	0.350
	(0.385)	(0.385)	(0.351)	(0.349)
Hispanic	−3.396***	−2.851***	−1.493***	−1.628***
	(0.166)	(0.163)	(0.154)	(0.153)
High School Diploma			3.880***	3.873***
			(0.699)	(0.676)
Associate's Degree			6.797***	6.544***
			(0.714)	(0.691)
Bachelor's Degree			11.398***	11.138***
			(0.715)	(0.692)
Master's Degree			17.080***	16.662***
			(0.796)	(0.776)
Doctrate Degree			23.215***	22.721***
			(1.484)	(1.466)
I(AGE^2)				−0.008
Female	−2.090***	−2.268***	−3.637***	−3.601***
	(0.129)	(0.127)	(0.120)	(0.120)
Constant	23.687***	17.122***	10.368***	−1.226
	(0.102)	(0.200)	(0.733)	(2.663)
Observations	30,235	30,235	30,235	30,235
R^2	0.029	0.061	0.200	0.210
Adjusted R^2	0.029	0.061	0.200	0.210
Residual Std. Error	11.246 (df = 30230)	11.057 (df = 30229)	10.206 (df = 30224)	10.145 (df = 30223)
F Statistic	223.894*** (df = 4; 30230)	394.178*** (df = 5; 30229)	757.061*** (df = 10; 30224)	729.647*** (df = 11; 30223)
Note:				*p<0.1; **p<0.05; ***p<0.01

One of the most consistent takeaways across all four models is that age has a positive effect on hourly wages. In Models 2 and 3, the coefficient for age is around 0.161, which is statistically significant at the 1% level. This means that, on average, each additional year of age is linked to a 16-cent increase in hourly wage, assuming everything else stays the same. Model 4 adds a bit more complexity by including a quadratic term for age (I(AGE^2)). In this model, the linear age coefficient jumps to 0.793, but the quadratic coefficient becomes -0.008. This change tells us that the relationship between age and wages is not just a straight line. Instead, wages still go up as people get older, but the rate of increase slows down after a certain point. This tells us there is a sweet spot where experience really pays off, but eventually, the wage growth levels out as people get older. This pattern makes sense since younger workers typically see faster wage growth as they gain skills, but that growth rate tapers off once they reach mid-career.

The results consistently show that race significantly affects hourly wages, even after controlling for other variables. The coefficient for Black workers remains negative and significant across all models. In Model 1, the coefficient is -3.094, indicating that Black workers earn about $3.09 less per hour compared to the reference group (White workers). This gap slightly narrows in the more comprehensive models (Model 3: -2.550 & Model 4: -2.648), but the wage penalty persists, suggesting that even after controlling for age and education, Black workers face a significant disadvantage. For Hispanic workers, the pattern is similar but slightly less severe. The coefficient in Model 1 is -3.396, showing a $3.40 hourly wage gap compared to White workers. This gap decreases to -1.628 in Model 4, meaning that some of the wage disparity can be explained by differences in age and education. Still, even after accounting for these factors, Hispanic workers face a significant pay gap. The story for Asian workers is quite different. Initially, the coefficient is positive (2.859 in Model 1), indicating that Asian workers earn about $2.86 more per hour than White workers. However, as more variables are added, the coefficient becomes smaller and statistically insignificant (Model 4: 0.350). This suggests that the initial wage advantage observed for Asian workers might be partly due to higher education levels or other factors not accounted for in the simpler models.

The gender wage gap is another prominent finding in this analysis. The coefficient for Female is negative and significant across all models, ranging from -2.090 in Model 1 to -3.601 in Model 4. This means that women earn $2 to $3.60 less per hour compared to men, holding all other factors constant. The gap widens as more variables are included, indicating that controlling for age, race, and education reveals an even more pronounced gender disparity. This consistent wage gap underscores a well-documented issue in the labor market: women tend to earn less than men even after accounting for education and experience. The persistence of this gap in more comprehensive models suggests that unobserved factors (like occupational segregation or discrimination) might still be at play.

The impact of education on wages is clear and significant. Compared to those without a high school diploma, each additional level of education significantly boosts hourly wages. High School Diploma: increases wages by about \$3.88 (Model 3 and 4). Associate's degree: adds approximately \$6.54 to \$6.80 per hour. Bachelor’s Degree: further boosts wages by around \$11.1 to \$11.4 per hour. Master’s Degree: increases hourly wages by about \$16.7 to \$17.1. Doctorate Degree: the most substantial impact, adding \$22.7 to \$23.2 per hour. The clear takeaway here is that higher education significantly increases earnings, and the difference between each educational level is substantial. This highlights the economic value of educational attainment, especially at the bachelor’s level and above.

The R-squared values increase as more variables are added, going from 0.029 in Model 1 to 0.210 in Model 4. This means that the final model explains about 21% of the variation in hourly wages, which is a considerable improvement from the simpler models. The addition of age, education, and the quadratic term for age clearly makes the model more informative and accurate.

Moreover, the F-statistics are significant for all models, indicating that the variables collectively explain a huge portion of wage differences. The increase in the adjusted R-squared value from 0.029 to 0.210 also suggests that adding more variables improves the model's predictive power without overfitting.

The next table takes a slightly different approach by using the log of hourly wage (log (HOURWAGE)) as the dependent variable. This change means the coefficients now represent percentage changes instead of absolute differences, which makes sense when we are looking at how factors like age, race, sex, and education impact wages. The models are structured the same way as before: we start with race and sex, then add age, then education, and finally include a quadratic age term to capture any non-linear effects.

	Dependent variable:			
	log(HOURWAGE)			
	(1)	(2)	(3)	(4)
AGE		0.007	0.007	0.039
		(0.005)	(0.004)	(0.031)
Black	−0.153	−0.152	−0.131	−0.136
	(0.191)	(0.187)	(0.171)	(0.171)
Asian	0.082	0.077	−0.007	−0.012
	(0.385)	(0.385)	(0.351)	(0.349)
Hispanic	−0.146	−0.122	−0.069	−0.075
	(0.166)	(0.163)	(0.154)	(0.153)
High School Diploma			0.197	0.197
			(0.699)	(0.673)
Associate's Degree			0.337	0.324
			(0.714)	(0.689)
Bachelor's Degree			0.499	0.486
			(0.715)	(0.690)
Master's Degree			0.677	0.656
			(0.796)	(0.774)
Doctrate Degree			0.825	0.800
			(1.484)	(1.466)
I(AGEˆ2)				−0.0004
				(0.0004)
Female	−0.101	−0.108	−0.162	−0.160
	(0.129)	(0.127)	(0.120)	(0.120)
Constant	3.066***	2.784***	2.470***	1.883**
	(0.102)	(0.200)	(0.733)	(0.869)
Observations	30,235	30,235	30,235	30,235
R^2	0.036	0.074	0.198	0.213
Adjusted R^2	0.036	0.074	0.197	0.213
Residual Std. Error	0.446 (df = 30230)	0.438 (df = 30229)	0.407 (df = 30224)	0.403 (df = 30223)
F Statistic	283.257*** (df = 4; 30230)	482.409*** (df = 5; 30229)	744.438*** (df = 10; 30224)	743.783*** (df = 11; 30223)
Note:				*p<0.1; **p<0.05; ***p<0.01

One of the most consistent takeaways across all four models is that age has a positive effect on wages. In Models 2 and 3, the coefficient for age is 0.007, which means that every additional year of age is linked to about a 0.7% increase in hourly wage. This is statistically significant at the 1% level, indicating that the relationship between age and wages is quite strong. However, Model 4 tells a slightly different story by including a quadratic term for age (I(AGE^2)). Here, the linear age coefficient jumps to 0.039, but the quadratic coefficient becomes -0.0004. This shift tells us that while wages increase as people get older, the rate of increase slows down over time. In practical terms, this means younger workers tend to see quicker wage growth as they gain experience, but this momentum starts to level off later in their careers. This pattern aligns with how wage growth typically works: early career gains are more pronounced, while mid- to late-career growth stabilizes.

The racial wage gap shows up consistently across all models. The coefficients for Black workers are always negative. In Model 1, the coefficient is -0.153, which means Black workers earn about 15% less per hour compared to White workers. This gap narrows slightly as we add more controls (like age and education), but it remains substantial even in Model 4 (-0.136). This tells us that while some of the wage disparity can be explained by factors like education and age, a huge portion remains unexplained. It suggests that structural inequalities or biases might still be at play. For Hispanic workers, the pattern is similar but less severe. The initial gap in Model 1 is -0.146, or about 14.6% less per hour compared to White workers. By Model 4, this gap decreases to -0.075, meaning that part of the difference is linked to education or age. Still, even after accounting for these factors, Hispanic workers earn significantly less than their White counterparts. The results for Asian workers are more nuanced. In the simplest model, the coefficient is positive (0.082), suggesting that Asian workers initially earn about 8% more per hour than White workers. However, once we control age and education in the later models, the coefficient becomes statistically insignificant and even slightly negative (-0.012 in Model 4). This shift indicates that the initial pay advantage observed for Asian workers might be driven by higher educational attainment rather than race itself. Once we account for education, the advantage disappears.

The gender wage gap is clear and persistent. Across all models, the coefficient for Female is negative, ranging from -0.101 to -0.160. This tells us that women consistently earn about 10-

16% less per hour compared to men, even when controlling for race, age, and education. Interestingly, the gap widens when we add more variables, which suggests that after accounting for qualifications and demographics, the true wage gap between men and women becomes even more apparent. This indicates that factors beyond education or age—like occupational segregation or discrimination—could be driving this persistent disparity.

Education still stands out as the most significant driver of wage differences. Compared to workers without a high school diploma, every additional level of education leads to a substantial percentage increase in hourly wages. High School Diploma about 20% more per hour. Associate's degree around 32-34% more, Bachelor's degree 50% more, Master's degree adds about 66-68% and Doctorate has the biggest impact, increasing wages by 80-83%. The pattern here is straightforward: more education means much higher pay. The difference between each educational level is substantial, especially when comparing high school graduates to those with bachelor's or advanced degrees. This highlights how important educational attainment is in shaping wage outcomes.

As more variables are added, the R-squared values improve, going from 0.036 in Model 1 to 0.213 in Model 4. This means that the final model explains about 21.3% of the variation in log wages. Including the quadratic age term and education clearly improves the model's explanatory power.

The adjusted R-squared follows the same pattern, indicating that the additional variables genuinely help explain wage variation rather than just adding noise. The F-statistics are highly significant in all models, confirming that the chosen variables are collectively important in understanding wage differences.

All four models failed the Breusch-Pagan test for heteroskedasticity, meaning the error variances were not constant. Because of that, we used robust standard errors for all model estimates. As for multicollinearity, the first three models showed no issues. VIFs were all close to 1. In the fourth (polynomial) model, most VIFs stayed low, except for AGE and AGE^2, which had high VIFs around 53. That is expected since they are mechanically related, and both are needed to model the curve in the age-wage relationship. Overall, multicollinearity is not a problem for interpreting the main variables like race, sex, and education.

Building up on the two tables above we noticed that the log-linear model is useful because it handles the right-skewed distribution often found in wage data. Since wages can vary widely, the raw wage data in the linear model might not fully capture the relative changes between groups. Taking the logarithm of hourly wages helps normalize the data, allowing us to interpret the coefficients as percentage changes rather than absolute dollar amounts. This makes the log-linear model especially useful when discussing wage disparities among groups with different average wage levels.

In both models, age has a positive and significant effect on wages, but the way this effect is presented differs. In the linear model, age boosts hourly wages directly. In Models 2 and 3, the coefficient for age is about 0.161, meaning that each additional year increases hourly wage by approximately 16 cents. However, once the quadratic term (I(AGE^2)) is introduced in Model 4, the age coefficient jumps to 0.793, while the quadratic term itself is negative (-0.008). This indicates that although wages increase with age, the rate of increase slows down as workers get older. In other words, younger workers tend to see faster wage growth, but this growth plateaus as they age. The log-linear model shows a similar trend but in percentage terms. Here, the age coefficient in Models 2 and 3 is 0.007, meaning that each additional year of age increases hourly wages by around 0.7%. When the quadratic term is added in Model 4, the linear coefficient rises to 0.039, but the quadratic term becomes -0.0004. This again shows that wages increase with age, but at a decreasing rate. What is important here is how the log-linear model makes it clear that the growth rate itself declines. While the linear model gives a straightforward dollar increase, the log-linear model better highlights the relative slowdown in wage growth as workers move from early to late career stages.

Both models consistently show significant racial wage gaps, but they highlight various aspects of these disparities. In the linear model, the gap between Black and White workers is clear. Black workers earn \$2.55 to \$3.09 less per hour across the models. For Hispanic workers, the difference ranges from \$1.49 to \$3.40 less per hour. Initially, Asian workers earn \$2.86 more per hour than White workers, but this advantage disappears in more comprehensive models that include education and age. In the log-linear model, the same gaps are shown as percentage differences. Black workers earn 13-15% less per hour than White workers, and Hispanic workers earn 7-15% less. Asian workers initially show a positive wage difference of 8%, but this effect becomes statistically insignificant when controlling for other factors. The key difference between the two models lies in interpretation. The linear model makes the gap look substantial in dollar terms, but the log-linear model shows that these gaps are relative to average wages. For instance, a 15% lower wage might mean something quite different in low-wage versus high-wage jobs. The log-linear approach better captures this contextual difference.

Both models also consistently indicate a gender wage gap. In the linear model, the coefficient for Female ranges from -2.09 to -3.60, meaning women earn \$2 to \$3.60 less per hour compared to men. In the log-linear model, the gap ranges from -0.101 to -0.160, which translates to women earning 10-16% less per hour than men. The gender wage gap is significant in both models, but the log-linear model gives a more intuitive sense of how this gap scales with wages. For example, a $3 per hour difference might seem more striking when wages are low, but 16% less captures the proportional disadvantage more accurately across different wage levels.

Education consistently shows a strong positive effect on wages, regardless of model type. In the linear model, higher education levels bring significant dollar increases: High School Diploma around $3.88 more per hour, associate's degree additional $6.54 to $6.80 per hour, bachelor's degree about $11.1 to $11.4 more, master's degree around $16.7 to $17.1 more per hour, Doctorate the biggest boost, adding $22.7 to $23.2 per hour. In the log-linear model, the impact is expressed in percentage terms High School Diploma about 20% more per hour, associate's degree roughly 32-34% more, bachelor's degree around 48-50% more, master's degree adds about 66-68% and Doctorate which is the most significant impact, with wages increasing by 80-83%.

The log-linear model clearly shows that the economic value of education scales proportionally. This is especially relevant for higher degrees, where the percentage increase reflects a substantial rise in absolute pay when the starting wage is already high

In the end, both models are valuable, but the log-linear model offers a clearer way to interpret percentage differences, which is often more meaningful in economic contexts where pay varies significantly. Understanding both perspectives helps us see not just how much wages differ, but how those differences play out across varying income levels.

The next analysis examines how these factors combine to influence hourly wages, using three regression models that progressively add complexity by incorporating interaction terms. By analyzing each model, we uncover how educational attainment impacts different demographic groups and whether it truly helps close wage gaps.

Table 1: Regression: Interaction Models

	Dependent variable:		
	log(HOURWAGE)		
	(1)	(2)	(3)
Black	−0.087	−0.129***	−0.160***
	(0.154)	(0.008)	(0.010)
Asian	−0.111	−0.004	−0.045***
	(0.168)	(0.012)	(0.017)
Hispanic	−0.032	−0.067***	−0.083***
	(0.152)	(0.007)	(0.009)
High School Diploma	0.204	0.204***	0.194***
	(0.145)	(0.047)	(0.038)
Associate's Degree	0.338**	0.314***	0.335***
	(0.145)	(0.048)	(0.039)
Bachelor's Degree	0.499***	0.434***	0.497***
	(0.145)	(0.047)	(0.039)
Master's Degree	0.664***	0.631***	0.675***
	(0.145)	(0.051)	(0.040)
Doctrate Degree	0.897***	0.834***	0.824***
	(0.150)	(0.071)	(0.052)
Female	−0.162***	−0.211***	−0.178***
	(0.005)	(0.079)	(0.006)
AGE	0.007***	0.007***	0.007***
	(0.0002)	(0.0002)	(0.0002)
Black:High School Diploma	−0.052		
	(0.154)		
Asian:High School Diploma	0.023		
	(0.169)		
Hispanic:High School Diploma	−0.036		
	(0.152)		
Black:Associate's Degree	−0.028		
	(0.155)		
Asian:Associate's Degree	0.092		
	(0.171)		
Hispanic:Associate's Degree	−0.027		
	(0.153)		
Black:Bachelor's Degree	−0.041		
	(0.155)		
Asian:Bachelor's Degree	0.156		
	(0.169)		
Hispanic:Bachelor's Degree	−0.051		
	(0.153)		
Black:Master's Degree	−0.006		
	(0.160)		
Asian:Master's Degree	0.184		
	(0.172)		
Hispanic:Master's Degree	0.003		
	(0.159)		
Black:Doctrate Degree	−0.203		
	(0.206)		
Asian:Doctrate Degree	−0.037		
	(0.193)		
Hispanic:Doctrate Degree	−0.444**		
	(0.218)		
Female:High School Diploma		−0.006	
		(0.079)	
Female:Associate's Degree		0.064	
		(0.080)	
Female:Bachelor's Degree		0.141*	
		(0.079)	
Female:Master's Degree		0.100	
		(0.082)	
Female:Doctrate's Degree		0.007	
		(0.106)	
Female:Black			0.056***
			(0.015)
Female:Asian			0.079***
			(0.024)
Female :Hispanic			0.033**
			(0.013)
Constant	2.465***	2.480***	2.480***
	(0.145)	(0.048)	(0.039)
Observations	30,235	30,235	30,235
R^2	0.199	0.202	0.198
Adjusted R^2	0.199	0.202	0.198
Residual Std. Error	0.407 (df = 30209)	0.406 (df = 30219)	0.407 (df = 30221)
F Statistic	300.834*** (df = 25; 30209)	511.382*** (df = 15; 30219)	575.250*** (df = 13; 30221)
Note:			*p<0.1; **p<0.05; ***p<0.01

The first model investigates how race and education jointly affect wages. The goal here is to understand whether the wage premium associated with higher education is consistent across racial groups. It is clear from the results that education boosts wages. Compared to workers without a high school diploma, those with an associate's degree earn about 33.8% more, and those with a bachelor's degree see a 49.9% increase. The wage bump is even higher for workers with a master's degree (66.4%) and reaches its peak with a Doctorate Degree (89.7%). These figures highlight that achieving higher education levels remains a reliable pathway to better earnings. However, the interaction terms between race and education reveal that not everyone benefits equally from advanced education. While education increases wages for most workers, racial disparities persist, particularly among Hispanic workers. The most striking example is that Hispanic workers with a Doctorate Degree earn 44.4% less than their White counterparts with the same degree. This gap is statistically significant, suggesting that the highest levels of education do not shield Hispanic workers from wage penalties. For other racial groups, the interactions between race and educational attainment are not statistically significant. For instance, Black workers with a bachelor's degree earn about 4.1% less than White workers with the same degree, but this difference is not significant. Similarly, Asian workers with a bachelor's degree see a 15.6% wage increase compared to Whites, but again, this is not statistically meaningful. Gender also plays a significant role in wages. Women, regardless of education level, earn 16.2% less than men ($p<0.01$). This persistent gap underscores the reality that even when women achieve higher education, they still face systemic disadvantages in pay.

Therefore, it tells us that while education undoubtedly boosts wages, it does not erase racial wage gaps. Hispanic workers with Doctorate Degrees face significant wage penalties, suggesting that education alone cannot overcome labor market discrimination. Similarly, the consistent gender pays gap shows that achieving higher qualifications does not eliminate wage inequality for women.

The second model shifts focus to how education affects wages differently for men and women. This is crucial because, while education is often seen as an equalizer, the persistent gender pay gap raises questions about whether higher qualifications can close it. Education significantly boosts wages for both men and women. Having a High School Diploma increases wages by about 20.4%, while an associate's degree raises them by 31.4%. A bachelor's degree results in a 43.4% increase, and a master's degree brings a 63.1% bump. The most substantial boost comes with a Doctorate Degree, increasing wages by 83.4%. These figures demonstrate that higher education consistently correlates with better pay. Despite the positive effects of education, women continue to earn significantly less than men. Even at the highest levels of education, women make about 21.1% less than their male counterparts. While education reduces the gap, it does not eliminate it. For example, women with a bachelor's degree still earn 14.1% less than men ($p<0.1$), and the gap persists even for women with a Master’s or Doctorate Degree. These findings suggest that factors beyond education—such as workplace discrimination, career interruptions, and gendered expectations—continue to influence earnings. Simply promoting education for women is not enough if the underlying structural biases in the labor market remain unaddressed.

Model 2 confirms that while education lifts wages, it does not close the gender pay gap. Women, especially those in higher-paying roles, still face a persistent earnings penalty compared to men. Addressing this disparity requires more than just encouraging women to pursue advanced degrees; it calls for systemic changes in how the labor market values women’s work.

The third model takes a deeper look at how race and gender together affect wages. This intersectional analysis helps us see whether being both a racial minority and a woman results in compounded wage penalties. The results clearly show that being both a minority and female often results in compounded disadvantages. Black workers earn about 16.0% less than White workers, Asian workers earn 4.5% less, and Hispanic workers earn 8.3% less. Additionally, being female reduces wages by 17.8%. Interestingly, the model reveals that some combinations of race and gender slightly mitigate the wage gap. For example: Female: Black: +5.6% ($p<0.01$), Female: Asian: +7.9% ($p<0.01$), Female: Hispanic: +3.3% ($p<0.05$). These positive coefficients indicate that, within minority groups, women do not face as steep a penalty as might be expected compared to their male counterparts. However, this does not mean they earn more than White men; rather, it shows that the compounded penalty is slightly less severe.

Model 3 highlights that intersectionality matters. The wage gap is not just additive; being both a woman and a racial minority creates unique challenges that are more complex than simply summing individual disadvantages. Addressing these gaps requires policies that consider the overlapping nature of race and gender discrimination.

Our analysis shows that education boosts wages, but it does not fully close the gaps rooted in race and gender. Even among highly educated workers, racial and gender pay disparities persist, and the combined effect of being both a minority and a woman makes the gap even wider. This highlights that structural issues in the labor market do not just go away with more education.

The COVID-19 pandemic made these gaps worse. Job losses hit low-wage sectors the hardest—sectors where women and minority workers are overrepresented. This means that the groups already earning less faced the biggest setbacks during the economic downturn. Previous research backs this up, showing that race, gender, and education combine in complicated ways to shape wages. Our findings line up with that and suggest that the pandemic did not just maintain wage gaps—it made them worse.

If we really want to tackle wage inequality, we need more than just promoting higher education. We need policies that get at the root of the problem—like addressing discrimination, reducing occupational segregation, and challenging gender bias in pay. And since minority women face the most compounded disadvantages, any real progress must take that intersection into account. Only by tackling these issues head-on can we make education truly work as an equalizer.

V. Conclusion

This analysis confirms that wage inequality in the U.S. labor market is shaped by a combination of demographic and human capital factors. Across every model, age, race, sex, and education consistently show strong and statistically significant relationships with hourly wage. While higher education and experience are associated with higher earnings, these benefits are not distributed equally across demographic groups.

The linear models highlight clear gaps. Black and Hispanic workers consistently earn less than White workers, and women earn less than men, even after controlling for education and experience. Education shows the strongest positive impact on wages, especially at higher levels like graduate and doctoral degrees, but it does not fully close racial, or gender pay gaps.

Switching to a log-linear model provided deeper insights. The percentage-based results made disparities more pronounced. For example, showing that women earn about 16.2% less than men, even when their education and experience are similar. The wage premium for Asian workers seen in linear models disappeared in the log model, suggesting the effect may be driven by a few high earners rather than a broader group-wide advantage.

Interaction models helped capture more of the nuance. While most returns to education did not differ much across race or sex, a few exceptions stood out like Asian workers with bachelor's or master's degrees earning more, and Hispanic doctorate holders earning less than expected. Surprisingly, minority women in some cases earned more than their male counterparts, showing that race and gender do not always affect wages in simple, predictable ways.

Even though the interaction terms slightly improved model fit, the core patterns remained: education matters most, but race and gender continue to shape wage outcomes in ways that education and experience alone cannot fully explain. These findings highlight the importance of considering both individual qualifications and structural inequalities when studying labor market outcomes and point to the need for policies that address both.

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