Multiplicative Intersectional Wage Differentials for College Graduates

Lower Returns to Selectivity and Positive Attitudes Toward Hard Work

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Abstract

I examine the combined effects of positive attitudes towards hard work and the selectivity of respondents' undergraduate institutions on the wages of graduates and the racial wage differentials. I use data on respondents from the 1997 cohort of the National Longitudinal Survey of Youth (NLSY97), Kitagawa-Oaxaca-Blinder decompositions, the Cotton method, and machine learning variable selection to determine the magnitude of unexplained wage differentials between white graduates and Latino, mixed-race, and Black (grouped together as "non-white") graduates. I find substantial wage gaps between the wages of the white and non-white graduates, especially when decomposing differences between the wages of white men, non-white graduates (both men and women), and non-white women. The interaction between positive attitudes towards hard work and college selectivity contributes the most toward the unexplained difference in returns to characteristics between the two groups analyzed. I extend the methods to propose an approach for analyzing racial earnings inequality using causal inference. A theoretical framework of persistent inequities from learning-by-doing labor market discrimination, monopsony power, disproportionate monitoring of marginalized workers, and two-sided statistical discrimination in the labor market help to explain the results.

JEL Codes: I21-Analysis of Education I23-Higher Education I24-Education and Inequality I26-Returns to Education J15-Economics of Minorities, Races, Indigenous Peoples, and Immigrants J31-Wage Differentials J42-Segmented Labor Markets J64-Unemployment: Models, Duration, Incidence, and Job Search J71-Discrimination Z13-Social and Economic Stratification

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Introduction

Selective undergraduate institutions are often presented in policy discussions around improving the lives of disproportionately Black and Latino low-income citizens as "equalizers" for graduates from marginalized groups. However, it is certainly plausible that their hard work and graduation from a selective school do not exclude these college graduates from racial wage differentials. There is an old Black proverb that one must work twice as hard to get half as far as a white person with similar aspirations, due to persistent racism and discrimination.

That proverb is the inspiration behind the research questions below. I estimate the effects of college selectivity and positive attitudes toward hard work on the wages of white and marginalized college graduates to understand how these effects might influence the racial wage differential between college graduates across various majors in the NLSY97. The main research questions addressed are the following:

1. How do the combined effects of college selectivity and positive attitudes toward hard work on the wages of white and marginalized graduates differ? In addition, what are the wage costs to the marginalized group and the wage benefits for the white graduates?

2. How do these differences in the combined effects of college selectivity and positive attitudes toward hard work affect the explained and unexplained component of the racial wage differential experienced by graduates of each major from marginalized groups?

This paper is also motivated by the idea that we need to understand which investments in education improve the living conditions of the poor and marginalized. The first essay of my PhD thesis seeks to understand how high school STEM education can change labor market outcomes, and this paper seeks to understand the ways in which even the most exceptional Black, Latino, and mixed-race college graduates get less renumeration for their hard work and dedication to scholastic pursuits. Ideally, one could walk away from reading the thesis and understand more about the labor market outcomes for an individual from a non-white, marginalized group that decides to develop STEM skills in high school, has positive attitudes towards hard work, and attends a selective undergraduate institution. These three things are regularly touted as some of the essential decisions to succeed for working class, non-white youth in the United States. Ultimately, there is considerable reason to question this prescription for prosperity, as these recommendations fail to consider some of the fundamental, systemic features of our economy and society that prevent this advice from being more fruitful.

I study the effects of an interaction between college selectivity and attitude toward hard work on racial wage differentials between college graduates. I found that the hard work and college selectivity interaction accounts for the most significant portion of the unexplained gap in wages between the marginalized and white graduates when controlling for attainment of a graduate degree, ASVAB percentile score, years of experience working, whether health limits the amount of work one can perform, and majoring in business, marketing, or management. In comparison with graduates that are white men, non-white women graduates experience an unexplained wage gap of 25.60%, where 14.11% is a wage cost of being a marginalized woman and 10.07% is the wage benefit of being a white man. Non-white graduates experience an unexplained differential of 15.48% in comparison with graduates that are white men, with 6.82% a wage cost for being non-white graduates and the remaining percentage a wage benefit to being white men.

1 Literature

1.1 Kitagawa-Oaxaca-Blinder Decomposition

The mean decomposition technique popularized in economics by Oaxaca (1973) and Blinder (1973) originated in the sociology literature with Evelyn Kitagawa's 1955 article *Components of a Difference Between Two Rates* (I will refer to the method as the KOB or Kitagawa-Oaxaca-Blinder decomposition).

In the article, Kitagawa explains that the technique is meant to "explain the difference between the two rates of two groups in terms of differences in their specific rates and differences in their composition" Kitagawa (1955). Kitagawa begins by detailing the method with two factors that may be quantitative or non-quantitative, and then extends the method to deal with three or more factors Kitagawa (1955).

Over time numerous studies attributed much of the unexplained racial wage differential to differences in Armed Forces Qualifying Test scores (AFQT), an imprecise proxy for cognitive ability. Despite Rodgers and Spriggs (1996) finding that AFQT composite scores produced biased estimates of discrimination in the labor market, their study has been widely overlooked. Using NLSY91, an AFQT test score model, and KOB decompositions, Rodgers III and Spriggs (1996) found that psychological variables capture any racial differences in self-confidence from less supportive background environments and psychological effects of pre-labor market discrimination. A two-step measure reduces the mean square error of the wage equation and provides an unbiased estimate of labor market discrimination Rodgers and Spriggs (1996). As an example, a study by Blackburn (2004) still uses the AFQT and finds that while AFQT scores account for some of the racial differential, they only account for a small part of the gender differences in wages.

My study uses personality scale variables measuring attitudes toward hard work to determine the combined effects of an orientation toward hard work and the selectivity of one's undergraduate institution on racial wage differentials across different majors. William Darity Jr., Arthur Goldsmith, and Jonathan Veum (1997, 1998) are two examples of studies I have found besides Rodgers III and Spriggs that use psychological capital measures in the study of racial wage differentials. Their studies examine one's self-esteem and locus of control and found that even when including AFQT composite scores and the higher scores on self-esteem exhibited by black workers in their study, the effect of being black still had a significant negative effect on real wages (see Goldsmith et al. (1997) and Goldsmith et al. (1998)).

Mason (2007) also uses psychological characteristics such as motivation to study interracial differences in economic outcomes between white and Black people in the U.S. I recognize that the self-reported personality scales in the NLSY97 may be biased because respondents may wish to appear as if they have more positive attitudes towards hard work than they have. In our society, laziness is frowned upon regardless of racial group. However, these measures of laziness are the best proxy for attitudes towards hard work available with the NLSY97 data.

For my study, I decided to combine Black and Latino workers into one group, called the marginalized group, and white workers into another group due to the relatively small sample sizes in the NLSY97. This decision does have some theoretical grounding in the literature, as there is evidence that Black and Latino workers experience wage discrimination that differs by skin shade.Goldsmith et al. (2006) found that by the early 1990s, skin shade had an important effect on wages with darker skinned black men losing at least 10 percent in wages relative to white men, whereas the effects were indistinguishable from a slightly negative value near zero for light skin complexioned black men. A more recent study by Kreisman and Rangel (2015) found that skin color plays a significant role in earnings and employment for black men. Wage gaps between darker-skinned and lighter-skinned workers were shown to widen with experience, with gaps between light-skinned workers and white workers remaining constant Kreisman and Rangel (2015).

Although gender differentials are not examined in the dissertation for the sake of time and brevity, there is also troubling evidence that the negative effects of unemployment on mental health increase for black women in the US as skin shade darkens Diette et al. (2015). These skin shade wage penalties have also been found for Latin American immigrants using the New Immigrant Survey Rosenblum et al. (2015). There is also evidence that darker skinned Brazilian women experience significant wage discrimination in the Brazilian labor market, a sign that these skin shade penalties are transcontinental Fernandes (2015). These results reinforce arguments that the further one is from a white phenotype, the worse the wage penalty. Unfortunately, our NLSY97 data do not include a skin shade variable to discern whether the effects of attitudes toward hard work and selectivity of one's undergraduate institution on racial wage penalties across different majors differ by skin shade.

1.2 Returns to Major and Educational Attainment

Choice of a college major has been shown to affect earnings premiums from college and predictably affects the racial wage disparities experienced in the labor market. Barrow and Rouse (2005) found little evidence of differences in return to schooling across racial and ethnic groups when controlling for ability and measurement error biases. They concluded that policies increasing educational attainment for marginalized groups have a good possibility of increasing their well-being and reducing inequality. Urzua (2008) supports the conclusion that even after controlling for respondents' abilities, there are significant racial labor market gaps and the results suggest that the standard practice of equating observed test scores may overcompensate for differences in ability. Dickson (2010) found significant gender and racial differences in college major choice persist even when controlling for SAT scores and high school class ranks, where gender differences were even greater than racial and ethnic disparities. Nonwhite women were more likely than men to switch away from an initial major in engineering. This result was not true for white women Dickson (2010).

Webber (2014) presents a recent, high-quality examination of lifetime college earnings premiums and finds that there is a significant range in lifetime college earnings premiums, from $700,000 for arts and humanities graduates to $1.5 million for STEM graduates. These differentials are even larger when allowing for differential unemployment probabilities across majors Webber (2014). The Caroline Hoxby and Sarah Turner (2015) study on an intervention to get low-income, high-achieving college students to apply to more selective colleges shows that providing these students with information on cost of college, availability of curricula and peers they seek, and the different types of colleges available to them does increase their application and acceptance to selective institutions. This result has potentially large implications for high-achieving students from marginalized groups who are disproportionately more likely to come from low-income households Hoxby and Turner (2015). McClough and Benedict (2017) found that academic majors and first education institutions have significant effects on one's final occupation, which influences racial salary disparities. They recommend that public policy should build awareness around high school students from marginalized groups aspiring for college to prepare for majors with earnings premiums McClough and Benedict (2017).

1.3 College Selectivity and Earnings

We can establish some hypotheses on how the inclusion of the college selectivity variable in the wage equation may affect marginalized and white groups differently based on a small number of studies examining college selectivity and earnings. Alsalam et al. (1989) found one should choose a selective private eastern college to maximize earnings. Loury and Garman (1995) found that previous studies overstate the earnings premiums of college selectivity for whites and understate it for blacks by omitting measures of college performance like grade point average. They also note that the larger black earnings gain is offset by students whose own SAT scores are below the median of the college they attend Loury and Garman (1995).

Dickerson and Jacobs (2006) found that the system of higher education in the United States is segregated, with white graduates much more likely to attend selective schools. They conclude that Blacks under representation in STEM fields that characterize highly selective schools may explain some of the racial disparity in selectivity of schools attended Dickerson and Jacobs (2006).Dale and Krueger (2011) found that the estimates of returns to selectivity are essentially zero when controlling for the average SAT score of the schools to which students have applied. The return to college selectivity remains large for Black and Latino students from less educated families Dale and Krueger (2011). Another potentially significant finding by Hoxby and Avery (2013) is that more affluent high achieving students apply to several peer schools where their achievement match the typical applicant, a few reach schools where their achievements are below that of the typical applicant, and a couple safety colleges where their achievements are above the typical applicant. Low-income-typical students typically do not apply to selective colleges Hoxby and Avery (2013).

1.4 Underemployment and Educational Attainment

Georgetown University's Center on Education and the Workforce released a 2019 report by Campbell et al. (2019) entitled *The Unequal Race for Good Jobs: How Whites Made Outsized Gains in Education and Good Jobs Compared to Blacks and Latinos*.The study details the inequities between white and Black and Latino workers in access to what they categorize as 'good jobs' (those that pay at least $35,000 per year, at least $45,000 for workers 45 and older and $65,000 in median earnings in 2016 using data from the U.S). Their data is from the U.S. Census Bureau and the U.S. Bureau of Labor Statistics, Current Population Survey 1992-2017. At every level of education that they examined (high school diploma or less, middle skills, and college degree or higher), Black and Latino workers 2016 median earnings were lower in good jobs Campbell et al. (2019).

Of interest to my study is the finding that for workers with a bachelors degree or higher, the median 2016 earnings for white workers was $75,000 whereas the 2016 median earnings for Black and Latino workers was $65,000. Campbell et al. (2019) calculated that the total annual earnings advantage of white workers from good jobs was $554 billion in 2016, compared with a situation in which jobs were equitably distributed. These findings indicate that we would expect to find evidence of wage penalties for marginalized workers and wage benefits for white workers using our NLSY97 data on college graduates, even after controlling for the typical and relevant variables in our wage equations. Another study Williams and Wilson (2019) found that nearly 40% of Black workers with a college or advanced degree are in a job that typically does not require a college degree, compared to 31% of white graduates. These rather stark differences in underemployment and access to good jobs most likely contribute to any significant racial wage differentials I find among the college graduates.

1.4.1 Contribution to Literature

This is the first study to quantify the contribution of different returns to positive attitudes towards hard work and selective collegiate institutions to racial wage differentials. No other study I have found has studied the effects of an interaction between attitudes towards hard work and college selectivity on wages using the NLSY97. I have also not found studies that match NLSY97 youth to their colleges, then calculate a college selectivity variable using the codes for schools from which they graduated. This study provides a useful update by using the newer NLSY97 cohort rather than the NLSY79 cohort to study the racial wage differentials among college graduates.

This study is also novel in applying the intersectional identity wage differential framework of Darity Jr. et al. (2022) using the Cotton Cotton (1988) method of weighting the coefficients of the demographic groups by the group proportions to establish the wage that would prevail without discrimination. There are numerous ways to calculate this non discriminatory wage, and results from another approach by Neumark (1988) using the coefficients from a pooled regression are also presented.

The use of the least absolute shrinkage and selection operator (lasso), a machine learning method to minimize error in the wage equations is also a novel contribution. After detailing the empirical strategy, I propose an extension of these methods to panel data to study racial earnings inequality using causal inference. First I detail the interventionist difference-in-differences approach with Kitagawa-Oaxaca-Blinder decomposition and the Cotton method, then I explain how synthetic control difference-in-differences quasi experimental methods can be used to study these wage differentials. I use some work from behavioral economics literature to explain how improved perceived ability and updating of beliefs modelled using Bayes theorem help us to understand racial earnings inequality, and discuss some problems associated with longitudinal wage equations and two way causality.

2 Data

I started with the entire NLSY97 dataset of 8,984 individuals. I dropped cases with missing data on 2019 wage and salary income (3,572 deleted), the attitude toward hard work personality measures (403 deleted), whether or not their health limited the amount of work they could perform (3 deleted), the occupation type of their main job (157 deleted), and their marital status for 2019 (17 deleted). Next, I also dropped cases missing data on whether they live in a metropolitan statistical area (49 deleted), their highest degree obtained (16 deleted), ASVAB score percentile (818 deleted) and their household structure in 1997 (16 deleted). Next, I matched respondents to the undergraduate institution where they earned their bachelors degree (2,882 deleted). This left me with a sample of 1,051 college graduates. Finally, I created a college selectivity variable that is the total SAT score of the 75th percentile in 2016 (or the ACT score of the 75th percentile converted to an SAT score) for undergraduate colleges using data from the Integrated Postsecondary Education Data System (IPEDS). I was left with a sample of 860 college graduates since there was no ACT or SAT data for the schools of all 1,051 graduates.

The variable names and definitions for the variables used in the analyses are listed in Table 1. In the subsections following this one I present the descriptive statistics for different demographic groups analyzed in this paper. I start with the pooled sample, then describe descriptive statistics for the white college graduates and marginalized college graduates. Next I present statistics for non-white women, white women, non-white men, and white men. The National Longitudinal Survey of Youth 1997 cohort consists of 8,984 men and women born between 1980 and 1984. Respondents were interviewed annually between 1997 and 2011 then biennially since 2011. I use data from round 1 (1997-1998), round 3 (1999-2000), round 12 (2008-2009), and round 19 (2019-2020).

2.1 Pooled Sample

Of the 854 people in the sample, 54.3% are female (n=467) and 45.7% are male (n=393). With regard to racial composition, 70.58% are white (n=607) and 29.42% (n=253) are members of the non-white racial group consisting of 142 black college graduates, 102 Latino college graduates, and 9 mixed-race college graduates. With regard to major, 7% of the sample graduated with a degree in business, marketing, or management (n=63), the only major found to have a significant effect on income from wages and salary. 64.88% (n=558) of the sample was married at least one month in 2019. 2.21% (n=19) of respondents reported that their health limited the amount that they could work in 2019, and 36.74% (n=316) of the sample has attained a graduate degree.

The mean age of the pooled sample is 36.90 years and the mean ASVAB percentile score is 70.40. Out of a possible 28 points total, the mean attitude toward hard personality scale score is 24.55. The mean SAT score of the 75th percentile score for the colleges attended is 1,226.70 points. The mean number of years of experience for the pooled sample is 16.84 years. The mean income from salaries and jobs in 2019 is $83,484.07. The mean log of income from wages and salaries in 2019 is 11.07.

2.2 Non-White Graduates

With the non-white group, 59.29% (n = 150) are women, 6.32% (n = 16) graduated with a degree in business, marketing or management, 50.59% (n=128) were married in 2019, 2.37% (n=6) reported that health problems limit the amount they can work and 37.15% (n = 94) have attained a graduate degree. They had a mean income from wages and salaries of $75,249.02 in 2019.

The mean age for the non-white graduates is 36.92 years. The mean ASVAB percentile score is 58.01 and the mean attitude toward hard work personality scale score is 24.84 out of 28 total possible points. The mean SAT score for the 75th percentile for the colleges attended is 1,188.84, significantly lower than that of the white graduates which aligns with past research on the distribution of white and marginalized graduates at selective colleges. The mean number of years of experience working is 16.20 years, nearly one year less than the mean years of experience for the white graduates. The mean log of income from wages and salaries in 2019 is 11.01, signifying that the mean income of the non-white graduates is 8 percent lower than the mean income of the white graduates.

2.3 White Graduates

52.22% (n = 317) of the white graduates in the sample are female, 7.74% (n = 47) graduated with degrees in business, marketing, or management, 70.84% (n = 430) were married in 2019, 2.14% (n = 13) have health problems that limit the amount they can work and 36.57% (n = 222) have obtained a graduate degree.

Group	Mean	St.Dev.	N
Non-White Men	11.128	.617	103
Non-White Women	10.935	.666	150
White Men	11.358	.659	288
White Women	10.848	.934	313

Table 1: Log of wage and salary income by group

Whites had a mean income from wages and salaries of $87,784.19. The mean ASVAB percentile score is 75.51. The mean number of years of experience working is 17.11 and at the mean their colleges had a 75th percentile SAT score of 1,242.08. Their mean score on the attitude toward hard work personality scale is 24.44 out of 28 points. The mean log of wage income from wages and salaries in 2019 is 11.09. The mean age of the white graduates is 36.89 years.

3 Theoretical Framework

3.1 Long-Run Persistent Discrimination Dynamics in a Beckerian Learning-by-Doing Model

One of the puzzles of the neoclassical economics of race has been persistence of racial wage discrimination in the long-run. Such an outcome is deemed inefficient and bound to fail any firm operating in this manner. Andrews Andrews (1999) presents a model with a convincing explanation of how discrimination in who gets to develop their skill-set can result in persistent racial differences in economic conditions that are not the result of "cultural" differences between two groups. Suppose there is a one-commodity economy in which firms produce one composite good in an environment with perfect competition. The economy is open and capital is perfectly mobile. Rate of return on capital is uniform across the world at a rate of $r*$. The firms are small and owner-managed with two inputs, labor (L) and capital (K) and produce output according to the following production function:

$$Y^j = min[K^j, hE^j]$$

for firm j, where E^j is the level of employment offered by firm j and h is the efficiency of labor. Imagine that this is right after the end of Reconstruction and the vast majority of enterprises are owned by whites, some who are ”color-blind” and others who only hire and work with other whites. If we are assuming a situation in which this is surplus labor, the colorblind enterprise owner owns $0 < \lambda < 1$ percent of capital and produce $Y^c = \lambda K$ units of output. Racist and color-blind firm owners deem it profitable if the rate of profit in local markets is at or above the world rate of return on capital (hence there is a clear scenario where outsourcing occurs and marginalized and white workers both suffer).

Assume that with a real wage for white workers w, the rate of profit for the racist enterprise owner is $r^w = r^w = 1 - \frac{w}{h^w}$ where h^w is the efficiency of white labor. Color-blind firm owners distribute job offers to marginalized (Black, mixed-race, and Latino) and white workers so that the rate of profit from hiring marginalized labor is equal to the rate associated with hiring white labor, $r^b = 1 - \frac{\beta}{h^b}$ and β is the real wage earned by marginalized workers and h^b is the efficiency of marginalized labor.

Firms pay efficiency wages to prevent lack of effort in the workplace. The utility of work is the difference between real wages the cost of work effort. Employment rates for marginalized and white workers depend on the proportions of colorblind and racist firm owners, the fraction of the work force that is marginalized, and the racial composition of employment offered by the colorblind enterprise owner. Colorblind enterprise owners offer jobs to marginalized workers to equate returns from using each type of worker. In addition, racist and colorblind firm owners move capital between the local markets and world economies until the rates of return are equal to the world rate of return. If marginalized labor is more efficient that the economy-wide average degree of labor efficiency, the fraction jobs offered to marginalized workers is greater than or equal to the proportion of marginalized workers in the labor force Andrews (1999).

Many models of neoclassical and Post-Keynesian economic growth now assume that labor efficiency is the result of on-the-job training and experience and conscious, deliberate investments in education. Andrews models this insight by assuming that the growth rate of labor efficiency for workers in each racial group depends on the employment rate for the group:

$$Dh^i = (\epsilon e^i - \delta)h^i, i = m, w$$

where $D = d/dt$ is the differential operator, $0 > \delta > 1$ is depreciation for labor skills and $\epsilon > 0$ is the skill development or learning coefficient associated with employment. Andrews presents a model with equations for the employment rates in the short run, the medium-term levels of the capital-output ratio and racial composition of employment for colorblind firm owners, and the growth rate of labor efficiency dependent on opportunities to receive additional training. The result is a two-dimensional nonlinear system in labor efficiency units studied using dynamical methods Andrews (1999). The results indicate that if work experience matters for further development productive capabilities and increases in wages, competitive capitalism is not sufficient to guarantee the closure of gaps produced by discrimination.

3.2 Discrimination and Monopsony

Another reasonable explanation for the wage undervaluation and overvaluation seen in the results of this paper is a model proposed by Bahn and Stelzner Bahn and Stelzner (2021). In their model, they incorporate "firm competition for workers, employee movement between jobs in response to market signals, potential monetary frictions in the job transition process, and workers' collective action which is a function of government support" Bahn and Stelzner (2021). Due to the history of race and gender specific economic relations, women and racially marginalized workers are easier to exploit, with their wages pushed below the marginal revenue product of their labor (MRPL). This occurs because they can be offered a lower wage that the employer knows they will be more eager to accept without a position of leverage to negotiate for a higher wage.

Also, their model replicates the empirical evidence from this study that the cumulative wage gap for non-White women is greater than the additive gaps of being non-male and non-White (multiplicative wage undervaluation due to being a marginalized woman) Bahn and Stelzner (2021). Lastly, the Bahn and Stelzner model shows that a reduction in government support for collective action enables employers to wield monopsony power without credible threat of sufficient punishment, "independent of changes in employer concentration" Bahn and Stelzner (2021).

3.3 Monitoring Decisions and Disproportionate Punishment of Black Workers

African Americans experience shorter employment duration's in the labor force than Whites with similar productive characteristics. Cavounidis and co-authors Cavounidis and Lang (2015) advanced a theory and empirical evidence that employers discriminate in acquiring or acting on ability-relevant information. Essentially, Black workers are monitored more closely than white workers and this their errors are more likely to be caught and penalized (either placed on probationary systems or eventually fired). This reduces firms' beliefs about ability, and incentivizes ever more discriminatory monitoring. Their empirical evidence confirm that layoffs are initially higher for Black than non-Black workers, but that they converge with seniority and decline more with the Armed Forces Qualification Test as a proxy for unobserved 'aptitude' of Black workers Cavounidis and Lang (2015).

3.4 Two-Sided Labor Market Statistical Discrimination

For those unconvinced by the economic theory presented above to explain the persistence and magnitude of racial wage differentials between marginalized and white college graduates with other similar observable productive traits, there is a promising explanation of two-sided statistical discrimination. Craig and Fryer Craig and Fryer (2018). They contribute a model that illuminates problems associated with a labor market coordination problem in which employers use stereotypes about a group to guess their productivity and workers try to guess whether firms will have an environment conducive to their success (no workplace discrimination, opportunity for advancement, on-the-job training, and a truly welcoming company culture).

They propose an insurance system in which the government hires workers whom they believe to be competent but are not offered employment. Curiously, this insurance system is similar in application to the universal job guarantee proposals by some non-neoclassical economists. The universal job guarantee is not dependent on the government determining workers are being discriminated against, hence the 'universal' moniker in comparison to the insurance scheme which is based on some government imposed criteria. They both arrive at a similar policy solutions but from different original assumptions. Both policies effectively place a floor on adverse consequences for the wage of workers experiencing undervaluation of their marginal revenue product of labor and higher unexplained spells of unemployment.

4 Empirical Strategy

The NLSY97 collects data on four personality scale variables related to attitudes toward hard work. They measure the extent to which respondents believe they work as hard as the majority of people around them, do the bare minimum work and nothing more, have high standards for their work and strive toward them, and make every effort to do more than is expected of them. I used these variables to study how they affect the Oaxaca-Blinder decompositions examined in my study.

I began by selecting variables from the NLSY97 that are typically used in estimating wage equations and studying racial gaps in wages. The variables selected were marital status in 2019, gender, age, experience in years, experience in years squared, experience in years to the fourth power (see Thomas Lemieux 2006), residence in the southern United States, ASVAB score percentile as an imperfect measure of "ability" or "intelligence", attainment of a graduate degree, a major in business,marketing, or management, a major in liberal arts, general sciences, or humanities, and whether the respondent's health limits the amount of work they can perform. To decide which variables to include in our model, I used the least absolute shrinkage and selector operator (lasso).

With a dependent variable y_i and independent variables x_{ij} where i=1,2,3,...,N and j=1,2,3,...,p, the lasso finds $\beta = \{\beta_j\}$ to minimize

$$\sum_{i=1}^{N}(y_i - \sum_{j} x_{ij}\beta_j)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \tag{1}$$

where we're minimizing the sum of squares with a constraint of the form $\sum|\beta_j| \leq s$ Tibshirani (2011). The λ controls the strength of the penalty and amount of shrinkage, so that as λ goes to infinity all the coefficients would be eliminated, and a λ value of 0 would mean that the lasso is equivalent to the procedure for ordinary least squares regression. The lasso does variable selection, and I used the lasso command in Stata to select the independent variables for our model from the list mentioned above. The independent variables selected by the lasso are the selectivity and hard work interaction variable of interest for my dissertation, marital status, gender, age, experience in years to the fourth power, ASVAB score percentile, attainment of a graduate degree, a major in business, marketing, or management, and whether or not one's health limits the amount of work they can perform.

First, I estimate wage equations for white and marginalized graduates from each major with an interaction term examining the combined effects of positive attitudes toward hard work as measured by our personality scale variables and a measure of college selectivity. We have two groups, White (W) and Marginalized (M), which consists of Black, Latino, and mixed-race respondents), an outcome variable, W, and independent variables selected using the lasso listed above, as well as our variable of interest, the interaction of college selectivity and attitudes toward hard work. We want to know how much of the mean outcome difference, where $E(W)$ denotes the expected value of the outcome variable wages, is explained by group differences in the predictors (with a focus on our interaction term), where:

$$D = E(W_W) - E(W_M) \tag{2}$$

We are working with a linear wage equation model:

$$W_L = X_L^{'}\beta_L + \epsilon_L \tag{3}$$

where $E(\epsilon) = 0$ and $L \in (W, M)$. X is a vector containing the predictors and a constant, β contains the slope parameters and the intercept, and ϵ is the error term. The mean outcome difference can be expressed as the difference in the linear prediction of the group-specific means of our regressors:

$$D = E(W_W) - E(W_M) = E(X_W)'\beta_W - E(X_M)'\beta_M \tag{4}$$

We want to examine a "twofold" decomposition in which the outcome difference is separated into the following two components:

$$D = E + C \tag{5}$$

The first component is the part of the differential attributed to group differences in the predictors (the "endowments effect"):

$$E = (E(X_W) - E(X_M))'\beta_M \tag{6}$$

The second component is the part of the differential attributed to the differences between the coefficients and the intercept:

$$C = E(X_M)'(\beta_W - \beta_M) \tag{7}$$

Some economists (e.g., Cotton (1988)) argue that when there are racial wage differentials, the undervaluation of one group (wage cost) is accompanied by the overvaluation of another (wage benefit; see Figure 1). We wish to examine this alternative decomposition. The general idea is that there is a non-discriminatory coefficient vector β^* that can be used to examine the contribution of differences in predictor variables to the difference in outcomes. Following Ben Jann Jann (2008), the outcome difference is written as

$$D = (E(X_W) - E(X_M))'\beta^* + (E(X_W)'(\beta_W - \beta^*) + E(X_M)'(\beta^* - \beta_M)) \tag{8}$$

which is a twofold composition:

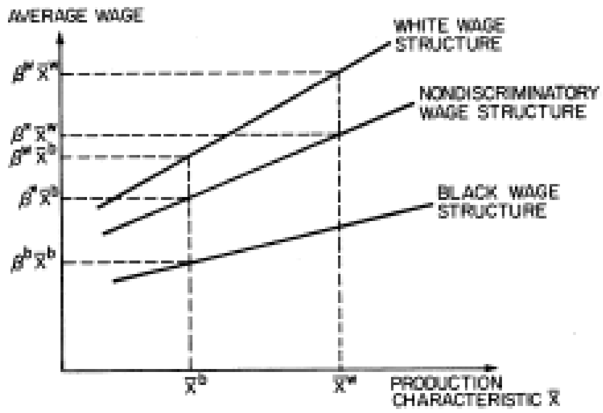

Figure 1: Source: Cotton 1988

$$D = Q + U \tag{9}$$

We will follow Jann (2008) so that the first component is as follows:

$$Q = (E(X_W) - E(X_M))'\beta^* \tag{10}$$

This is the portion of the outcome differential that is explained by differences in the predictors (a "quantity effect"), where the second component

$$U = (E(X_W)'(\beta_W - \beta^*) + E(X_M)'(\beta^* - \beta_M)) \tag{11}$$

is the unexplained part of the outcome differential. To understand the benefit to one group and the cost to the other, we can use the Cotton (1988) method of weighting the coefficients by group sizes n_W and n_M which is shown as follows.

$$\widehat{\beta^*} = \frac{n_W}{n_W + n_M}\widehat{\beta_W} + \frac{n_M}{n_W + n_M}\widehat{\beta_M} \tag{12}$$

To answer research question 2, we can use a detailed decomposition method that will help us investigate how much of the explained differential between white and marginalized (Black and Latino) graduates can be attributed to the effects of our college selectivity and hard work interaction predictors. Isolating the effects of our college selectivity and hard work interaction predictor is fairly straightforward. Following (Jann 2008), the total component of the explained part is a sum over the individual contributions

$$\widehat{Q} = (\overline{X}_W - \overline{X}_M)'\widehat{\beta_W} = (\overline{X}_{1W} - \overline{X}_{1M})\widehat{\beta_{1W}} + (\overline{X}_{2W} - \overline{X}_{2M})\widehat{\beta_{2W}} + ... \quad (13)$$

where $\overline{X}_1, \overline{X}_2$...represent the means of the single regressors and $\widehat{\beta_1}, \widehat{\beta_2}$...are associated coefficients. I estimate decompositions with the pooled and Cotton methods to compare the results. It should be noted that in our particular case, the interpretation of the coefficient differences as discrimination warrant some caution. There is an advantage in the constant term of the marginalized graduates wage equations that is unexplained. I will also discuss some of the debate surrounding inclusion of the AFQT or ASVAB score in wage equations for each racial group in the results section.

4.1 Extension to Panel Data and Causal Inference

For each group of graduates, white men, non-white women, non-white men, and white women, we have an equation estimating the relationship between their salary in the initial year of the ten year period, Y_t (natural log of a continuous salary income variable measured in current years dollars), their vector of endowments in the initial year t, X_t, and a vector containing the returns to their characteristics in the initial year β_t and an intercept in the initial year. ϵ_t is an error term. Thus, we have the following equations for the salaries of non-white women and white men at initial year t and end year s:

$$Non-white\ women\ at\ time\ t: Y_t^{BW} = X_t^{BW}\beta_t^{BW} + \upsilon_t^{BW} + \epsilon_t^{BW}, \quad E(\epsilon_t^{BW}) = 0$$

$$\mathrm{COV}(\mathrm{X}_t, \epsilon_t) = 0 \quad (14)$$

$$Non-white\ women\ at\ time\ s: Y_s^{BW} = X_s^{BW}\beta_s^{BW} + \upsilon_s^{BW} + \epsilon_s^{BW}, \quad E(\epsilon_s^{BW}) = 0$$

$$\mathrm{COV}(\mathrm{X}_s, \epsilon_s) = 0 \quad (15)$$

$$White\ men\ at\ time\ t: Y_t^{WM} = X_t^{WM}\beta_t^{WM} + \upsilon_t^{WM} + \epsilon_t^{WM}, \quad E(\epsilon_t^{WM}) = 0$$

$$\mathrm{COV}(\mathrm{X}_t, \epsilon_t) = 0 \quad (16)$$

$$White\ men\ at\ time\ s: Y_s^{WM} = X_s^{WM}\beta_s^{WM} + \upsilon_s^{WM} + \epsilon_s^{WM}, \quad E(\epsilon_s^{WM}) = 0$$

$\text{COV}(X_s, \epsilon_s) = 0 \quad (17)$

With a three-fold decomposition in a panel regression, there is the explained difference between the endowments of non-white Women and white Men at time t we call E_t, the unexplained difference between the returns to the characteristics of non-white women and white men at time t we call C_t, and the difference between the time-constant error terms of non-white women and white men at t, U_t. So we have:

$$\Delta Y_t = E_t + C_t + U_t \tag{18}$$

$$E_t = [E(X_t^{WM}) - E(X_t^{BW})]'\beta_t^{BW} \tag{19}$$

$$C_t = E(X_t^{BW})'(\beta_t^{WM} - \beta_t^{BW}) \tag{20}$$

$$U_t = E[v^{WM}] - E[v^{BW}] \tag{21}$$

Some economists (e.g., Cotton (1988)) argue that when there are racial wage differentials, the undervaluation of one group (wage cost) is accompanied by the overvaluation of another (wage benefit; see Figure 1). We wish to examine this alternative decomposition. The general idea is that there is a non-discriminatory coefficient vector β_t^* that can be used to examine the contribution of differences in endowment variables to the difference in outcomes. The salary disparity at time t is written as

$$\Delta Y_t = [E(X_t^{WM}) - E(X_t^{BW})]'\beta_t^* + (E(X_t^{WM})'(\beta_t^{WM} - \beta_t^*) + E(X_t^{BW})'(\beta_t^* - \beta_t^{BW})) + E[v^{WM}] - E[v^{BW}] \tag{22}$$

To understand the benefit to one group and the cost to the other, we can use the Cotton (1988) method of weighting the coefficients by group sizes n_{WM}, n_{WW}, n_{BM} n_{BW} which is shown as follows.

$$\widehat{\beta_t^*} = \frac{n_{WM}}{n_{WM} + n_{BW} + n_{BM} + n_{WW}}\widehat{\beta_t^{WM}} + \frac{n_{BW}}{n_{WM} + n_{BW} + n_{WW} + n_{BM}}\widehat{\beta_t^{BW}} + \ldots \tag{23}$$

We can use a detailed decomposition method that will help us investigate how much of the unexplained differential between white men and Black women at times t and s can be attributed to the effects of our college selectivity, effort, degree attainment, and achievement variables. Isolating the effects of our various explanatory variables is fairly straightforward. The total component of the unexplained part is a sum over the individual contributions

$$\widehat{Q} = (\overline{X}_{WM} - \overline{X}_{BW})'\widehat{\beta_{WM}} = (\overline{X}_{1WM} - \overline{X}_{1BW})\widehat{\beta_{1WM}} + (\overline{X}_{2BW} - \overline{X}_{2BW})\widehat{\beta_{2WM}} + ... \tag{24}$$

where $\overline{X}_1, \overline{X}_2$...represent the means of the single regressors and $\widehat{\beta_1}, \widehat{\beta_2}$...are associated coefficients.

Ultimately, if we consider the attendance of an HBCU or supportive, high-quality, high-mobility school to be an 'intervention' and the salaries of graduates at times t and s to be our outcomes, utilize appropriate fixed or random effects, and control for relevant observable characteristics, we can look at differences in the differences between the wages of Black graduates and white graduates between 1993 and 2003 and 2008 and 2018 and quantify 'overvaluation' and 'undervaluation' of salaries using the frameworks of Cotton (1988) and Darity Jr. et al. (2022). We have the difference in disparities in the salaries of non-white women and white men over time below:

$$\Delta Y_S - \Delta Y_t = DiD \tag{25}$$

$$\Delta Y_s = [E(X_s^{WM}) - E(X_s^{BW})]'\beta_s^* + (E(X_s^{WM})'(\beta_t^{WM} - \beta_s^*) + E(X_s^{BW})'(\beta_s^* - \beta_s^{BW})) + E[v^{WM}] - E[v^{BW}] \tag{26}$$

$$\Delta Y_t = [E(X_t^{WM}) - E(X_t^{BW})]'\beta_t^* + (E(X_t^{WM})'(\beta_t^{WM} - \beta_t^*) + E(X^{BW})'(\beta_t^* - \beta^{BW})) + E[v^{WM}] - E[v^{BW}] \tag{27}$$

4.2 Synthetic Control Difference-in-Differences and Cotton Decomposition Method

An alternative to estimating the value added of selective institutions and decomposing the contributions of different independent variables and drivers of the equalizing effects of selective school attendance on earnings is to combine synthetic control difference-in-differences, the Cotton decomposition, and theory on the intersectionality of identities when studying racial inequality. For the sake of the reader I will refer them to the seminal article on synthetic difference-in-differences by Arkhangelsky et. al Arkhangelsky et al. (2021) rather than reproducing their explanation. A recent article by Rambachan and Roth discusses how violations of the parallel trends assumption can be treated using some new methods Rambachan and Roth (2023). The synthetic control difference-in-differences estimator for average treatment effects on the treated is represented by the following equation, which is merely a combination of the mathematics behind the synthetic control method and the difference-in-difference estimator:

$$(\hat{\chi}^{\text{sdid}}, \hat{\alpha}, \hat{\mu}, \hat{\beta}) = \arg\min_{\alpha,\mu,\beta} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\chi)^2 \, \widehat{w_i^{\text{sdid}}} \, \widehat{\lambda_t^{\text{sdid}}} \right\} \tag{28}$$

The same logic applies here. We can decompose the differences between non-white women and white men college graduates from HBCUs and PWIs (or Black men and white men, or hypothetically any mix of race, sex, sexual orientation and gender identities given data available), and split it into an undervaluation and overvaluation. This can be expressed via percentages or in dollar terms, with intuitive application to understanding how this could impact household wealth disparities under a counterfactual scenario in which graduates invest these saved earnings in relatively safe, interest accruing assets.

4.3 Bayesian Beliefs of Perceived Ability and Imposter Syndrome for Marginalized Girls and Women

The effects of distorted beliefs about ones competencies on investment in education are explored in depth in a 2011 paper by Filippin and Paccagnella. The authors present a model of this process of making educational attainment decisions while dealing with uncertainty about ones ability level. Imagine studens from marginalized groups with ability a that is unknown to them at the beginning of their schooling and professional careers. Suppose that our student has to decide an academic track in high school, an academic major in college, and an occupation post college graduate according to their own perceived ability, a function of beliefs about their ability represented by a density function $v(a)$. We have perceived ability which is a function of beliefs and actual ability level

$$\Theta(a) = \int a v(a) da \tag{29}$$

where an upper middle class white male child may overestimate $\Theta(a) > a$ and an under confident marginalized female from a working class background underestimates their ability $\Theta(a) < a$. The marginalized girl then woman choosing classes in high school, college major, or occupation post undergraduate studies selects academic preparation, path, or career ψ. Some paths are understandably more difficult with regard to rigor of coursework and complexity of ideas and effort needed to succeed. Probability of success with the preparation or occupation is a function of ability and difficulty of the path or occupation $p(s) = f(a, \psi)$. This is the expression given by Filippin and Paccagnella (2011). Here we will depart from their formulation and include effort, e, with diminishing returns to effort. This allows a scenario in which one may not naturally process information as quickly or efficiently as another but can achieve extraordinary outcomes by applying themselves. Essentially, intelligence is liquid and improvable. So we have probability of success is a function of ability, difficulty of path, and effort

$$p(s) = f(a, \psi, e) \tag{30}$$

and success is increasing with respect to increased ability $\frac{\partial f}{\partial a} > 0$ and effort $\frac{\partial f}{\partial e} > 0$, and decreasing with respect to difficulty of preparation or career path chosen $\frac{\partial f}{\partial \psi} < 0$. Students update beliefs about their competency using Bayes Rule, where they have a given density of prior beliefs, where there is a signal implicit in the outcome $o = [s; f]$

$$\Theta(a|o) = \frac{p(o)v(a)}{\int p(o)v(a)da} \tag{31}$$

where successful outcomes with the path or occupation allow one to add human capital $k(\psi|s)$ to productivity. Agents maximize utility which is a function of human capital acquired with success in the path or occupation with convex costs of human capital acquisition

$$U[p(s)k(\psi) - \psi^2] \tag{32}$$

4.4 Perceived Ability and the Two Way Causality of the Wage Equations in Systemically Unequal Economies

Now, consider a wage equation with typical demographic characteristics and some unobserved variables as co-variates: health status, marital status, educational attainment, experience, discriminatory reactions to increased status or earnings, ability, perceived ability, and strength of coalitions or trust among the marginalized, selectivity of college attended, effort, locus of control, quality of social network, and our perceived ability variable that evolves with successful experiences or setbacks. The wage is a continuous dependent variable Y, where we transform the function using natural logs to account for the skewed wage distribution.

$$Y_t = X_t\beta_t - D[Y_t, a, \Theta(a)] + \Theta(a) + \lambda_t + \pi_t + \epsilon_t \tag{33}$$

Here we see the two way causality present when estimating wage equations to calculate undervaluation and overvaluation of wages using the Kitagawa-Oaxaca-Blinder mean decomposition technique of components of differences in the rates of two variable. If we have wages of Black female and white male graduates at time t and s, we can calculate causal estimates of interventions meant to improve the human capital acquisition of marginalized graduates.

Using the method of Cotton (1988) we can understand the undervaluation of marginalized women's wages the overvaluation of white men's wages, assuming a non-discriminatory wage prevails without discrimination that is determined by weighting the coefficients of the individual groups with multiple identities by their group sizes. Increased self-image and social networks increases wages, and the success of mobility within ones field raises these co-variates. We also have to account for discriminatory reactions to gains. The net effects depend on market conditions and the discriminatory attitudes and actions prevalent in the economy.

5 Results

5.1 Non-White Graduates and White Graduates

5.1.1 Wage Costs and Wage Benefits

Using Cottons' (1988) decomposition method, I found that the unexplained wage gap between white graduates and non-white graduates in my sample is .103 log points, or approximately 10.84 percentage points if we compute $(e^{.103} - 1) * 100$. The wage cost affecting the wages of the non-white graduates is .075 log points or approximately 7.78 percentage points. The wage benefit accruing to the white graduates is .028 log points or approximately 2.83 percentage points. Splitting the penalty and wage benefit using pooled methodology produces significantly different results. The unexplained gap is smaller at .082 log points or approximately 8.54 percentage points, with a wage penalty experienced by non-white graduates of .058 log points (5.97 percentage points) and a wage benefit accruing to white graduates of .024 log points (2.43 percentage points). Although a 10.84% gap may seem insignificant, we can consider a case with two graduates possessing the same characteristics. The marginalized graduate earns $100,000 per year while the white graduate earns $110,000 per year. The loss in earnings over a 10 year period is $100,000. As is typically the case with high-income earners, we can assume that the lost $100,000 may have been invested in a mutual fund during those years. Quickly we see the stark difference in wealth that such unexplained gaps in wages and salaries can produce, even if considering the unlikely case that the graduates from the two racial groups have the same amount of wealth inherited from previous generations.

5.1.2 Detailed Decomposition Results

The gap between non-white graduates and white graduates' logarithmic wages is 8.11%. For the non-white graduate-white graduate decomposition's, the controls that were selected explain more than 100 percent of the gap in log wages. If non-white graduates had the same characteristics as white graduates, their wages would increase by 19.48%. This indicates that the non-white graduates actually have a higher wage structure than the white graduates at the beginning of their wage function. This seems to be due to an unexplained benefit of group membership that increases the y-intercept (constant term) of their wage function higher. However, the slope is less steep, indicating lower returns to their characteristics. Put simply, their wage functions intersect at a low level of characteristics and for the rest of the wage structure, white graduates have a wage advantage due to differences in coefficients.The unexplained portion of the differential is 10.84%, indicating that rather than having the advantage of their higher constant term and higher coefficients throughout the wage structure, there is an unexplained penalty due to their coefficients.

The characteristics that have the largest effects on the explained part of the differential are the selectivity and hard work interaction, ASVAB percentile, experience to the fourth power, and the marital status dummy. The marginalized graduates attended less selective schools on average, but had slightly higher scores on the attitudes towards hard work scale, according to the summary statistics. This explains the significance of the interaction on the explained part of the differential. The ASVAB (or AFQT) is a controversial and imperfect measure of ability, so with the large effects of the scores on the explained differential it is plausible that the ASVAB is a biased indicator for racial wage gaps, explaining more of the effects of discrimination with its inclusion.

A higher percentage of non-white graduates are female compared to white graduates (52.22 percent vs. 59.29 percent), and the non-white women in our sample have larger unexplained gaps in their wages compared to the white men, so if the women in the non-white group were men, more of the differential would be explained. The significance of experience in explaining some of the gap makes sense, as non-white workers are the last hired and first fired, a structural characteristic of the economy that perpetuates gaps in resumes.

The characteristics that have the largest effects on the unexplained part of the wage differential are college selectivity and attitudes toward hard work interaction, work experience in years, ASVAB percentile, and the constant term. As explained earlier, the difference in constant terms cannot be analyzed, given that it represents unexplained differences in the wage structures of the two groups strictly due to group membership. The large differences in coefficients for the selectivity and hard work interaction term may be measuring what this study set out to understand, differences in the returns to hard work and attending a selective school. The difference in coefficients for the experience in years characteristic could be explained by the research on the smaller number of marginalized graduates in 'good jobs', which seems to indicate less promotions for non-white employees, which would result in smaller returns to years of experience in an occupation. A theoretical model by Costas Cavounidis and Kevin Lang (2015) which posits that non-white workers are more closely monitored and penalized for minor errors compared to their white colleagues could also help to make sense of these results. In their model, black employees are more closely monitored than white employees, leading to poorer performance reviews due to relatively minor errors, which would also lead to slower advancement and smaller returns to experience. With regard to ASVAB percentile, it makes sense that the "natural ability" of non-white workers is undervalued if we assume that there is widespread discrimination in wages Cavounidis and Lang (2015).

Now that we have analyzed the source of gaps in non-white and white graduates' wages, I will turn toward more detailed analysis by looking at main sources of racial gaps by gender. I look at the gaps between non-white women and white men and non-white graduates and white men.

5.2 Non-White Graduates and White Men

5.2.1 Wage Costs and Wage Benefits

The economic advantage of white men over the non-white graduates is obscured by the lower wages of the white women in the sample. I estimated my results using white men and non-white graduates (both men and women). I found that the unexplained wage gap is 15.48% using the Cotton method. The wage cost experienced by non-white graduates is 6.82%. A wage benefit of 8.11% is experienced by the white men. The results for using pooled coefficients instead of Cotton's methodology produce an unexplained wage gap of 12.29%, with a 6.39% wage penalty for non-white graduates and a 5.54% wage benefit for the white men. The results are presented in table 5.

5.2.2 Detailed Decomposition Results

The detailed decompositions for white men graduates and non-white graduates are presented in table 6. The total wage gap between the wages of non-white graduates and white men is 41.05%. The Cotton decomposition produces an explained wage gap of 21.65% and an unexplained wage gap of 15.48%. The results of the pooled decomposition indicate a smaller unexplained part of the gap. These decomposition results appear to confirm that the gap between non-white graduates and white graduates that I calculated is significantly reduced by the inclusion of white women, who have lower wages than both the marginalized men and women in my sample. With the explained part of the gap, ASVAB percentile score is once again the largest contribution when looking at the detailed decomposition. Again, the verdict is still out on whether including the ASVAB in racial wage differential equations does not introduce bias due to biases in the testing and preparation for the testing resulting from one's environment (those with higher ASVAB scores may just have had higher socioeconomic status). Marital status is important but far less influential on the explained gap than ASVAB percentile, which is important considering mass incarceration and recent research into how that has affected marriage rates in non-white communities (essentially a large pool of potential partners is incarcerated). The remaining independent variables contribute small percentages to the overall explained gap, with our college selectivity and hard work score interaction term the next most significant contribution to the explained part of the gap.

The unexplained part of the wage differential is once again impacted significantly by the college selectivity and attitude toward hard work personality score interaction term. This contributes the most to the unexplained differential by far. Next is the contribution of the constant term, which in this scenario is lowering the unexplained gap between the two groups. The constant term is the unexplained part of the gap that we have no explanation for, so there is no insight to be gained. The ASVAB percentile score variable detracts from the unexplained part of the differential because the non-white graduates actually have a larger coefficient for the effect of ASVAB percentile on wages. Experience and experience to the fourth power have opposite but significant effects on the unexplained part of the differential. The non-white graduates also do not have the same return to marital status as the white graduates, and a graduate degree is rewarded slightly more when a non-white graduate has one (they may have to face higher standards when hired or evaluated due to discrimination).

5.3 Non-White Women and White Men

5.3.1 Wage Costs and Wage Benefits

As shown in table 7, the Cotton methodology of calculating the wage benefit and wage penalty associated with differentials reveals that the unexplained gap between the non-white women graduates and white men is 25.60%. There is a wage cost experienced by non-white women of 14.11%. The wage benefit accruing to white men is 10.07%. Again, the results are different when using pooled coefficients, with an unexplained wage gap of 18.88%. With the pooled methodology the wage cost is 12.07% and the wage benefit is 6.07%.

5.3.2 Detailed Decomposition Results

The detailed decomposition results for the white men and non-white women graduates are presented in table 8. The wage gap between non-white women and white men is 52.65%. Using Cotton decomposition methods, of the 52.65% total gap, 18.29% is explained by differences in the control characteristics that we used and 25.60% was unexplained. This gap is the largest of the race by gender gaps I analyzed, most likely reflecting what Holder (2020) has named the "double gap" wage penalty experienced by black women. The double gap reflects the fact that there is evidence of a wage penalty on Black women for being women and an additional penalty for being Black. I think this may also hold true for our aggregate non-white women group in my sample consisting of Latina, Black, and mixed-race women.

The difference in ASVAB percentile characteristics contributes the most to the explained part of the gap between the non-white women and white men graduates. As discussed before, the AFQT, which the ASVAB is based on, has been questioned as a biased indicator for racial wage gaps, so that its importance in the explained part of the wage gap may be measuring some type of racial bias or discrimination. Our selectivity and hard work interaction term the explains the rest of the gap, again reflecting the differences in selectivity for colleges attended between marginalized and white graduates. Marital status is crucial here, as educated black women tend to have lower marriage rates than other demographics. The explained part of the gap would be larger if not for the higher educational attainment of the marginalized women in the sample, the most educated demographic out the four groups in this sample (see data section for summary statistics for each demographic).

Here, we see the importance and contribution of the college selectivity and attitudes toward hard work interaction term to the unexplained part of the wage gap between non-white women and white men. Marital status is also salient, with non-white women not getting the same return to marriage as white men in the sample. ASVAB percentile is also significant, although as discussed before there is serious debate about what exactly these armed forces tests truly measure. The difference in experience in years coefficients contributes some to the unexplained gap, but differences in the returns to college selectivity and attitudes towards hard work are the main effects impacting the unexplained part of the differential.

It seems that the non-white women college graduates in our sample are at a significant disadvantage when we examine whether their pursuit of high quality education and high work ethic pays off in the same way as white men in our sample. This result confirms our hypothesis that non-white graduates have to be more exceptional than their white peers with comparable attitude toward hard work personality scores and college selectivity in order to achieve the same wages. It should also be noted that although Black women, Latina women, and mixed-race women have become increasingly educated in terms of graduate degrees and bachelors degrees attained, these results indicate that this achievement is not being reflected in their income from wages and salaries.

6 Conclusion and Extensions

6.1 Conclusion

I found that the college selectivity and attitude towards hard work personality scale score interaction was statistically significant for all of the decompositions between different demographics studied. The regression equations for each group reveal that college selectivity and the interaction have an insignificant effect on wages for the marginalized graduates. For the white graduates, college selectivity is insignificant but the interaction is significant at the .001 level. For non-white women neither variable is significant. The white men's regression equation shows that college selectivity is significant at the .10 level, whereas the interaction is significant at the .001 level. These results reflect some of the findings of Dale and Krueger Dale and Krueger (2011), with the exception that I found a significant effect of the college selectivity and hard work interaction on the wages of white graduates and statistically significant effects of the interaction and college selectivity on the wages of white men. I do not run regressions to see if the significant effects of selectivity for Black and Latino students from less educated households found in their study are reflected in my study.

On average, non-white graduates attend less selective undergraduate institutions, while their average score on the attitudes towards hard work scale is slightly higher. These results imply that it may be important to include controls that measure the selectivity of the institutions attended when comparing the wages of marginalized and white college graduates. According to Rachel Baker, Daniel Klasik, and Sean Reardon (2018), there have been persistent gaps in college enrollment selectivity between white and Latino graduates in the nearly 30 years of their study, between 1986 and 2014. They also found that Black students have attended increasingly less selective institutions than whites, a fact that they find concerning because of the implications for long term economic inequality Baker et al. (2018). My results seem to provide some evidence that these differences in college selectivity can have major implications for one's income, with consequences for lifetime earnings that will simply accumulate throughout one's lifespan.

By studying the racial decomposition's by a gender dimension, I found that the gaps between non-white women and white men are the largest, mainly due to differences in the returns to college selectivity and the attitudes towards hard work personality scale score. The non-white women experience an unexplained wage gap of 25.60%, with 14.11% a wage cost for being a marginalized woman and 10.07% a wage benefit for being a white man. This finding reinforces Holder's Holder (2020) findings that marginalized women experience a "double gap", a wage penalty due to being women, and an additional penalty due to being women from marginalized racial groups. Non-white men also experience an unexplained wage gap compared to white men. Non-white men had a wage advantage over white women, mainly due to wage penalties for being a woman and a difference in the constant term for the two groups. When comparing the non-white graduates and white men, they experienced an unexplained gap of 15.48%, with 6.82% a wage cost to being a non-white graduate and the remaining percentage the wage benefit of being a white male graduate.

6.2 Extensions

Moving forward, a larger dataset with information on labor market outcomes, college selectivity, and a set of rich demographic characteristic independent variables would help to understand the complexities in differences in returns to college selectivity and positive attitudes toward hard work or high motivation influence racial wage differentials. The main conjectures were proven to be true, and the same differences in returns to college selectivity and positive attitudes towards hard work may hold true with an analysis by gender.

Another potential extension would be to look at differences in the returns to these characteristics for immigrants from marginalized groups in comparison with white American graduates. For example, sometimes immigrant non-white graduates are viewed more favorably and as more hard working than people from marginalized groups born in the U.S. This difference in perception may be reflected in the differences in their returns to our interaction term in comparison with native born graduates from marginalized groups. There is also the possibility of calculating wage gaps by considering differences in the returns to these characteristics through an intersectional lens where people hold multiple marginalized identities (for example a disabled woman that is also queer and Black, Latino, or Native American) Darity Jr. et al. (2022). Previous research in this area suggests that the combination of two more socially marginalized identities does not necessarily interact in additive ways. These research questions warrant further investigation with a larger data set so that results can be generalized to the U.S. population, shedding light on the wage penalties and disparate rewards for achievement between marginalized and white college graduates.

7 Appendix

7.1 An Alternative to Funding Education - Mass Incarceration

Marcellus Andrews Andrews (1993) begins his examination of the emergence of an educational underclass and the attempts to control such a 'surplus' population by explaining the features of the economy. There is one produced commodity used for either investment or consumption. Investment is either increases in capital deepening or expenditures on education to increase 'human capital'. The population is composed of four groups: educated workers (N), students (S), unemployable members of the underclass (U), and prisoners (P). Workers own all capital and receive all profits. Firms produce output through a fixed coefficients production function with educated workers (N) and capital goods (K)

$$Y^S = min[aN, K/s] \tag{34}$$

where a is level of output per worker (a measure of productivity) and x is the capital-output ratio. Andrews assumes that output is constrained by the supply of educated workers.

An 'educational underclass" can develop if the supply of high quality education is less than the number of students that require training (see Blair and Smetters (2021) for evidence of this with elite colleges artificially keeping supply low and welfare loss consequences). Alternatively, an educational underclass can develop if a significant segment of the population cannot complete the required training to become an educated worker for whatever reasons.

Andrews assumes a rate of population growth (g) for all classes, and the number of new students in need of training at any time is gT. A fraction of the society's existing population will fail and become unemployable ($0 < f(b) < 1$). If education system capacity is sufficient for population growth and needs, the growth of the student population is

$$DS = gT - hS \tag{35}$$

where $0 < h < 1$ is the graduation rate. The increase in the size of the underclass at any time is

$$DU = f(b)S \tag{36}$$

where be is the level of education spending per student and the failure rate $f(b)$ is negatively related to b. If education supplied is insufficient $S = E$, then

$$DS = DE - hS \tag{37}$$

and

$$DU = gT - DE + f(b)S \tag{38}$$

There is a tax rate β, and a government budget constraint expressed as

$$\beta Y = bS + vDE + rU \tag{39}$$

where v is the cost of building a unit of educational system capacity and r is the level of poor relief per member of the educational underclass. If one assumes a balanced budget, the increase in the capacity of the education system is described by the following equation

$$DE = v^{-1}[\beta a(N/T) - b(S/T) - r(U/T)] \tag{40}$$

where S/T and U/T are the fraction of the total population in school (schooling ratio) and fraction in the underclass (underclass rate).

After examining the mathematical properties of the system, Andrews finds that society has a stable (though potentially high) underclass rate if choosing to spend more on education per student than poor relief.

Jails are introduced into the model as the government in this scenario enforces laws of contract and public safety on behalf of an educated population. Police and prisons are used for controlling crime and detaining members of the evolving underclass. He finds that the larger the apprehension rate, the smaller the equilibrium underclass rate and the larger is the equilibrium incarceration rate. In short, the strategy of imprisoning the under educated rather than spending the money to educate them simply moves those in the unemployable underclass from deprivation in the general population to deprivation of a different kind in jails. In the end, poverty is not alleviated and this theoretical exercise confirms the fears of many criminal justice reform advocates: : incarceration is an extremely costly reaction to a symptom caused by poverty and lack of investment in human beings mental capabilities and primary functionings (health, education, productive employment, housing security, and civil rights/dignity).

7.2 A Model from the Stratification Economics School

This paper stems from a doctoral thesis written between August 2018 and December 2022. Since then, an elegant contribution to formalize and explain these dynamics in a two-period model has emerged. A recent working paper by Brundage and Tavani Brundage and Tavani (2024) situates the racial economic conflict of the technologically advanced U.S. economy and persistent inequality in a model inspired by W. Arthur Lewis and contributions from The Stratification Economics School. They present a model of group conflict, racial conflict, and stratification. They assume two groups, one dominant and the other marginalized. Both groups live for two periods, a pre-market period in which they investment in schooling and a market-phase in which they utilize their investments. For the sake of brevity we will not present their full, rather sophisticated model in its entirety here and will describe it with written language.

An individual in the marginalized group chooses how to invest in the pre-market phase to maximize their net material resources. Increased discriminatory efforts by the dominant group reduce the effectiveness of the pre-market investments of the marginalized group. A key feature of this theoretical framework is that as the productivity of the marginalized group increases, the dominant group must increase their discriminatory effort to reduce the material resources obtained by the marginalized group. This is a theoretical explanation of the historically witnessed ”backlash” to development of ”middle class” members of marginalized groups in the United States (see the history of Reconstruction and increased political participation, as well as hate group resurgence in recent years as progress was made toward racial harmony) Brundage and Tavani (2024).

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