ERASMUS UNIVERSITY ROTTERDAM

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To what extent is education correlated with a variation of racial inequalities in the U.S. labour market?

The present thesis exploits Current Population Survey (CPS) data to determine the racial difference that might exist in the correlation between attending college education and a wage or employment probability increase. The racial wage gap and employment gap have been estimated at 20.9% and 46.8%, respectively. Moreover, it resulted that White individuals have a 4.4% greater wage increase after attending college education than their Black peers. Results about the correlation between education and employment probability indicate that attending college education is correlated with a decrease in the racial employment gap, although this result was not statistically significant. Correlation between race and non-college education, as well as the role of sex, and mechanisms that might, partially, explain racial labour inequalities were discussed.

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Introduction

The U.S. has a long history of racial inequalities and discrimination; the fight for equal rights between African-Americans and White Americans has many famous figures, from Martin Luther King and Rosa Park in the last century to Barack Obama, the first African-American to become U.S. president. In 2020, the death of George Floyd triggered the mass movement ‘Black Lives Matters’ which protested against those racial inequalities, while engaging an international reflection on what should be the place of immigrants in societies. This popular movement wishes that White and Black Americans enjoy similar rights and opportunities (Campbell, 2021). This campaign emerged in a context of rising inequalities, the last decades witnessed an important increase in national inequality, the fraction of the national resources controlled by the richest 1% of North Americans was just above 24% in the first quarter of 1992, whereas it was 31% in the first quarter of 2016 (Federal Reserve Economic Data, 2022). Moreover, racial inequalities also increased in the last decades, the racial wealth gap more than doubled from 1992 to 2016 (Aladangady, et al., 2021). The mechanisms which maintain those racial inequalities over time are not yet fully understood. Some scientists argue that racial inequalities observed in the U.S. are partly due to racial educational differences (Hargis et al., 2006), while others stress that even when controlling for education, racial inequalities are still present in the U.S. labour market (Elvira & Zatzick, 2002; Fryer et al., 2013).

The present study aims at finding if college education might be correlated with a reduction of inequalities between the Black and White people in the U.S. labour market. The main research question will, therefore, be: *“To what extent is education correlated with a variation of racial inequalities in the U.S. labour market?”.*

Labour-related racial inequalities will be measured as both wage and employment probability inequalities. On the other hand, education will mainly be defined as whether the individual followed a college education or not. In order to answer the research question, a regression will measure the racial wage gap, and the correlation which exists between holding a college degree and one’s later wage and employment probability, given that the individual is either black or white. The research question will be answered using 2021 survey data from the Current Population Survey (CPS) (US Census Bureau, 2021).

The phenomenon of racial inequalities in the labour market has been extensively studied in the literature, it resulted that racial inequalities (both in the labour market and in education) exist, although, it was not clear if they were due to racial discrimination (Bertrand and Mullainathan, 2004; Agan and Starr, 2018) or structural differences (Hargis et al, 2006). The present study aims at evaluating to what extent can education be correlated with an exacerbation or alleviation of racial inequalities in the labour market.

The answer to the research questions will be of special interest to politicians and policy makers. A thorough understanding of the impact that education can have on racial inequalities will enable them to propose more efficient policies to reduce those racial disparities. Governmental programs that can efficiently reduce racial inequalities will be of special interest to political movements such as Black Live Matter. Moreover, it is also of importance for voting citizens who will have a better understanding of the consequences that educational policy could have on racial inequalities, and will be able to make electoral choices that are more in line with their political opinion. Finally, teachers and school directors will gain knowledge about their impact on society. If their impact does not contribute to what they think is right for society, they might reevaluate their way of working in order to be in agreement with their personal beliefs.

It resulted that there are significant racial inequalities in both wage and probability of employment, White individuals have on average 20.9% higher wages and are 46.8% more likely to be employed. It has been calculated that (when controlling for the full set of control variables) there is a 4.4% greater wage return on the obtention of a university diploma for White compared to Black individuals, this difference is statistically significant at a 5% significance level. The results were less statistically significant for the racial employment gap, however, it seems that college education is correlated with a decrease in the racial employment gap.

Literature review

The impact of education on racial inequalities in the labour market

The literature presents different arguments to explain racial labour inequalities, and the role that education has to alleviate or exacerbate those inequalities. The first is to say that racial inequalities are driven by racial differences in education and that when controlling for those educational disparities, races are no longer significantly influencing one's economic outcome (Hargis et al., 2006). In addition, Dickerson (2007) explains that the quality of public schools is responsible for some of the racial employment gap. On the other hand, some studies argue that even when controlling for racial disparities (including education) there is still a race effect (Elvira & Zatzick, 2002; Fryer et al., 2013). This view suggests that a diploma obtained by a White individual will always be more valued than the same diploma earned by a Black student. One could, therefore, argue that even if the educational level of White and Black individuals is, on average, equal there will still be labour inequalities since the return on a diploma is greater for White compared to Black individuals (Lang and Manove, 2011). Moreover, if the average educational attainment of both white and black individuals would increase, racial labour inequalities might be exacerbated (Bertrand and Mullainathan, 2004).

Hargis et al (2006) analysed the influence that race has on employment termination. Their study is based on 548 employees of a large hotel chain. It was concluded that race is correlated with employment termination, however, when controlling for education, race is no longer correlated with employment termination. They argue that in order to alleviate racial disparities in employment, it is important to reduce the educational inequalities between whites and African-Americans. Moreover, it has been argued by Dickerson (2007) that the level of public schools, in residential sectors with a high proportion of Black inhabitants partly explains racial employment inequalities.

Nonetheless, their conclusion is challenged by the study of Elvira & Zatzick (2002), in the financial firm studied, they found out that even when controlling for variables such as performance rating, black workers were more likely to be laid off than white workers. The study made by Chetty et al. (2020) expanded this conclusion to the racial income gap. They demonstrated that variables such as parental marital status, education, and wealth are not important factors to explain the racial income gap, given that parental income is accounted for. Finally, they argue that the racial income gap is still present for individuals who grew up in the same neighbourhood. Fryer et al. (2013) demonstrated that discrimination is responsible for, at least, one third of the racial wage gap.

In the same line of thought, Bertrand and Mullainathan (2004) defended the argument that the return on education is greater for whites. They conducted a field experiment in which they responded to help-wanted advertisements in Chicago and Boston. Half of the fake applications had been given a typical white American name, whereas the other half were named by African-American names (the same strategy which was later used by Edelman et al (2017)). It resulted from Bertrand and Mullainathen's (2004) study that when varying the quality of the resumes that were sent, having a higher quality resume led to a 30% increase in the chance of being called back for white, while it had a much smaller effect for African names, e.i., higher qualification increased the racial inequality in callbacks. This conclusion was extended to the racial wage inequality by Lang and Manove (2011) who argued that when controlling for education and cognitive abilities white workers earn a noticeably greater wage, they rejected the hypothesis that the racial wage inequality might be due to a difference in the schooling quality. In addition, Fryer (2011) explains that as a result of having a greater return on education for White compared to Black individuals, Black students complete fewer years of education than their White peers, a phenomenon that reinforces racial labour inequalities.

Racial labour inequality theories

Three main theories explain racial inequalities in the labour market. The first one was developed by Becker (1957) and is called 'taste base discrimination' its main assumption is that people prefer to work, employ, or be served by white compared to black individuals. The second one is called statistical discrimination, which happens when an employer makes an assumption about an individual based on the group one belongs to (in our case race) (Arrow, 1971; Phelps, 1972; Aigner & Cain, 1977). Finally, the third theory is called occupational crowding, in this situation, some groups of workers (e.g., Black workers) are not allowed in some industries or managerial positions (Bergmann, 1971).

Racial inequalities in hiring decisions is a topic that has been studied on many occasions since the apparition of Becker's book "The economics of Discrimination" (1957). In that book Becker proposed a theoretical framework that analyses the consequences of gender (although the theory holds for races) taste-based labour discrimination, he distinguishes three different types of prejudice, prejudiced employers, coworkers, or customers. In the first case some employers have a disutility of employing women (or Black) workers, assuming that employers are maximising their utility, they will exclusively employ the sex (or race) who has the lower utility cost for him. The employer's utility cost is derived from the labour cost and distaste to employ female (or Black) workers. Since some employers are discriminating on gender (or race), at market equilibrium the wage of female (or Black) employees will be lower than the wage of male (or White) workers. In the situation of prejudiced coworkers, White workers experience disutility from working with Black workers. A White worker will, therefore, ask for a greater wage to work with a Black coworker, to compensate for the disutility. Finally, the last situation is customer prejudice, in such a case customers have a lower willingness to pay if they are served by Black workers. It will result in a segregated workforce where firms employing Black workers only will not be able to afford the higher wage of White workers, and in firms with only White workers who will be able to ask a premium from their consumers to be served by a White person (Boeri & Ours, 2021). An example of taste based discrimination is provided by the research completed by Edelman et al (2017). They sent 6400 messages to hosts on the platform using similar profiles in all respects, but names that were either typical White or African American. Their results indicate that typical white names had a 16 percent greater chance of success than typical African American names. Surprisingly they indicate that even African American hosts were discriminating against guests with African American names. Moreover, they priced the cost of discrimination, for the median host, between $65 and $100 of forgone revenue.

The theory of statistical discrimination can be illustrated by the natural experiment referenced in the article of Agan and Starr (2018). They analysed the effect that the Ban the Box policy had in New Jersey and New York City. Before the implementation of the Ban the Box policy in 2015, employers were allowed to ask in the initial job application, or during the first interview if an applicant had a criminal record or not, after 2015 this right was revoked. Once employers could not know whether an applicant had committed a crime or not they used race as a proxy for criminality, which increased the racial gap in callback rates. Agan and Starr (2015) argue that having a GED, compared to a high school diploma is a much better predictor of having a criminal background, however, this variable was not truly considered by employers. This study shows how, incorrect, racial stereotypes are still enrooted within modern American culture, and how they have a concrete impact, in this case, on the labour market. This paper highlight a statistical discrimination issue, since as a result of having less information about a candidate a heuristic about its race was wrongly used. The fact that when information about the criminal record is available the employment gap is reduced demonstrates that there is not (only) a distaste for Balck workers but a wrong assumption about them e.i., statistical discrimination occurred. Altonji and Pierret (2001) explain that a company that would use statistical discrimination in order to approximate the productivity of a potential employee, will revise their opinion about their employee’s productivity once new, and harder to observe, information becomes available. A black worker might be wrongly judged unproductive by a company on its debut, however, once the company knows more about its productivity they will update their judgement.

Finally, the occupational crowding theory claims that certain jobs are reserved for certain types of workers, e.g., some types of work or positions are restricted to White workers. For those jobs the labour supply will decrease since only a fraction of the workforce can apply for them; in the meantime, the labour supply for non-restricted jobs will increase, since those who were banned from the restricted jobs have to find another job. Therefore, the average wage will be higher for restricted jobs than for non-restricted jobs (Bergmann, 1971).

Racial achievement gap

It is clear from the literature that there is a racial achievement gap in education, e.i., White students have, on average, better academic results than their black peers (Neal, 2006; Reardon, Robinson-Cimpian, and Weathers, 2015; Reardon and Kalogrides, 2019). Fryer and Levitt (2004) demonstrated that when adding a set of control variables there are no racial differences in the test result of Black and White children entering kindergarten. However, during the first two years of education test results of Black children are falling behind those of White children. Moreover, Morris and Perry (2016) argue that racial differences in punishment could partly explain the racial achievement gap.

Reardon and Kalogrides (2019) estimated the racial achievement gap using 200,000 results of national tests, on Mathematics, and English Language and Art (ELA); those tests have been taken by elementary and middle school students, from 2009 to 2013. It resulted from their analysis that the racial gaps in the result were, on average, 0.5 to 0.7 standard deviation. They demonstrate that the strongest predictor of the racial achievement gap is racial segregation, and differences in parental variables such as parental income, and parental education. Fryer and Levitt (2004) suggest that, when including a set of control variables, there are no racial differences in reading and maths test results when children enter kindergarten; this difference is, however, developed during the first two years of schooling. They argue that the presence of a racial achievement gap after two years of education could be due to a school fixed effect, e.i., white children would attend higher school quality than their black peers. In their article, Morris and Perry (2016) argue that even within a school white students might have preferential treatment over their black peers. They indicate that racial differences in punishment could also be a factor that, partly, explains the achievement gap. They demonstrate that there are significant racial differences in punishment rate, and that having a higher punishment rate is correlated with lower educational outcomes. Finally, they conclude that racial differences in punishment rates are explaining twenty percent of the racial achievement gap (Morris and Perry, 2016).

Racial discrimination in American society

This section analyses the different forms that racial discrimination can take in the U.S. society (English et al, 2020) and their consequences (Benner et al, 2018).

English et al (2020) analysed the daily racial discrimination faced by a group of 101 Black U.S. American teenagers. Their survey included questions about both online, such as racist jokes, threats, or exclusions from a website, and offline discrimination, e.g., jokes or racist comments about physical appearance, family, or Black people in general. Interviewed individuals experienced, on average, 5 discriminations per day, mainly on the Internet. Moreover, they stressed the negative effect that those discriminations have on the mental health of discriminated individuals. The consequences of those discriminations were studied by Benner et al (2018). Their meta analytic research concluded that discrimination has a consistently negative impact on socioemotional distress, academic performance, and health behaviour. They also warned that those effects can have negative long term consequences on one morbidity or mortality rate.

Hypotheses

Several hypotheses will be tested through this research.

Hypothesis 1: college education is, on average, correlated with a significantly greater wage increase for White compared to Black individuals.

Hypothesis 2: college education is, on average, correlated with a significantly greater increase in employment probability for White compared to Black individuals.

The first two hypotheses are the most important since they will answer the research question.

Hypothesis 3: white individuals have, on average, significantly greater educational levels than black individuals.

The last hypothesis is used to verify the presence of racial educational disparities.

Data

The data set used to answer the research question is retrieved from the 2021 Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS). The Current Population Survey is a well-known American survey aiming at measuring economic and social variables such as employment, earnings, and education (US Census Bureau, 2021). The survey is jointly financed by the U.S. Census Bureau and the Bureau of Labour Statistics (BLS).

The 2021 Annual Social and Economic Supplement (ASEC) records observations at the family, household, and individual levels. This research will focus on the data retrieved at the individual level. The ASEC collected observations about 163 543 individuals; those observations concern different topics, such as demography, work experience, and income. Individuals who were neither only white nor only black were dropped from the sample, as well as those who were not in the labour force, children, and individuals who were in the armed force. It resulted in a final sample of 69 564 observations.

Table 1 describes the mean, standard deviation, minimum and maximum, per race, the t-test of difference for all the main variables that will be used in this research, and the combined Kolmogorov-Smirnov test (K-S) for the continuous variables. The first racial difference is the number of observations, the share of Black individuals in the sample is 12.8% ($\frac{8922}{8922+60642} = 12.8\%$), whereas 87.2% of observations are White ($\frac{60642}{8922+60642} = 87.2\%$). There are very small racial differences in age, the mean age for both Black and White individuals is slightly above 42 years old, with a very similar standard deviation (note that all respondents older than 85 years old were registered as 85 years in the data); the T-test equal to 0.514 confirm that there are no significant age differences across both group, whereas the t-test for all the other variables is equal to 0.000, e.i., there are significant racial differences, at a 1% significance level, for those variables. The combined K-S test, however, indicates that there are significant (at a 1% significance level) differences in the age distribution of Black and White people. It is important to note that the percentage of males within the sample of Black individuals is 46.1% whereas it is 53.1% for White individuals (this difference is significant at a 1% significance level). The variables Education (a dummy variable equal to 1 if the individual has a University degree and to 0 otherwise), Employment, and Wage are higher for White than for Black respondents; 29.7% of Blacks hold a University degree, whereas 36.9% of Whites do, 90.6% of Blacks are employed and they earn an average yearly (pre-tax) wage of more than $44 000, whereas 94.8% of White are employed and earn an average yearly (pre-tax) wage of greater than $55 000, all those differences are significant at a 1% significance level, the result of the combined K-S test. Poverty measures the percentage of individuals living above the poverty threshold[1], it is 91.6% for Black individuals whereas it is 95% for White (this difference is significant at a 1% significance level). The variable experience is a dummy variable taking the value 0 if the individual's longest working class was without pay, and one if her class of worker was in another sector (e.g., private, public, local); this variable is a proxy for work experience, an individual whose longest working class is without pay is likely to have less professional experience than one who has another longest working class, given that they have the same age. Since there is no significant racial age difference, it seems that White workers have slightly, but statistically significant, higher experience than Black workers. Those racial inequalities can be seen as a vicious circle, as Black individuals earn a lower wage and are less likely to be employed, they are less able to afford their children's education who will as a result be less educated, earn a lower wage, and are more likely to experience poverty. The racial difference in both variables experience and employment could suggest that there is racial discrimination against Black worker, or that this racial inequality is due to racial structural differences, e.g., educational differences.

[1] The poverty threshold was adopted by a Federal Interagency Committee in 1969, before being slightly adapted in 1981 (US Census Bureau, 2021).

Table1: Descriptive statistics per race, T-test of difference, and combined K-S test.

	N	Mean	Standard deviation	Min	Max	T-test of difference	Combined K-S test
BLACK							
Age	8922	42.39	14.525	15	85	0.514	0.002
Male	8922	0.461	0.498	0	1	0.000	
Education	8922	0.297	0.457	0	1	0.000	
Employment	8922	0.906	0.292	0	1	0.000	
Wage	8922	44347.779	62374.130	0	1099999	0.000	0.000
Poverty	8922	0.916	0.278	0	1	0.000	
Experience	8922	0.945	0.228	0	1	0.000	
WHITE							
Age	60642	42.496	14.373	15	85		
Male	60642	0.531	0.499	0	1		
Education	60642	0.369	0.482	0	1		
Employment	60642	0.948	0.223	0	1		
Wage	60642	55836.607	77172.720	0	2099999		
Poverty	60642	0.95	0.219	0	1		
Experience	60642	0.964	0.187	0	1		

Notes: The above table presents the number of observations, mean, standard deviation, minimum, maximum, per race, T-test of difference for each of the variables, and combined K-S test for the continuous variables. Age is a continuous variable taking the value of the individual's age, the variable Age takes the value of 85 if the individual is aged 85 or more. The variable Male is a dummy variable that takes the value 0 if the individual is a female and 1 if the individual is a male. Education is a dummy variable that takes the value of 1 if the individual holds a university degree, and the value of 0 otherwise. Wage is a continuous variable taking the value of the pre-tax yearly wage of an individual. Poverty is a dummy variable taking the value 1 if the individual is below the poverty threshold, and 0 otherwise. The variable experience is a dummy variable that takes the value 1 if the respondent's longest class of worker is not without pay, and 0 otherwise. The t-test of difference measures if the variables present in the table are significantly different for both races, and the combined K-S test measures if continuous variables have a similar distribution across races.

Methodology

OLS regression

Labour inequalities will be measured as wage inequality as well as employment inequality. In order to estimate racial wage inequality, conditional on the level of education, four Mincer equations will be estimated (Mincer, 1974). The variable wage has been transformed into its logarithmic form in order to normalise its distribution, figures 1.A., and B. in the appendix graphically illustrate the wage distribution under its initial and natural logarithmic form. Due to this transformation of the variable wage, individuals who did not earn any wage in the year prior to the survey were dropped from the sample; the final sample for this regression is of 63 106 observations. Equation (1) will regress the dummy variable White on the logarithmic variable wage. In a world without racial inequalities, there should not be a correlation between those variables. However, if there are inequalities it is likely that a correlation will be found.

(1) $lnWage_I = \alpha + \beta White_I + \epsilon$

In Equation (1) α and β are parameters, $White_I$ is a dummy variable equal to zero if the respondent is white, and equal to one if the individual is black (note that the sample was restricted to black and white individuals, other races such as Hispanics, or Indians have been dropped from the sample). ϵ is an error term, and $lnWage_I$ is the natural logarithm of the individual (pre-tax) yearly wage. The subscript I indicates that the variable is decided at the individual level.

Equation (2) will regress the variable $White_I$ controlling for $Education_I$, a dummy variable taking the value 1 if the individual holds a university degree and 0 otherwise. Equation (3) will add the interaction term between the variable $White_I$ and $Education_I$ to the equation.

(2) $lnWage_I = \gamma + \delta White_I + \zeta Education_I + \eta$

(3) $lnWage_I = \varphi + \sigma White_I + \omega Education_I + \upsilon White_I * Education_I + \rho$

γ, δ,ζ π, φ, σ, ω, and υ are parameters, and η, and ρ are error terms.

In Equation (4), a set of control variables has been added. Those control variables are poverty, Male, Experience, Occupation, Industry, and State.

(4) $lnWage_I = \theta + \vartheta White_I + \iota Education_I + \kappa White_I * Education_I + \mu Controls_I + \lambda$

θ, ϑ, ι, and κ are parameters, λ, is an error term. The variable $Controls_I$ represents a set of control variables, namely, Poverty, Male, Experience, Occupation, Industry, and State. Poverty is a dummy variable taking the value 0 if the individual is below the poverty threshold, and 1 otherwise. The variable Male is a dummy variable that takes the value 0 if the individual is a female and 1 if the individual is a male. The variable Experience is a dummy variable that takes the value 1 if the respondent's longest class of worker is not without pay, and 0 otherwise. The variables Occupation, Industry, and State are all categorical variables.

Logit regression

The second part of the analysis aims at measuring the extensive employment margin, e.i., having a job or not. It will be done using a logit function which will measure the likelihood, or probability, of finding a job given variables such as race and education.

In Equations (5) to (8) employment is defined as anyone having a job, regardless of whether they were working at the time of the survey or not; reasons for not working while having a job include, among others, vacations, illness, and bad weather. Unemployment is defined as both individuals currently looking for a job and those on layoff (waiting to be called back to a specific job) (US Census Bureau, 2021). The variable *Pr(employed)* measures the probability that an individual is employed.

(5) $Pr(employed) = \alpha + \beta White_I + \epsilon$

In Equation (5),α, and β are parameters, ϵ is an error term. This equation aims at measuring racial inequalities in the likelihood of being employed.

(6) $Pr(employed) = \xi + \mu White_I + o Education_I + \psi$

(7) $Pr(employed) = \gamma + \delta White_I + \zeta Education_I + \pi White_I * Education_I + \eta$

In Equations (6) and (7), ζ, ξ, μ, ο, γ, δ, and π, are parameters, and ψ and η are error terms. It aims at evaluating the influence that education might have on employment probability, given that the individual is either White or Black.

(8) $Pr(employed) = \theta + \vartheta White_I + \iota Education_I + \kappa White_I * Education_I + \mu Controls_I + \lambda$

In Equation (8), θ, ϑ, ι, and, κ are parameters, λ, is an error term. This equation adds a set of control variables, namely, Poverty, Male, Experience, Occupation, Industry, and State, to Equation (7).

Results

In this section both the results of the OLS and the logit regressions will be discussed.

<u>OLS regression</u>

Table 2: Multiple linear regressions of the natural logarithm of Wage over White, Education, their interaction and controlling for Poverty, Male, Experience, Occupation, Industry, and State.

Ln Wage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
White	0.209***	0.157***	0.161***	0.115***	0.0869***	0.0871***	0.0505***	0.0694***
	(0.0122)	(0.0116)	(0.0144)	(0.0133)	(0.0133)	(0.0133)	(0.0124)	(0.0129)
Education		0.695***	0.705***	0.603***	0.639***	0.639***	0.349***	0.333***
		(0.00799)	(0.0225)	(0.0212)	(0.0212)	(0.0212)	(0.0203)	(0.0203)
White*Education			-0.0113	0.0249	0.0196	0.0196	0.0353*	0.0440**
			(0.0240)	(0.0227)	(0.0227)	(0.0227)	(0.0211)	(0.0211)
Poverty				1.577***	1.532***	1.532***	1.295***	1.293***
				(0.0215)	(0.0217)	(0.0217)	(0.0229)	(0.0230)
Male					0.378***	0.378***	0.311***	0.311***
					(0.00743)	(0.00743)	(0.00817)	(0.00816)
Experience						1.212***	1.166***	1.181***
						(0.402)	(0.439)	(0.434)

Occupation FE	No	No	No	No	No	No	Yes	Yes
Industry FE	No	No	No	No	No	No	Yes	Yes
State FE	No	No	No	No	No	No	No	Yes
Constant	10.36***	10.15***	10.15***	8.701***	8.560***	7.348***	5.572***	5.589***
	(0.0113)	(0.0111)	(0.0132)	(0.0233)	(0.0236)	(0.403)	(0.622)	(0.615)
Observations	63,106	63,106	63,106	63,106	63,106	63,106	63,106	63,106
R-squared	0.004	0.106	0.106	0.191	0.223	0.223	0.356	0.359

Notes: This table presents eight OLS regressions with the natural logarithm of Wage as the dependent variable and White as the treatment variable. The variable Wage is a continuous variable taking the value of the (pre-tax) yearly wage of an individual. White is a dummy variable taking the value 1 if the individual is White and 0 if she is Black. The variable Education is a dummy variable taking the value 1 if the individual holds a University degree, and 0 otherwise. Male is a dummy variable taking the value 1 if the individual is a male, and 0 otherwise. The variable Poverty is a dummy variable taking the value 1 if the individual is living above the poverty threshold, and 0 otherwise. The variable Experience is a dummy that takes the value 1 if the individual's longest class of worker is not without pay, and takes the value 0 otherwise. The variables Occupation Fixed Effect (FE), Industry (FE), and State (FE) are all categorical variables. Tables 8 and 9 in the appendix present all the industry and occupation codes. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The number of observations and R-squared are represented in the last two rows.

Table 2 presents eight regressions on the natural logarithm of wage. The first equation regresses the variable White on the natural logarithm of wage, the coefficient of the variable White can be interpreted as the percentage of racial wage inequality, e.i., a White individual earns, on average, 20.9% more than a Black individual (this difference is significant at a 1% significance level), a twenty percent wage difference is economically significant. It has to be stressed that Table 2 measures correlation and that due to the nature of the data set used it cannot make causal statements. As acknowledged in Table1 both races are different in many respects, this explains the addition of a set of control variables in equations (2) to (8). Adding control variables decreases the coefficient of the variable White but does not affect its sign and significance level, e.i., those control variables may be partly responsible for the racial wage gap but even when taken into consideration White workers still earn more than Black workers.

The second and third equations are crucial to answer the research question; equation (2) adds the variable Education which is a dummy variable taking the value 1 if the individual holds a university degree, and 0 otherwise. The coefficient of this variable indicates that holding a university degree is correlated with a wage increase of, on average, 69.5%; this correlation is statistically significant at a 1% significance level. In equation (3), the interaction term between the variables Whites and Education indicates the extra wage increase of White university graduates, compared to their black peers. The interaction term is negative, in equation (3) only, and is statistically insignificant in equations (3) to (7). The interaction term becomes positive and statistically significant at a 5% significance level in equation (8) and is also positive and statistically significant at a 10% significance level in equation (7). Equation (8) suggests that holding a university degree is correlated with an average wage increase of 33.3%, moreover, if the individual is White, her wage will, on average, increase by an extra 4.4%; for a White individual the total, average, wage increase will be of 33.3%+4.4%= 37.7%, whereas it would have been of 33.3% if the individual is Black. According to Equation (8), there is, therefore, a 4.4% (pre-tax) racial wage difference for university graduates, this wage difference is likely to be attenuated by taxation (if higher incomes are more taxed than lower ones). One could therefore conclude that being both White and university diplomate is correlated with a wage increase which is statistically significant at a 5% significance level (at least in equation (8)); moreover, the size of this correlation is 4.4% of the pre-tax wage.

Columns (4) to (8) control for different variables, columns (3), (4), and (5) add poverty, gender, and experience, respectively. The fact that the coefficient of White changes as a result of the inclusion of those control variables suggests that they bias the estimate of the correlation between being White and one's wage. In the last three columns, occupation fixed effect, industry fixed effect, and state fixed effect are added as control variables, as a result, the coefficient of White decreases but stays significant at a 1% significance level, suggesting that the control variables added only partially explain the racial wage gap. Moreover, the increase in the statistical significance of the interaction term, as a result of controlling for State fixed effect may indicate that, within a given state, White students attend better schools than Black students; between state school level disparities might explain why national racial differences in the return to college education are less significant than the state racial difference in the return to college education. This hypothesis can, however, not be formally answered since the data set does not provide enough information to know whether Black and White students attend similar schools or not.

Logit regression

The present paragraph will discuss the results of the logit regression.

Table 3: Multiple logit regressions of Employment over White, Education, their interaction and controlling for Poverty, Male, Experience, Occupation, Industry, and State.

Employment	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
White	0.631***	0.587***	0.624***	0.562***	0.574***	0.537***	0.579***	0.655***
	(0.0406)	(0.0407)	(0.0449)	(0.0458)	(0.0458)	(0.0460)	(0.0490)	(0.0518)
Education		0.769***	0.939***	0.788***	0.775***	0.658***	0.294***	0.354***
		(0.0396)	(0.0992)	(0.100)	(0.1000)	(0.101)	(0.107)	(0.107)
White*Education			-0.205*	-0.170	-0.169	-0.134	-0.164	-0.200*
			(0.108)	(0.109)	(0.109)	(0.109)	(0.113)	(0.113)
Poverty				1.358***	1.372***	1.289***	1.111***	1.132***
				(0.0459)	(0.0460)	(0.0474)	(0.0504)	(0.0508)
Male					-0.157***	-0.165***	-0.00320	0.00670
					(0.0333)	(0.0334)	(0.0410)	(0.0409)
Experience						0.417***	0.337***	0.334***
						(0.0285)	(0.0241)	(0.0239)
Occupation FE	No	No	No	No	No	No	Yes	Yes
Industry FE	No	No	No	No	No	No	Yes	Yes
State FE	No	No	No	No	No	No	No	Yes
Constant	2.263***	2.080***	2.051***	0.916***	0.982***	0.545***	1.000***	1.315***
	(0.0362)	(0.0372)	(0.0398)	(0.0538)	(0.0554)	(0.0605)	(0.162)	(0.210)
Observations	69,564	69,564	69,564	69,564	69,564	69,564	69,341	69,341

Notes: This table presents eight logit regressions with Employment as the dependent variable and White as the treatment variable. The variable Employment is a dummy variable taking the value 1 if the individual is employed, and 0 otherwise. White is a dummy variable taking the value 1 if the individual is White and 0 if she is Black. The variable Education is a dummy variable taking the value 1 if the individual holds a University degree, and 0 otherwise. Male is a dummy variable taking the value 1 if the individual is a male, and 0 otherwise. The variable Poverty is a dummy variable taking the value 1 if the individual is living above the poverty threshold, and 0 otherwise. The variable Experience is a dummy that takes the value 1 if the individual's longest class of worker is not without pay, and takes the value 0 otherwise. The variables Occupation Fixed Effect (FE), Industry (FE), and State (FE) are all categorical variables. Tables 8 and 9 in the appendix present all the industry and occupation codes. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is represented in the last row.

Table 3 presents eight logit equations, regressing the dummy variable employment on variables White, Education, the interaction term between White and Education, and controlling for a set of control variables. From equation (1), the racial employment gap can be deduced, the odds ratio can be calculated from the coefficient of White, namely, $e^{0.631} = 1.879$, e.i., being White is correlated with an increase in the odds of being employed by 87.9%. The odds can be transformed into probability, according to the formula $\pi = \frac{\omega}{1+\omega}$ (where ω stand for the odd, and π for probability), hence $\pi = \frac{0.879}{1+0.879} = 0.468 = 46.8\%$; being White is, therefore, correlated with an increase in the probability of being employed by 46.8%. It is important to note that the correlation between being White on the probability of being employed is statistically significant at a 1% significance level. Interestingly the addition of control variables in equations (2) to (8) has only a limited effect on the coefficient of the variable White, suggesting that those variables do not explain the racial employment inequality.

Equation (2) adds the variable Education; in equations (2) to (8) the coefficient of the variable Education is positive and statistically significant at a 1% significance level. Similarly as for the variable White, the percentage increase in employment probability correlated with the obtention of a university degree can be calculated using the coefficient of the variable Education (in this situation the variable White can be seen as a control variable). The odd ratio can be calculated as follow $e^{0.769} = 2.158$, holding a university degree is, therefore, correlated with an increase in the odds of being employed by 115.8%. Transforming the odd increase into a probability increase, $\pi = \frac{1.158}{1+1.158} = 0.537 = 53.7\%$; holding a university degree is correlated with a 53.7% increase in the probability of being employed.

Equation (3) includes the interaction term between the variable White and Education, the coefficient is negative and only significant at a 10% significance level. Moreover, in equations (4) to (7), the coefficient becomes statistically insignificant, while staying negative. One could, therefore, conclude that college education may be correlated with a lower racial difference in employment probability; this correlation has, however, a low statistical significance.

Further analysis and robustness checks

This section will investigate other potential sources of racial inequalities within the U.S. labour market.

Education as categorical variable

In this section, the variable education has been modified as a categorical variable instead of a dummy variable. The categorical variable can take a value from 0 to 5, 0 being no diploma, the variable takes the value 1 if the individual holds a high school diploma, and the value 2 in case she holds an associate or professional degree. The variable Education takes the values 3, 4, and 5 if the individual holds a Bachelor, a Master, or a Ph.D. diploma, respectively. All of the other variables were kept unchanged compared to the main analysis.

Table 4: Multiple linear regression of the natural logarithm of Wage on White, Education as a categorical variable, and interaction term between Education and White, controlling for Poverty, Male, Experience, Occupation, Industry, and State.

lnWage	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
White	0.209***	0.169***	0.0878	-0.0147	-0.0510	-0.0508	-0.0875*	-0.0826*
	(0.0122)	(0.0113)	(0.0534)	(0.0525)	(0.0518)	(0.0518)	(0.0489)	(0.0491)
Education High School		0.654***	0.567***	0.428***	0.439***	0.439***	0.269***	0.267***
		(0.0181)	(0.0524)	(0.0512)	(0.0506)	(0.0506)	(0.0479)	(0.0481)
Education Associate or Professional degree		1.023***	0.936***	0.741***	0.791***	0.791***	0.449***	0.445***
		(0.0202)	(0.0576)	(0.0560)	(0.0556)	(0.0556)	(0.0524)	(0.0525)
Education Bachelor degree		1.242***	1.165***	0.942***	0.986***	0.986***	0.574***	0.558***
		(0.0187)	(0.0552)	(0.0540)	(0.0534)	(0.0534)	(0.0507)	(0.0509)
Education Master degree		1.466***	1.443***	1.197***	1.277***	1.277***	0.843***	0.821***
		(0.0203)	(0.0585)	(0.0575)	(0.0570)	(0.0570)	(0.0544)	(0.0545)
Education PhD. degree		1.872***	1.846***	1.602***	1.648***	1.648***	1.123***	1.093***
		(0.0284)	(0.0911)	(0.0884)	(0.0907)	(0.0907)	(0.0876)	(0.0867)
White*Education High School			0.0985*	0.157***	0.167***	0.166***	0.164***	0.178***
			(0.0558)	(0.0546)	(0.0538)	(0.0538)	(0.0508)	(0.0510)
White*Education Associate Or Professional degree			0.0976	0.177***	0.177***	0.177***	0.170***	0.186***
			(0.0614)	(0.0598)	(0.0591)	(0.0591)	(0.0555)	(0.0557)
White*Education Bachelor degree			0.0850	0.174***	0.179***	0.179***	0.190***	0.213***
			(0.0586)	(0.0574)	(0.0566)	(0.0566)	(0.0533)	(0.0535)
White*Education Master degree			0.0247	0.126**	0.124**	0.124**	0.152***	0.171***
			(0.0624)	(0.0612)	(0.0605)	(0.0605)	(0.0571)	(0.0572)

White*Education PhD. degree			0.0296	0.124	0.104	0.104	0.152*	0.183**
			(0.0959)	(0.0932)	(0.0952)	(0.0952)	(0.0914)	(0.0905)
Poverty				1.474***	1.421***	1.422***	1.255***	1.254***
				(0.0223)	(0.0225)	(0.0225)	(0.0231)	(0.0232)
Male					0.403***	0.403***	0.299***	0.299***
					(0.00723)	(0.00723)	(0.00805)	(0.00804)
Experience FE						1.131***	1.142**	1.158***
						(0.430)	(0.449)	(0.444)
Occupation FE	No	No	No	No	No	No	Yes	Yes
Industry FE	No	No	No	No	No	No	Yes	Yes
State FE	No	No	No	No	No	No	No	Yes
Constant	10.36***	9.495***	9.568***	8.351***	8.189***	7.058***	5.427***	5.436***
	(0.0113)	(0.0198)	(0.0502)	(0.0524)	(0.0520)	(0.433)	(0.625)	(0.619)
Observations	63,106	63,106	63,106	63,106	63,106	63,106	63,106	63,106
R-squared	0.004	0.162	0.162	0.235	0.272	0.272	0.376	0.380

Notes: This table presents eight OLS regressions with the natural logarithm of Wage as the dependent variable and White as the treatment variable. The variable Wage is a continuous variable taking the value of the (pre-tax) yearly wage of an individual. White is a dummy variable taking the value 1 if the individual is White and 0 if she is Black. Education categorical is a categorical variable taking the value 0 if the individual does not hold any diploma (base category), the variable takes the value 1 if the individual holds a high school diploma, and the value 2 in case she holds an associate or professional degree. It takes the values 3, 4, and 5 if the individual holds a Bachelor, a Master, or a Ph.D. diploma, respectively. Male is a dummy variable taking the value 1 if the individual is a male, and 0 otherwise. The variable experience is a dummy that takes the value 1 if the individual's longest class of worker is not without pay, and takes the value 0 otherwise. The variables Occupation Fixed Effect (FE), Industry (FE), and State (FE) are all categorical variables. Tables 8 and 9 in the appendix present all the industry and occupation codes. *** p<0.01, ** p<0.05, * p<0.1. The number of observations and R-squared are represented in the last two rows

Table 4 presents the same analysis as done in Table 2, but the variable Education is now a categorical variable, whereas it was a dummy variable in Table 2. Equation (1) is similar to the first equation of Table 2, it gives the racial wage difference. However, when adding control variables the statistical significance and the size of the coefficient decrease, it even becomes negative in equations (4) to (8). From equations (3) to (8), the coefficient of the variable White is not statistically significant at a 5% significance level; those results differ from the ones obtained in Table 2 and would suggest that when using a more precise definition of Education, and a set of control variables there might not have significant racial wage difference.

The second equation adds the five dummy variables about education (the base category is ‘no diploma’), confirming previous results, the coefficients are all positive and significant at a 1% significance level. Moreover, the coefficients are all increasing as the level of education increases, meaning that obtaining a better type of diploma is correlated with a wage increase.

Equation (3) adds the interaction term between the variables White and the dummy variables about education. The sign of all the interaction terms is positive, however, the statistical significance varies. In equation (3) none of the interaction terms is statistically significant at a 5% significance level, whereas in equations (4) to (8) all of the interaction terms, but the one about Ph.D. degree, are statistically significant at (at least) a 5% significance level. The higher statistical significance compared to Table 2 may be due to a difference in specifications, in Table 5, the base category of the variable Education is having no diploma, whereas Table 2 compared holding a University degree or not; it is, therefore, likely to have more significant results as the specifications are more precise. The sign of the interaction term’s coefficient is in line with the results of Table 2.

The present paragraph will discuss the results of the logit regression.

Table 5: Multiple logit regressions of Employment over White, Education as a categorical variable, and interaction term between Education and White, controlling for Poverty, Male, Experience, Occupation, Industry, and State.

Employment	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
White	0.631***	0.597***	0.616***	0.508***	0.519***	0.529***	0.551***	0.666***
	(0.0406)	(0.0408)	(0.116)	(0.123)	(0.123)	(0.134)	(0.148)	(0.148)
Education High School		0.418***	0.382***	0.219*	0.214*	0.0698	-0.213	-0.185
		(0.0477)	(0.116)	(0.123)	(0.123)	(0.134)	(0.147)	(0.147)
Education Associate or Professional degree		0.892***	0.994***	0.757***	0.738***	0.513***	0.0106	0.0463
		(0.0662)	(0.161)	(0.166)	(0.166)	(0.173)	(0.187)	(0.188)
Education Bachelor degree		1.082***	1.216***	0.930***	0.915***	0.732***	0.108	0.182
		(0.0588)	(0.151)	(0.156)	(0.156)	(0.166)	(0.181)	(0.180)

Education Master degree		1.363***	1.691***	1.372***	1.345***	1.163***	0.330	0.441*
		(0.0827)	(0.217)	(0.220)	(0.220)	(0.227)	(0.240)	(0.241)
Education PhD. degree		2.127***	1.573***	1.245***	1.230***	1.040**	-0.0422	0.117
		(0.235)	(0.469)	(0.473)	(0.474)	(0.466)	(0.474)	(0.471)
White*Education High School			0.0486 (0.128)	0.0971 (0.134)	0.0949 (0.134)	0.0541 (0.145)	0.0680 (0.158)	0.0212 (0.158)
White*Education Associate Or Professional degree			-0.124 (0.177)	-0.0578 (0.181)	-0.0573 (0.181)	-0.0548 (0.189)	-0.104 (0.201)	-0.178 (0.202)
White*Education Bachelor degree			-0.158 (0.164)	-0.0802 (0.169)	-0.0827 (0.169)	-0.122 (0.179)	-0.110 (0.191)	-0.189 (0.192)
White*Education Master degree			-0.392* (0.235)	-0.302 (0.237)	-0.301 (0.237)	-0.377 (0.244)	-0.372 (0.254)	-0.460* (0.255)
White*Education PhD. degree			0.694 (0.542)	0.781 (0.546)	0.785 (0.546)	0.762 (0.538)	0.760 (0.543)	0.605 (0.541)
Poverty				1.289***	1.302***	0.805***	0.755***	0.775***
				(0.0470)	(0.0471)	(0.0558)	(0.0559)	(0.0565)
Male					-0.131***	-0.155***	0.00289	0.0124
					(0.0335)	(0.0346)	(0.0419)	(0.0418)
Experience FE						2.116***	1.826***	1.820***
						(0.0511)	(0.0569)	(0.0572)
Occupation FE	No	No	No	No	No	No	Yes	Yes
Industry FE	No	No	No	No	No	No	Yes	Yes
State FE	No	No	No	No	No	No	No	Yes

Constant	2.263***	1.646***	1.630***	0.706***	0.766***	-0.517***	0.559***	0.853***
	(0.0362)	(0.0545)	(0.107)	(0.116)	(0.117)	(0.132)	(0.208)	(0.247)
Observations	69,564	69,564	69,564	69,564	69,564	69,564	69,341	69,341

Notes: This table presents eight logit regressions with Employment as the dependent variable and White as the treatment variable. The variable Employment is a dummy variable taking the value 1 if the individual is employed, and 0 otherwise. White is a dummy variable taking the value 1 if the individual is White and 0 if she is Black. Education categorical is a categorical variable taking the value 0 (base category) if the individual does not hold any diploma, the variable takes the value 1 if the individual holds a high school diploma, and the value 2 in case she holds an associate or professional degree. It takes the values 3, 4, and 5 if the individual holds a Bachelor, a Master, or a Ph.D. diploma, respectively. Male is a dummy variable taking the value 1 if the individual is a male, and 0 otherwise. The variable experience is a dummy that takes the value 1 if the individual's longest class of worker is not without pay, and takes the value 0 otherwise. The variables occupation, industry, and State are all categorical variables, the entire table can be found in the appendix, Table 9.2. *** p<0.01, ** p<0.05, * p<0.1. The number of observations is represented in the last row.

Table 5 displays the same eight logit regressions as Table 3, but the variable Education is now a categorical variable, whereas it was a dummy variable in Table 3. Equation (1) is similar to the first equation of Table 3, from which it was deduced that White individuals have, on average, a 46.8% greater probability of being employed than Black individuals. In all eight regressions, the coefficient of the variable White is positive and statistically significant at a 1% significance level, as in Table 3.

Equation (2) adds the five dummy variables about education, 'no diploma' being the base category. In equations (2) to (6), all the coefficients of the categorical variable Education, but the dummy about high school diploma, are significant (at a 1% significance level). This confirms the results of Table 3, that a greater education increases one's probability of employment. However, when controlling for Occupation, Industry, and State fixed effects, the significance of all coefficients but the one of Ph.D. diplomate decreased; this may indicate that the specific level of education searched might differ across States or industries.

Finally, equation (3) shows the logit regression of the variable Employment (a dummy variable) over the variables White, Education (a categorical variable), and their interaction term. The coefficients of the interaction terms between the variables White, Associate or Professional degree, Bachelor, and Master degree are all negative; the absolute value of those interaction terms is increasing with the educational level, meaning that the racial employment gap decreases as the educational level increases, this conclusion only holds for those three levels of education. The statistical significance of the interaction terms is low, only two coefficients are statistically significant at a 10% significance level, whereas the others are statistically insignificant. Those results are more precise than the ones obtained in Table 3, although they do not change the main conclusion, namely, that education might be correlated with a reduction of the racial employment gap, at least when individuals obtain an

Associate or Professional degree, Bachelor, or Master degree. The statistical significance of this correlation is, however, low.

Figures 2 and 3, in the appendix, illustrate the increase in the racial wage gap per level of education, as well as the slight decrease in the racial employment gap per level of education. Moreover, Figure 3 indicates that there is a small but consistent decrease in the racial employment gap between the level of education 1 to 4 (high school diploma, associate or professional degree, Bachelor diploma, Master diploma), as suggested by Table 5. For the highest level of education (Ph.D. diploma) the racial employment gap increased, compared to the previous educational level (Master diploma). A deeper study into this particular type of worker might explain this racial difference in employment.

Gender

The following section will analyse how sex and its interaction with race and education can affect both the wage and employment level.

Table 6: Multiple linear regression of Wage on White, Male, Education, their first and second order interaction, and controlling for Poverty, Experience, Occupation fixed effect, Industry fixed effect, and and State fixed effect.

lnWage	(1)	(2)	(3)	(4)	(5)	(6)	(7)
White	0.125***	0.0407**	0.0523***	-0.0117	-0.0114	-0.00727	0.0114
	(0.0115)	(0.0184)	(0.0202)	(0.0187)	(0.0187)	(0.0175)	(0.0178)
Male	0.406***	0.254***	0.274***	0.194***	0.194***	0.208***	0.207***
	(0.00779)	(0.0221)	(0.0262)	(0.0242)	(0.0242)	(0.0232)	(0.0232)
Education	0.726***	0.733***	0.762***	0.625***	0.625***	0.348***	0.330***
	(0.00784)	(0.0234)	(0.0298)	(0.0281)	(0.0281)	(0.0268)	(0.0268)
White*Male		0.180***	0.157***	0.202***	0.202***	0.118***	0.118***
		(0.0231)	(0.0285)	(0.0264)	(0.0264)	(0.0246)	(0.0246)
Male*Education		-0.0157	-0.0835*	-0.00517	-0.00516	-0.0191	-0.0149
		(0.0157)	(0.0452)	(0.0427)	(0.0427)	(0.0398)	(0.0397)
White*Education		0.000963	-0.0319	0.0232	0.0231	0.0363	0.0465
		(0.0239)	(0.0321)	(0.0303)	(0.0303)	(0.0285)	(0.0285)
White*Male*Education			0.0766	0.0300	0.0303	0.0224	0.0188

			(0.0482)	(0.0456)	(0.0456)	(0.0424)	(0.0423)
Poverty				1.536***	1.536***	1.298***	1.296***
				(0.0216)	(0.0216)	(0.0229)	(0.0230)
Experience					1.212***	1.164***	1.179***
					(0.405)	(0.441)	(0.436)
Occupation FE	No	No	No	No	No	Yes	Yes
Industry FE	No	No	No	No	No	Yes	Yes
State FE	No	No	No	No	No	No	Yes
Constant	9.958***	10.03***	10.02***	8.645***	7.432***	5.622***	5.638***
	(0.0116)	(0.0170)	(0.0184)	(0.0259)	(0.406)	(0.623)	(0.616)
Observations	63,106	63,106	63,106	63,106	63,106	63,106	63,106
R-squared	0.143	0.144	0.144	0.224	0.224	0.356	0.359

Notes: This table presents eight OLS regression with Wage as the dependent variable and White, Male, Education, their interaction first and second order interaction, and controlling for the variables Poverty, Experience, Occupation fixed effect, Industry fixed effect, and State fixed effect. The variable lnWage is a continuous variable taking the value of the natural logarithm of the yearly wage on an individual. White is a dummy variable taking the value 1 if the individual is White and 0 if she is Black. The variable Male is a dummy variable taking the value 1 if the individual is a male and 0 otherwise. Education is a dummy variable taking the value 1 if the individual holds a University degree, 0 otherwise. The variable Poverty is a dummy variable taking the value 1 if the individual is living above the poverty threshold, and otherwise. The variable Experience is a dummy that takes the value 1 if the individual's longest class of worker is not without pay, and takes the value 0 otherwise. The variables Occupation Fixed Effect (FE), Industry (FE), and State (FE) are all categorical variables. The variables occupation, industry, and State are all categorical variables, the entire table can be found in the appendix, Table 9.2. Robust standard errors are presented in parentheses below the coefficient estimate. *** p<0.01, ** p<0.05, * p<0.1. Number of observations and R-squared are represented in the last two rows.

Table 6 regresses Wage on variables White, Male, Education, their first and second order interaction terms, and a set of control variables. The first equation confirms some of the results obtained in Tables 2 and 4, namely, that the variables White, Education, and Male positively and significantly (at a 1% significance level) increase the average yearly wage of individuals.

Equation (2) adds first order interaction terms White and Male, Male and Education, and, White and Education. The interaction term between the variables White and Male is the only interaction term to be statistically significant, at a 1% significance level, all the other interaction terms are statistically insignificant. Moreover, the coefficient of the interaction term between the variables Male and White suggests that being both Male and White is correlated with a wage increase of 18%, an economically significant increase. The sign and significance level of the interaction term (White and Male) is robust to the addition of control variables to the equation.

Finally, in equation (3) the triple interaction term is added but is not statistically significant at a 10% significance level. It is interesting to note that from Equation (4) to Equation (7), the coefficient of the variable White becomes statistically insignificant, one could, therefore, argue that it is not only being White that is correlated with a wage increase, but being a White male.

Table 7: Multiple logit regression of Employment on White, Male, Education, their first and second order interaction, and controlling for Poverty, Experience, Occupation fixed effect, Industry fixed effect, and State fixed effect.

Employment	(1)	(2)	(3)	(4)	(5)	(6)	(7)
White	0.596***	0.607***	0.595***	0.507***	0.532***	0.589***	0.663***
	(0.0408)	(0.0627)	(0.0661)	(0.0675)	(0.0711)	(0.0741)	(0.0765)
Male	-0.110***	-0.174**	-0.191**	-0.297***	-0.257***	-0.0489	-0.0325
	(0.0329)	(0.0741)	(0.0796)	(0.0814)	(0.0862)	(0.0914)	(0.0917)
Education	0.760***	0.880***	0.835***	0.633***	0.622***	0.181	0.247*
	(0.0397)	(0.106)	(0.130)	(0.132)	(0.138)	(0.143)	(0.143)
White*Male		0.0517	0.0728	0.132	0.0631	0.0197	0.0149
		(0.0821)	(0.0902)	(0.0918)	(0.0970)	(0.101)	(0.101)
Male*Education		0.105	0.211	0.309	0.252	0.314	0.305
		(0.0798)	(0.202)	(0.203)	(0.207)	(0.213)	(0.213)
White*Education		-0.207*	-0.152	-0.0930	-0.154	-0.120	-0.160
		(0.109)	(0.144)	(0.146)	(0.152)	(0.155)	(0.155)
White*Male*Education			-0.125	-0.180	-0.118	-0.197	-0.197
			(0.220)	(0.221)	(0.225)	(0.231)	(0.231)
Poverty				1.377***	0.837***	0.756***	0.775***
				(0.0460)	(0.0560)	(0.0558)	(0.0564)
Experience					2.149***	1.811***	1.805***

					(0.0505)	(0.0564)	(0.0567)
Occupation FE	No	No	No	No	No	Yes	Yes
Industry FE	No	No	No	No	No	Yes	Yes
State FE	No	No	No	No	No	No	Yes
Constant	2.135***	2.139***	2.148***	1.050***	-0.397***	0.443***	0.759***
	(0.0406)	(0.0553)	(0.0577)	(0.0674)	(0.0796)	(0.168)	(0.216)
Observations	69,564	69,564	69,564	69,564	69,564	69,341	69,341

Notes: This table presents eight logit regression with Wage as the dependent variable and White, Male, Education, their interaction first and second order interaction, and controlling for the variables Poverty, Experience, Occupation fixed effect, Industry fixed effect, and State fixed effect. The variable lnWage is a continuous variable taking the value of the natural logarithm of the yearly wage on an individual. White is a dummy variable taking the value 1 if the individual is White and 0 if she is Black. The variable Male is a dummy variable taking the value 1 if the individual is a male and 0 otherwise. Education is a dummy variable taking the value 1 if the individual holds a University degree, 0 otherwise. The variable Poverty is a dummy variable taking the value 1 if the individual is living above the poverty threshold, and otherwise. The variable Experience is a dummy that takes the value 1 if the individual's longest class of worker is not without pay, and takes the value 0 otherwise. The variables Occupation Fixed Effect (FE), Industry (FE), and State (FE) are all categorical variables. The variables occupation, industry, and State are all categorical variables, the entire table can be found in the appendix, Table 9.2. Robust standard errors are presented in parentheses below the coefficient estimate. Robust standard errors are presented in parentheses below the coefficient estimate. *** p<0.01, ** p<0.05, * p<0.1. Number of observations and R-squared are represented in the last two rows.

Table 7 presents seven logit regressions of Employment on variables White, Male, Education, their first and second order interaction terms, and controlling for a set of control variables. Equation (1) confirms the result obtained in Table 3, that being White as well as being Educated is correlated with an increase of one's probability to be employed (at a 1 percent significance level). It is interesting to note that males have slightly lower chances to be employed than females (at a 1% significance level).

Equations (2) and (3) add the first and second order interaction terms, however, none of them are statistically significant at a 5 percent significance level.

<u>Occupational crowding</u>

The present section is an attempt to test if the occupational crowding theory might (partly) explain the racial wage and employment disparity analysed in this research. It has to be stressed that the present section, due to the limitation of the data used, cannot ensure with certainty whether occupational crowding happened or not, it merely aims at suggesting the likelihood that occupational crowding could or not explain part of the racial wage gap.

This research investigates if this theory could explain some of the racial wage gap present in the data in two different ways. The first approach is to study if the occupational crowding theory could apply at an industry level, e.i., if Black workers are restricted to work in some industries. The second method is to analyse if the theory would apply at the occupational level, e.i., some positions would be restricted to White workers (Boeri & Ours, 2021).

The method used is to calculate the average wage and percentage of white workers within a certain industry or occupation, before calculating the percentage and percentage point difference compared to the whole sample (restricted to employed individuals). In case a given occupation or industry has a higher wage than average, combined with a higher percentage of White workers, it could indicate that occupational crowding might happen.

Table 14 and Figure 3, in the appendix, tend to indicate that there is no clear correlation between the percentage difference from mean Wage and the percentage point difference from mean White proportion. There is, therefore, no clear proof that occupational crowding might happen at the industry level.

Table 15 and Figure 3, in the appendix, presents a higher correlation between the percentage difference from mean Wage and the percentage point difference from mean White proportion, at the occupational level. It needs, however, to be stressed that the range is only 2.5% and that there are no clear outliers. The point at the extreme right of Figure F shows the highest correlation between the two variables of interest, it is the point representing the armed force.

From the evidence discussed in the present section, it appears that occupational crowding at the industry level may explain racial labour inequalities. It is, however, not clear whether occupational crowding might occur at the occupational level. It has to be stressed that the data set used in this research does not enable to answer the question with certainty.

Discussion and conclusion

The present study aims to determine if education can be used as an anti-racial inequalities tool, e.i., if increasing the educational level would be correlated with a decrease in racial inequalities in the labour market. Using 2021 data from the Current Population Survey (CPS) it analysed the return on education for both White and Black individuals. The first racial difference observed in the data is the educational level; 29.7% of the black population obtained a university degree, whereas 36.9% of the white population hold such a degree. This difference is likely to be the consequence of the achievement gap observed in earlier stages of the educational process, a phenomenon well studied in the literature (Neal, 2006; Reardon, Robinson-Cimpian, and Weathers, 2015; Reardon and Kalogrides, 2019). Moreover, it resulted that White individuals have, on average, a greater wage, and chance to be employed than Black people of 20.9% and 46.8%, respectively. Those racial differences are economically significant and statistically significant at a 1% significance level, their signs and significance levels are robust to the addition of several control variables. However, the size of the racial wage difference substantially decreased as control variables were added, this may suggest that part of the racial inequalities present in the labour market may be due to structural differences across races and that discrimination may not be able to fully explain those racial inequalities. Fryer et al. (2013) demonstrated that discrimination is responsible for, at least, a third of the racial wage gap. The size of the employment gap did not noticeably change when control variables were added.

The research question was “To what extent is education correlated with a variation of racial inequalities in the U.S. labour market?”. In order to answer this question, the extra return of being both White and a university graduate on one’s wage or probability of employment has been analysed. It resulted that when controlling for the full set of control variables there is a statistically significant (at a 5% significance level) greater wage increase correlated with being a university graduate for White compared to Black individuals. The economic significance of this greater return is 4.4% of the pre-tax wage. On the other hand, the racial difference in the increase of employment probability after the obtention of a university degree is likely to decrease, this correlation is, however, not statistically significant at a 5% significance level. This result implies that obtaining a university diploma may be correlated with a decrease in labour inequalities compared to their White peers (with similar levels of education). This latter finding is in line with the results obtained by Hargis et al (2006) who argued that education can be an efficient tool to reduce the racial gap in employment termination. Moreover, as discussed by Fryer et al. (2013) racial labour inequalities are partially due to structural inequalities, therefore, policies that would aim at improving the educational level of the Black population might reduce racial structural inequalities which will then reduce racial labour inequalities.

Several further analyses were also performed. The first one was to modify the specification of the variable Education. In the main analysis the variable Education was a dummy variable (having or not a university diploma) this specification has been changed to a categorical variable with 6 different levels of education (no diploma, high school diploma, associate or professional degree, Bachelor degree, Master degree, and Ph.D. diploma). This robustness test confirmed that the wage return on education is greater for White than Black individuals. The significance level of the interaction term increased due to the new specification. Moreover, the findings about the racial employment gap confirmed that education may be correlated with a reduction of the racial employment gap, but only for certain educational levels.

Furthermore, the variable sex has been added to the analysis. It was concluded from it that being a White male has a positive and statistically significant (at a 1%significance level) correlation with one's wage, whereas it did not have any significant correlation with one's employment. The other interaction term did not have a statistically significant (at a 5% significance level) correlation with one's future economic outcome.

Finally, the data has been investigated to determine whether occupational crowding could also play a role in explaining the racial inequalities in the labour market. Although the data does not allow to formally answer the question, it seems that occupational crowding at the industry level cannot be held responsible for racial labour market inequalities. It is, however, not clear if it might play a role at the occupational level.

An important limitation of this research is the potential presence of omitted variable bias which could bias the results presented. The present research discussed the presence of a potential correlation between college education and racial labour inequalities, future studies may wish to use other time series data, or experimental data in order to make a causation statement. Moreover, future work might try to investigate to which extent racial inequalities are due to discrimination (and which type of discrimination), or to structural inequalities. A better understanding of the mechanisms through which the return on education is different for Black and White students will enable politicians to provide efficient policies which might reduce racial labour inequalities. Finally, the present data set did not have the means to make a statement about the impact that school segregation might have on racial labour inequalities.

Appendix

Figure 1.1.: Histogram of the wage density

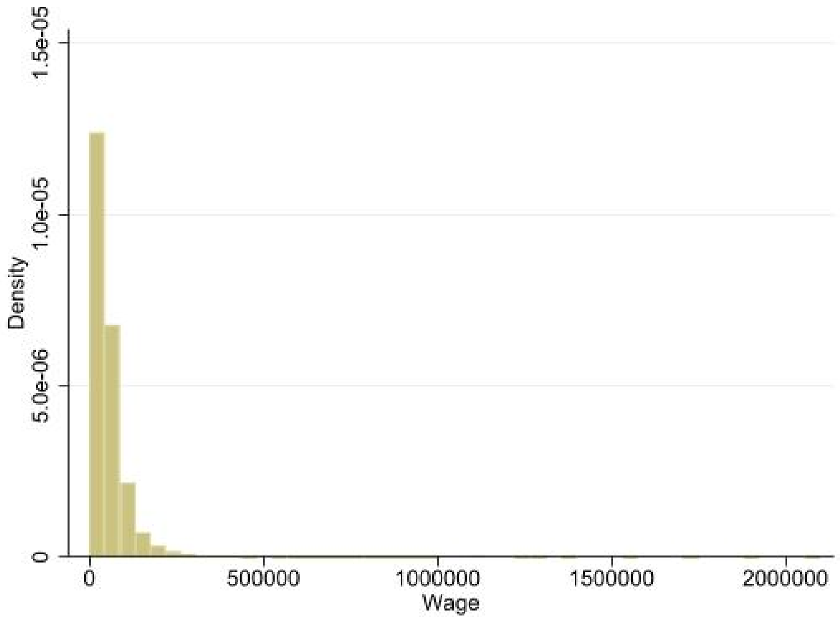

Figure 1.2.: Histogram of the natural logarithm of wage density

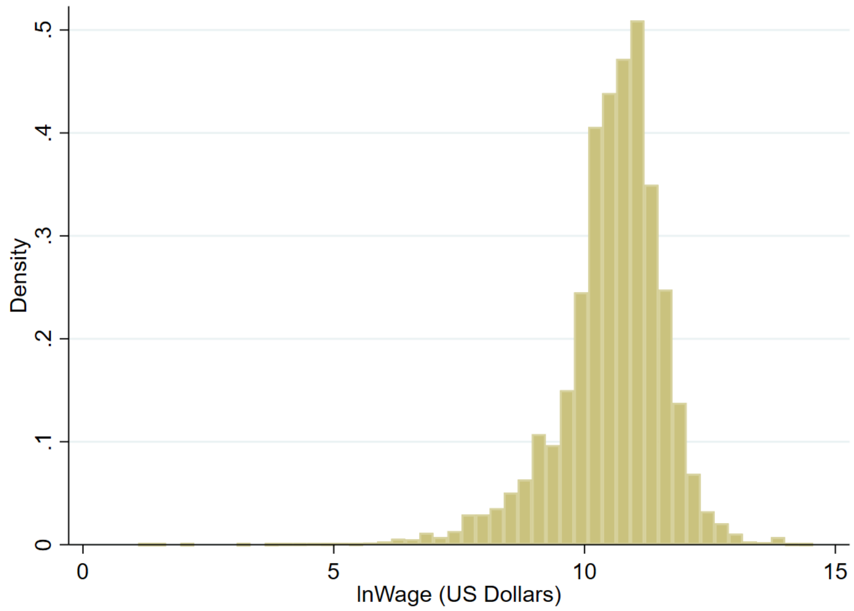

Table 8: Industry codes.

Code	Industry
1	Agriculture
2	Forestry, logging, fishing, hunting, and trapping
3	Mining
4	Construction
5	Nonmetallic mineral products
6	Primary metals and fabricated metal products
7	Machinery manufacturing
8	Computer and electronic products
9	Electrical equipment, appliance manufacturing
10	Transportation equipment manufacturing
11	Wood products
12	Furniture and fixtures manufacturing
13	Miscellaneous and not specified manufacturing
14	Food manufacturing
15	Beverage and tobacco products
16	Textile, apparel, and leather manufacturing
17	Paper and printing
18	Petroleum and coal products
19	Chemical manufacturing
20	Plastics and rubber products
21	Wholesale trade
22	Retail trade
23	Transportation and warehousing
24	Utilities
25	Publishing industries (except internet)
26	Motion picture and sound recording industries
27	Broadcasting (except internet)
28	Internet publishing and broadcasting
29	Telecommunications
30	Internet service providers and data processing services
31	Other information services
32	Finance
33	Insurance
34	Real estate
35	Rental and leasing services
36	Professional and technical services
37	Management of companies and enterprises
38	Administrative and support services
39	Waste management and remediation services
40	Educational services
41	Hospitals
42	Health care services, except hospitals
43	Social assistance
44	Arts, entertainment, and recreation

45	Accommodation
46	Food services and drinking places
47	Repair and maintenance
48	Personal and laundry services
49	Membership associations and organizations
50	Private households
51	Public administration
52	Armed forces

Table 9: Occupation codes.

Code	Occupation
1	Management occupations
2	Business and financial operations occupations
3	Computer and mathematical science occupations
4	Architecture and engineering occupations
5	Life, physical, and social science occupations
6	Community and social service occupation
7	Legal occupations
8	Education, training, and library occupations
9	Arts, design, entertainment, sports, and media occupations
10	Healthcare practitioner and technical occupations
11	Healthcare support occupations
12	Protective service occupations
13	Food preparation and serving related occupations
14	Building and grounds cleaning and maintenance occupations
15	Personal care and service occupations
16	Sales and related occupations
17	Office and administrative support occupations
18	Farming, fishing, and forestry occupations
19	Construction and extraction occupations
20	Installation, maintenance, and repair occupations
21	Production occupations
22	Transportation and material moving occupations
23	Armed Forces
24	Never Worked

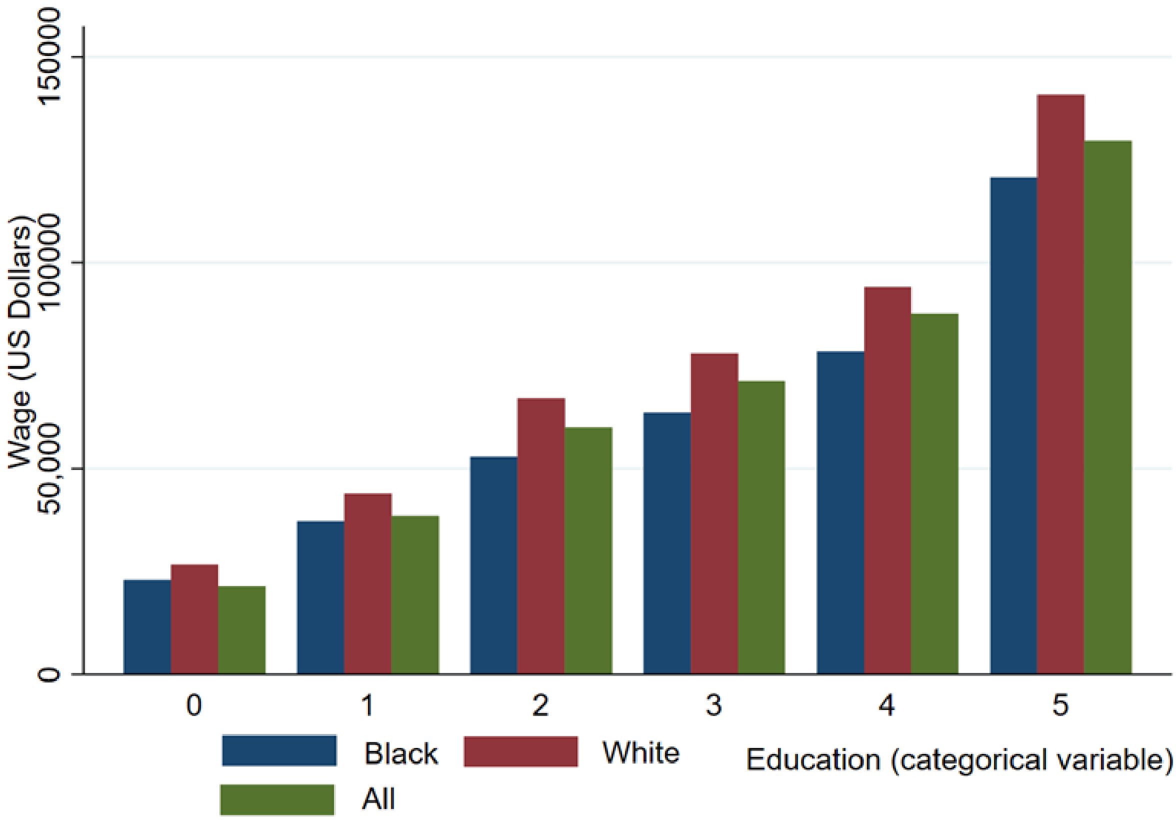

Figure 2: Histogram of the mean wage per race and level of education.

Notes: Education is a categorical variable taking the value 0 if the individual has no diploma, the value 1 if she has a high school diploma, the value 2 if she holds an associate or professional degree, and the values 3, 4, and 5 if she obtained a Bachelor, Master or PhD diploma, respectively.

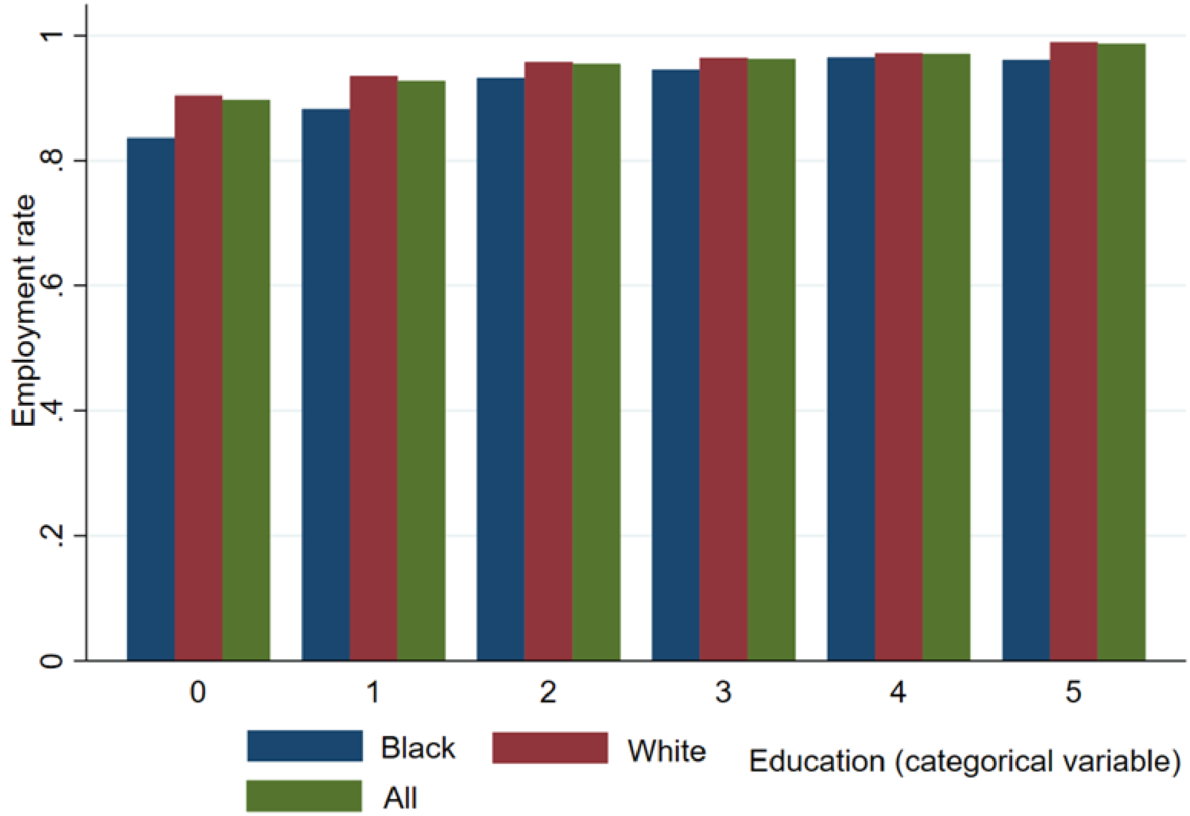

Figure 3: Histogram of the mean employment rate per race and level of education.

Notes: Education is a categorical variable taking the value 0 if the individual has no diploma, the value 1 if she has a high school diploma, the value 2 if she holds an associate or professional degree, and the values 3, 4, and 5 if she obtained a Bachelor, Master or PhD diploma, respectively.

Table 10: Matrix of correlation between percentage difference from mean wage and percentage point difference from mean White proportion, at the industry level .

Variables	(1)	(2)
(1) Percentage difference from mean Wage	1.000	
(2) Percentage point difference from mean White proportion	0.129	1.000

Notes: Variable Percentage difference from mean wage is the percentage difference between the mean wage of a given industry and the mean wage of the whole sample. The variable percentage point difference from mean White proportion is the percentage point difference between the percentage of White workers in a given industry and in the whole sample, e.i., across industries.

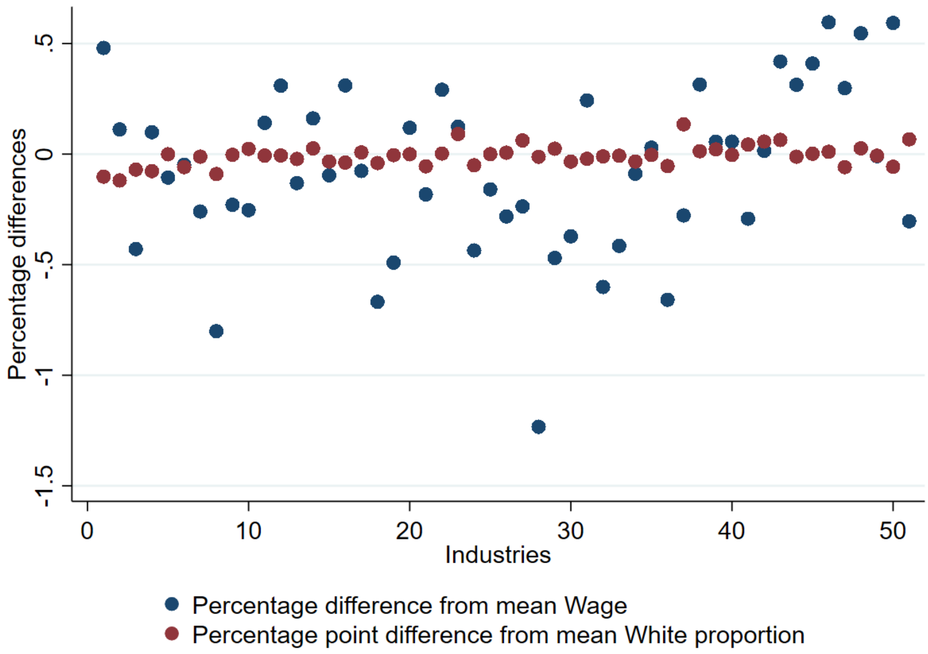

Figure 4: Wage difference and proportion of White workers difference from industries.

Notes: Variable Percentage difference from mean wage is the percentage difference between the mean wage of a given industry and the mean wage of the whole sample. The variable percentage point difference from mean White proportion is the percentage point difference between the percentage of White workers in a given industry and in the whole sample, e.i., across industries.

Table 11: Matrix of correlations between Percentage difference from mean Wage and Percentage point difference from mean White proportion, at the occupational level.

Variables	(1)	(2)
(1) Percentage difference from mean Wage	1.000	
(2) Percentage point difference from mean White proportion	0.518	1.000

Notes: Variable Percentage difference from mean wage is the percentage difference between the mean wage of a given occupation and the mean wage of the whole sample. The variable percentage point difference from mean White proportion is the percentage point difference between the percentage of White workers in a given occupation and in the whole sample, e.i., across occupations.

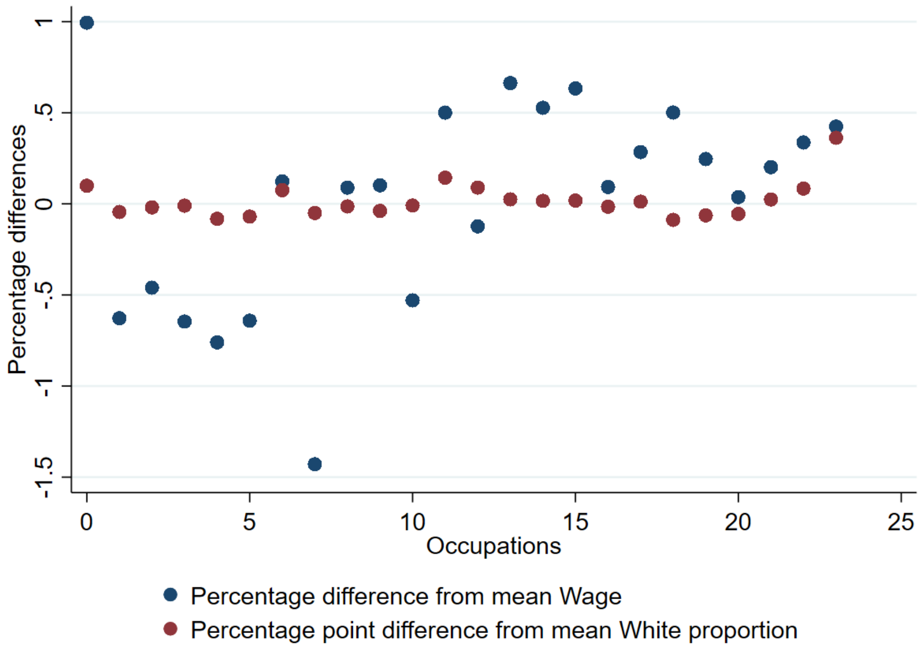

Figure 5: Wage difference and proportion of White workers difference from occupations.

Notes: Variable Percentage difference from mean wage is the percentage difference between the mean wage of a given occupation and the mean wage of the whole sample. The variable percentage point difference from mean White proportion is the percentage point difference between the percentage of White workers in a given occupation and in the whole sample, e.i., across occupations.

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