Black-White gap in skills, employment and experience-wage profiles

Maksym Kutsenko

April 22, 2025

Abstract

In this paper I study how the wage gap between black and white high school graduates evolves over the life-cycle using NLSY79 data. I document three main results. First, the black-white gap in median wages grows over the life-cycle. Second, individuals with higher levels of cognitive skills see their wages grow faster. Third, after equalizing the levels of cognitive, non-cognitive and social skills upon entering the labor market, the black-white gap in median wages continues to widen, but at a slower rate.

1 Introduction

Inequality in labor market outcomes between blacks and whites has persisted in the United States until the present day. In 1979, the average black male earned $15 per hour against $19 per hour for the average white male. Almost 40 years later, these numbers grew to $18 and $25 for black and white males respectively (Karageorge 2017). Many reasons have been put forward to explain these differences, such as differences in educational attainment (O'Gorman 2010), skills (Neal and Johnson 1996), labor market opportunities (Kline, Rose, and Walters 2022), residential segregation (Reardon and Bischoff 2011), or discrimination. While there exists a large body of evidence that these factors explain a considerable share of the black-white wage gap at a given point in time, we know little about how this gap evolves over the life-cycle. In particular, we do not know whether wages would diverge between a black and a white individual that have otherwise the same characteristics.

This study focuses on "potential experience-wage profiles", which, in this context, refer to the evolution of wages from the moment the individual leaves high school and enters the labor market. By convenience, I refer to those as "experience-wage profiles" and as "the evolution of wages over the life-cycle". Because different students leave high school at different ages, the measure of potential experience is preferred to the simple measure of age, as it better reflects the time the individual spent in the labor market. In particular, this paper documents how experience-wage profiles differ between black and white high school graduates after accounting for heterogeneity in cognitive, non-cognitive, and social ability, and the bias arising from the endogeneity of labor market participation.

Section 2 provides a review of the relevant literature motivating the research, and summarizes the contribution of this paper. Section 3 describes the data. Section 4 provides descriptive statistics on the distribution of skills, experience-wage and experience-employment profiles for black and white males. Section 5 presents the conceptual framework and the empirical strategy. Section 6 reports the results. Section 7 performs a robustness check. Section 8 concludes.

2 Literature review

A large part of the literature focused on how skills affected labor outcomes. (Deming 2017) presents evidence that cognitive, non-cognitive, and social skills are all predictive of labor market outcomes. Focusing on racial inequality, (Neal and Johnson 1996) showed that around 70% of the black-white wage gap at ages 26-29 could be attributed to differences in pre-market levels of cognitive skills, leaving an unexplained wage gap of roughly 7%. Accounting for the gap in employment using a regression to the median, they find that the adjusted unexplained gap rises to 13.4%.

They suggest that pre-market factors play the biggest role in differences in labor outcomes between white and black males. Replicating the exercise for the same cohort at ages 42-44, (G Jr 2011) also finds that around 70% of the wage gap can be explained by differences in cognitive skills, but the unexplained gap is 11%. Similarly, (Lang and Manove 2011) examine that cohort at ages 31-41, and find that 65% of the gap is explained by these skills, with an unexplained wage gap of 13%.

A second venue of explanation of the black-white wage gap is discrimination. (Becker 2010) presented pioneering work on the topic, suggesting a differentiation between taste-based and statistical discrimination. Since then, discrimination has been documented to affect the labor outcomes of blacks. (Kline, Rose, and Walters 2022) show that individuals with distinctively black names are less likely to be contacted back after applying for a job. Recent work has also presented evidence of new types of discrimination, one of which arises from inaccurate beliefs (Bohren et al. 2023). Together, these papers suggest that a discriminated group has both lower chances of being employed, and would receive lower wages.

Tying these potential sources of the black-white wage gap, (Lang and Manove 2011) present evidence that black individuals get more schooling for a given level of cognitive skills, consistent with the signaling and discrimination theories. Moreover, they also show that omitting education from the specification understates the wage gap, as directly comparing black and white males with similar cognitive skills is omitting that black individuals have a higher level of education, which is potentially aimed at counteracting labor market discrimination. (Arcidiacono, Bayer, and Hizmo 2010) focus on employer learning, and they show that wages for high school graduates increase faster for individuals with higher cognitive skills in the first 12 years after graduation, suggesting that employers learn about the productivity of their employees, and adjust their wages accordingly. Moreover, they argue against pooling both high school and college graduates and instead suggest conducting the analysis separately for both groups. They also find little evidence of divergence between the wages of black and white males, but their specification is not suited to answer that question as they included variables such as part-time employment, region of residence, and other variables that could be affected by labor market discrimination, and thus understate the actual divergence between black and white wages. It is, to the best of my knowledge, the research article that is most closely related to the content of this work.

While this literature review documents potential sources of wage differences between black and white males, little is known about their experience-wage profiles once one accounts for pre-market levels of cognitive, noncognitive, and social skills. Neal and Johnson 1996, G Jr 2011, and Lang and Manove 2011 present the wage gap at different points in the life-cycle for the same sample of individuals, but no systematic approach has been undertaken to estimate whether there is a significant widening. Neither has there been documentation on whether noncognitive and social skills contribute to wage growth over the life-cycle or if they only allow to get consistently higher wages without affecting their growth. Moreover, following the suggestion from (Arcidiacono, Bayer, and Hizmo 2010), it is of paramount importance to separate high school graduates who reveal their actual level of skills through work, and college graduates who reveal their skills through college graduation, especially if black and white males are not evenly distributed in each educational level. As a result, and for additional reasons presented later, my analysis will focus on black and white male high school graduates.

While this literature shed light on extremely important features of the black white wage gap, it is does not allow to understand whether this wage gap widens over the life-cycle. For example, contributing to the debate around whether it is the gap in skills or actual labor market discrimination that are most responsible for the black white wage gap, Neal and Johnson 1996 argues that pre-market skills play a bigger role at age 26-29. However, this is not necessarily reflective of how labor market discrimination, or for that matter other factors that differ between black and white workers, affects wages at later ages, and how it affects wage trajectories. This is important in two ways. First, knowing whether experience-wage profiles differ between black and white workers allows to assess the comparability of results between two distinct cohorts. For example, in his paper G Jr 2011 compares NLSY79 and NLSY97 cohorts during 2012. Knowing whether the wage gap conditional on cognitive skills grows or not would allow to assess the comparability of his results. Second, understanding experience wage profiles for high school graduates is a stepping stone in understanding how students choose whether to pursue a college degree or not. In other words, if one is able to recover median experience-wage profiles for black and white high school and college graduates, one can then make a cost-benefit analysis of attending college depending on the level of cognitive skills one has when finishing high school. As a result, the results from this paper are important to move forward the understanding of the wage gap between black and white males and the choice of attending college.

My contribution to this literature is the following. First, I focus on experience-wage profiles instead of wages at a given point in time. Second, I make use of the most recently updated NLSY79 dataset allowing me to exploit additional variation in experience as compared to the work of (Arcidiacono, Bayer, and Hizmo 2010). Third, I explore whether noncognitive and social skills matter for wage growth. Finally, this paper accounts for the endogeneity of employment, which has been shown to understate the wage gap between black and white males (Neal and Johnson 1996, Western and Pettit 2005).

3 Data

In order to conduct an analysis of how wages diverge over the life-cycle, and how much of this divergence occurs due to cognitive, social and non-cognitive skills, it is necessary to find a panel dataset that contains information on wages and the above-mentionned skills.

This paper uses NLSY79 data from the US Bureau of Labor Statistics, a longitudinal dataset containing information on 12686 individuals aged 14 to 22 when first surveyed in 1979. They were then surveyed annually until 1994, and then biennially until 2020. It contains information on the individual's demographics, such as their gender, race, age, year of birth, etc. Furthermore, it reports individuals' education, employment status, and wages during each year of the survey.

In addition to this, it contains variables that measure cognitive, non-cognitive, and social skills. Armed Forces Qualification Test (AFQT) scores have been widely used as a measure of pre-market cognitive skills (Neal and Johnson 1996, Lang and Manove 2011), the Rosenberg Self-Esteem and the Rotter Locus of Control scores have been used to measure non-cognitive skills (Heckman, Stixrud, and Urzua 2006), and reported sociability in 1981 and at age 6 have been used to measure social skills (Deming 2017). To the best of my knowledge, this dataset is the only one containing such information (except for its 1997 equivalent NLSY97 dataset).

My main sample is restricted similarly to (Neal and Johnson 1996) in that the oversample of poor non-black and non-Hispanic as well as the military oversample are dropped. However, two features of my sample differ from Neal and Johnson 1996. First, I do not include Hispanics in my sample. Moreover, I do not restrict the sample to only those individuals who took the AFQT test before or at the age of 18. As shown in the appendix, there is little evidence that the AFQT gap between black and white high school graduates increases after 18, indicating that labor market discrimination does not seem to be affecting skill investments between blacks and whites, at least those skills captured by the AFQT test. As a robustness check, analysis for both sub-populations of test takers is reported in Section 7.

4 Descriptive statistics

The first step is to show what the data look like, motivating the approach and methodology I am using to conduct my analysis. As a result, I present employment rates, wages, and the distribution of skills for the overall population, high school graduates, and college graduates. The distribution of educational attainment by age 30, showing that the educational category with the largest number of observations is the one of high school graduates, is reported in Figure 5 in the Appendix.

4.1 Employment rates

Figure 1 presents the employment rates for black and white individuals plotted against their years of potential experience. The first striking feature is the consistently lower employment rates for black workers in the overall population and for high school graduates. While the employment rate of white workers is consistently above 80% between the second year after high school graduation until roughly 33 years after it, employment rates for black high school graduates reach 80% only at 8 years of potential experience. Second, employment rates follow the pattern of an inverted-U curve, with generally increasing employment rates during the first 5 to 8 years after graduation, and decreasing rates after roughly 25 years of potential experience. This is important as a gap in employment can cause standard inference on the wage gap to be contaminated by the lack of observed wages for those not employed. This will be discussed more in detail later. Finally, employment rates for black college graduates are extremely volatile because there are only 44 individuals in that sample. Thus, the analysis focuses only on high school graduates.

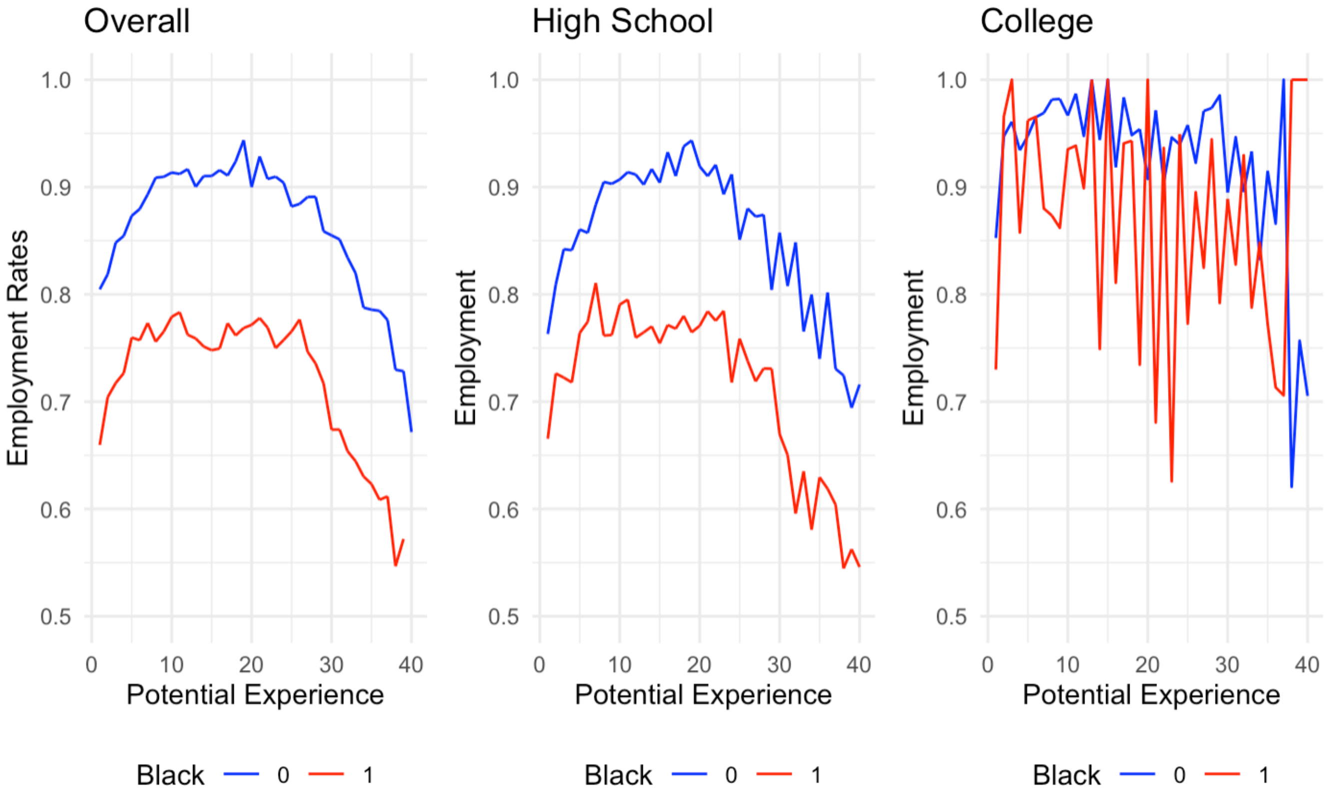

Figure 1: Employment-Experience Profiles

Note: Each line presents the evolution of the employment rate over potential years of experience for black and white males. Potential experience is recovered as the number of years since the last change in the years of education. The first plot has a sample size of 1753 whites and 966 blacks for 1 year of potential experience and 605 whites and 386 blacks for 40 years of potential experience. For High School graduates, I have 558 whites and 379 blacks for 1 year of potential experience, and 321 whites and 182 blacks for 40 years of potential experience. For College graduates, I have 249 whites and 60 blacks for 1 year of potential experience, and 22 whites and 11 blacks for 40 years of potential experience. Sample size varies because of varying attrition rates reported in Figure 6. Source: U.S. Bureau of Labor Statistics, NLSY79.

4.2 Wages

Figure 2 presents the wage-experience profiles for black and white conditional on being employed. The first graph presents the profiles for the entire sample, the second for high school graduates, and the third for college graduates. We can see that the profiles are flatter for black males than they are for white males for every sub-population considered.

When considering the entire population, there is almost a straight line from the point where white males have 1 year of experience to when they have 20. Over that period, wages grow by roughly 60%. When it comes to black workers, their wages grow by only 40%. Focusing on high school graduates, wages of white workers grew by 55% while those of black workers grew by 37%. [1] Finally, in line with increasing attrition throughout the interview years, there is a higher volatility in estimates of average wages at higher levels of potential experience.

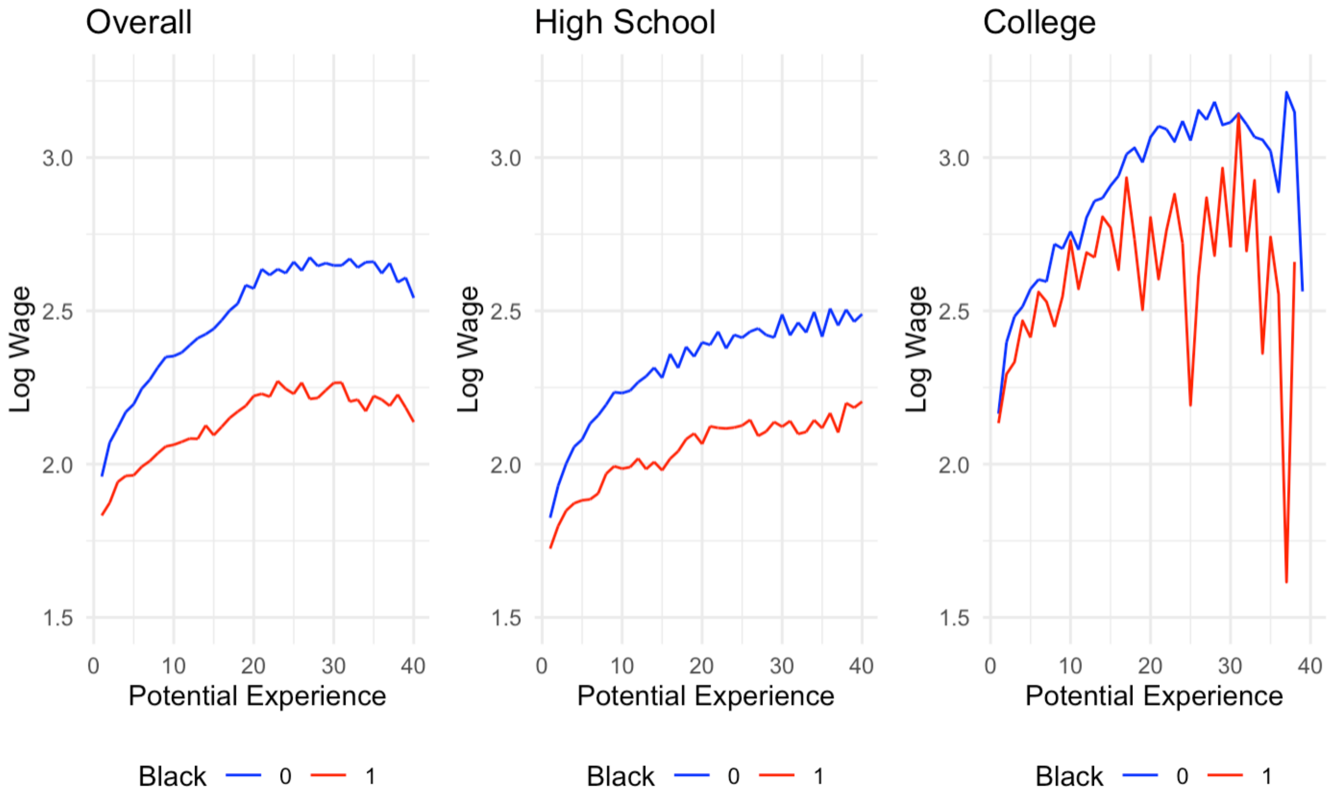

Figure 2: Wage-Experience Profiles

Note: Each line presents the evolution of the log of hourly wages (standardized to 1990 dollars) over potential years of experience for black and white males for level wages bounded between $1 and $100. Potential experience is recovered as the number of years since the last change in the years of education. Source: U.S. Bureau of Labor Statistics, NLSY79.

4.3 Skills

Figure 3 presents the distribution of cognitive, non-cognitive, and social skills for white and black males by education category. Cognitive skills are measured by the Armed Qualifying Test (AFQT) score, non-cognitive skills by the Rosenberg Self-Esteem and the Rotter Locus of Control scores, and social skills by self-reported sociability during the 1981 interview and, in retrospective, at age 6. The two tests were administered during the 1980 interview, while the sociability was self-reported in 1981, and these three measures have been widely used in the literature (Neal and Johnson 1996, Heckman, Stixrud, and Urzua 2006, Deming 2017). All scores are standardized to have a mean 0 and a standard deviation of 1 with respect to the entire sample.

The most striking feature presented in Figure 3 is the substantial gap in the distributions of cognitive skills between black and white males in both sub-samples. The distributions of non-cognitive skills are roughly identical for high school graduates while black college graduates seem to have higher levels of non-cognitive skills than white college graduates. Moreover, there seems to be a difference in cognitive and non-cognitive skills between high school and college graduates, with college graduates having slightly higher levels in both. Little substantial gap is noticeable in terms of social skills between both educational levels and black and white graduates in both sub-samples.

[1] Similar computations for the gap in wage growth between black and white college graduates are not reported due to the extreme volatility of the estimated mean wages of black workers.

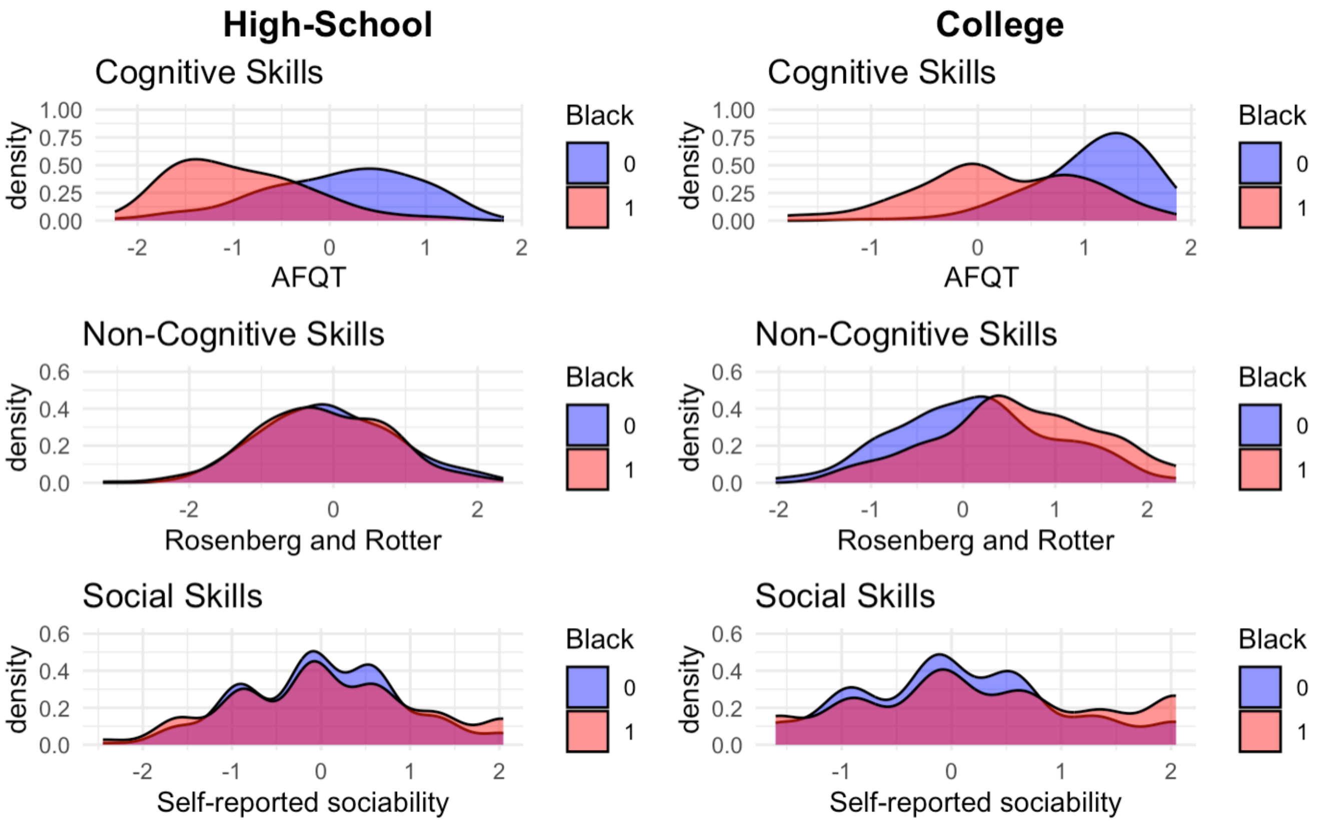

Figure 3: Distribution of skills

Note: Cognitive skills are measured by each respondent's score on the Armed Qualifying Test (AFQT), and are normalized to have a mean of 0 and a standard deviation of 1. I use the AFQT score crosswalk developed by Altonji, Bharadwaj, and Lange 2012. Social skills is a standardized composite of two variables (i) sociability in childhood, (ii) sociability in adulthood. My measure of non-cognitive skills is the normalized average of the Rotter and Rosenberg scores in the NLSY79 - *note copied and adapted from Deming 2017*. Source: U.S. Bureau of Labor Statistics, NLSY79.

4.4 Summary

There exist substantial gaps in employment rates, wages, and cognitive skills as measured by the AFQT. Moreover, the wage gap seems to be growing over the life cycle, even within educational subgroups. However, if for a given educational category wages are a function of skills, a growing wage gap within an educational category could result from differences in cognitive skills that the individuals bring to the market. As a result, it is important to understand how much of the gap in experience-wage profiles can be attributed to the gap in skills, and how much of it remains unexplained. Given the high variance in the wage-experience profiles for college graduates, the main focus is devoted to the wage-experience profiles of high-school graduates.

Section 6 provides a more detailed view of wage-experience profiles for black and white high school graduates by accounting for differences in skills.

5 Conceptual framework and Methodology

Conducting the analysis on only those whose wage are observed can lead to a substantial underestimation of the actual gap between black and white workers. In fact, Butler and Heckman 1977, Western and Pettit 2005, and Neal and Johnson 1996 show that failing to account for the gap in employment tends to understate the actual gap in wages. As a result, this part introduces the conceptual framework relating employment, wages, and unobserved characteristics, and the methodology implemented to solve this issue.

5.1 Employment gap

Potential wages and employment

Figure 4 presents the hypothetical unconditional wage distributions of blacks and whites at a given point in time. The shaded areas represent the unobserved wages, and the frontier between the observed and unobserved wages should be seen as a race-specific reservation wage.

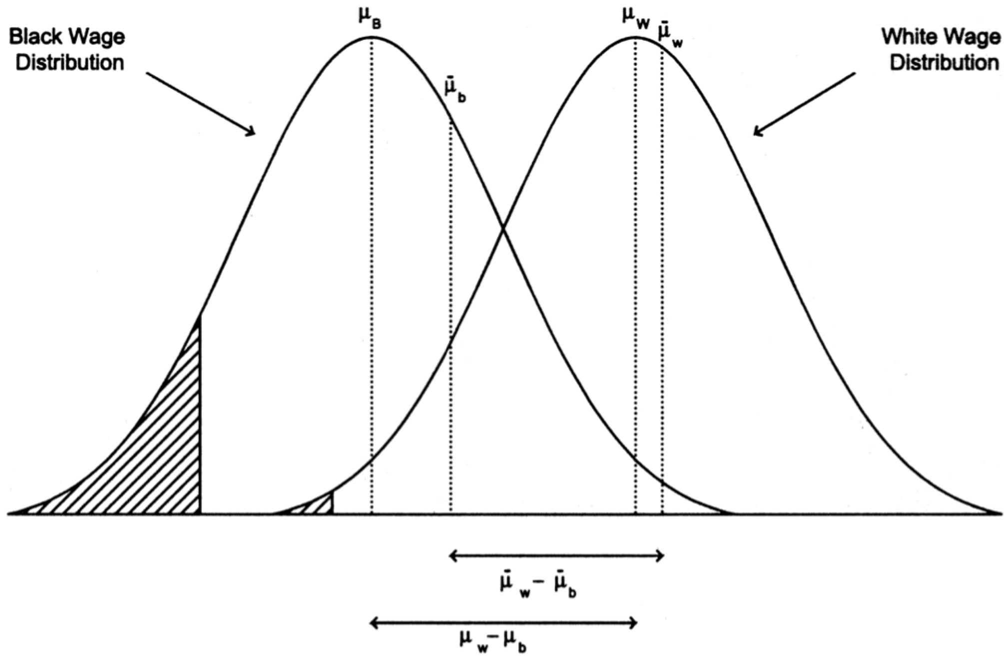

Figure 4: Gaps in potential and observed wages

Note: The figure is taken from Western and Pettit 2005. It presents an example of what the distributions of black and white wages could look like under this conceptual framework.

Figure 4 shows the main problem with estimating the wage gap based on observed wages. If the unobserved wages are those at the bottom of the distribution, and the share of unobserved wages of one group is larger, we will have a biased estimate of the difference in wages. In our case, if blacks have a distribution of wages to the left of the distribution of wages of whites, and their non-employment rate is higher, we are underestimating the wage gap.

In their study, Western and Pettit 2005 approached this issue by inferring the wages of the non-employed from the wages of those employed. Practically, they used the best linear predictor of wages given the level of education and the age of the population whose wages are observed and used that best linear predictor to predict the wages of those non-employed.

In an attempt to account for the gap in employment Neal and Johnson 1996 adopt an alternative approach by setting wages of those not employed to 0, and performing a median regression. They assume that the potential wages of those not employed are all below the race-specific median and that the mean wages are equal to median wages for both black and white workers. This allows them to claim that the gap in median wages is equal to the gap in mean wages. The latter approach is more convincing than the former and is therefore the one I adopted.

5.2 Methodology

I use Quantile Regression (QR) because it has an edge over the Ordinary Least Squares (OLS) method as it is, by construction, unaffected by outliers. Similarly to Neal and Johnson 1996, I assume that, conditional on observed characteristics, the potential wages of those not employed are below the median of the conditional distribution of potential wages. Combined with the properties of the minimization problem of QR, this assumption allows me to set the wages of those not employed to 0. Intuitively, while in OLS the coefficients aim to minimize the sum of squared errors, what matters in determining the penalty-minimizing coefficients in QR is the sign of the deviations from the predicted values. As a result, replacing slightly negative deviations with highly negative deviations will not affect the coefficients that minimize the penalty function. This can be easily seen in Figure 4. If one were to replace the wages in the shaded area with 0 or highly negative values, this would not alter the median of the distribution, nor any of the quantiles above it.

In order to motivate the use of this method, this section reports the relevant mathematical properties of median regression, a special case of QR. Those derivations are reproduced from Hansen 2022. More exhaustive derivations for general case of QR, also reproduced from Hansen 2022 and complemented by comments to match the context of this work, are provided in Section A of the Appendix.

The median of Y is defined as $m = med[Y]$ such that $\mathbb{P}[Y \leq m] = \mathbb{P}[Y \geq m]$[2]. In our case, this would mean that m is the wage such that half of the observations are below this wage, and half above. Define $m(x) = med[Y|X = x]$ such that $\mathbb{P}[Y \leq m(x)|X = x] = 0.5$. Similarly, one can define the random variable $m(X) = med[Y|X]$. This allows to define a median regression model as:

$$Y = m(X) + e$$
$$med[e|X] = 0$$

Notice that the condition $med[e|X] = 0$ is true by definition of m(X), because for any value X takes, $med[Y|X = x] = m(x)$ and thus $med[e|X = x] = med[Y|X = x] - m(x) = 0 \ \forall x$[3]. Usually, researchers focus on linear models, where they assume that:

$$Y = X'\beta + e$$
$$med[e|X] = 0$$

Notice that now, $med[e|X] = 0$ is an assumption, and if one mis-specifies the functional form of $med[Y|X = x]$, the condition $med[e|X] = 0$ does not hold anymore[4].

In this paper, I am leveraging the property that $med[e|X] = 0$. In particular, I leverage the fact that the median is not affected by the magnitude of e as long as it remains in the same position with respect to $med[e|X]$. In our case, if we assume that conditional offered wages Y of those not employed are all below the median of conditional wages $X'\beta$, then it must be that $e_i|X = x_i < med[e|X = x_i] = 0$. As a result, because $e_i|X = x_i < 0$, we can assign extremely low unconditional wages to those not employed, say 0, which would lead the conditional errors of those individuals to be negative, and this would still satisfy the condition that $med[e|X] = 0$.

In this paper, the estimated linear median regression model is:

$$Y_{it} = \sum_{k=0}^{2} \beta_{k,\tau} * ptexp_{it}^{k} + \sum_{k=3}^{5} \beta_{k,\tau} * ptexp_{it}^{k-3} * Black_i + \sum_{k=6}^{8} \beta_{k,\tau} * ptexp_{it}^{k-6} * AFQT_i + \beta_{9,\tau} * AFQT_i^2 + \sum_{j=1}^{2} \delta_\tau * t^j + e_{it} \quad (1)$$

Where:

- Y_{it} is the potential wages of individual i in period t. Notice that for those employed, I assume that the potential

[2] Notice that the function $med[\ .\ ]$ takes as an input a random variable and gives back a scalar, namely the median of the random variable.

[3] Thus, even though $med[e|X]$ is a random variable because X is a random variable, the only value this random variable takes is 0

[4] $med[e|X] = 0$ is the QR equivalent of $E(u|X) = 0$

wage corresponds to the realized wage, and for those not employed, it is not observable.

- $ptexp_t$ is the potential experience i.e., the number of years since the individual i last left school at period t.
- $Black_i$ is a dummy that takes the value of 1 when the individual is black, and 0 otherwise.
- $AFQT_i$ is the standardized AFQT score of individual i.
- t is the calendar year, for simplicity re-centered such that the first calendar year is 0.
- e_{it} is the time and individual varying idiosyncratic error term.

The first sum allows for an intercept and a quadratic function of potential experience for the sub-population of whites. Note that for k=0, we get $ptexp_{it}^0 = 1$ which leaves a simple intercept β_0 for white individuals. When k=1, we get a linear trend in potential experience, and when k=2, we obtain a quadratic trend in potential experience. Similarly, the second sum allows the intercept and the quadratic function of potential experience to diverge between black and white high school graduates. The third sum allows the intercept and the trajectories to vary by AFQT, our measure of cognitive skills. In order to stay consistent with the previous literature, AFQT^2 has also been added. Finally, the fourth sum allows for a linear and quadratic trend in calendar years as wages can vary even in the absence of changing individual characteristics.

To provide some intuition, I defined some of the coefficients in terms of population moments assuming that the model in Equation 1 is correctly specified:

- $\beta_0 = med[Y|X = 0]$ is the median potential wage of a white individual with 0 years of potential experience and average AFQT during the first considered calendar year.
- $\beta_3 = med[Y|\text{Black=1, ptexp=0}, X_{-(Black,ptexp)} = \tilde{x}] - med[Y|\text{Black=0, ptexp=0}, X_{-(Black,ptexp)} = \tilde{x}]$, namely the gap in median wages between a black and a white individual with 0 years of potential experience, but who have the same AFQT and are observed in the same year.
- The divergence in median wages over the life-cycle between black and white high school graduates conditional on AFQT and the calendar year will be determined by the coefficients β_4 and β_5 and by $ptexp_{it}$. $\frac{\partial^2 Y}{\partial Black_i \partial ptexp_{it}} = \beta_4 + ptexp_{it}\beta_5$. If this quantity is negative, the gap in median wages widens, it it is positive, then it shrinks.

Finally, because I observe the same individuals several times over their life cycle, I cluster the standard errors using the qreg2 wrapper command in Stata. [5]

6 Results

The baseline results are based on Equation 1. Then are discussed the issues that come along with estimating that equation, and the implications those issues could have. Finally, the third subsection of this part reports results where the appropriate adjustments have been undertaken to solve the issues previously described.

6.1 Baseline Results

Upon entering the labor market, the estimated gap in median wages between black and white workers is 18.7%. Moreover, it widens over the life cycle, and the approximation suggests that it does not converge at any point before 40 year of potential experience.

Once I control for cognitive skills, the gap in wages upon entering the labor market is reduced from 18.7% to 6.9%, a reduction of 63% similar to what has been reported in previous literature. Moreover, the rate at which the gap widens also reduces, but the coefficient on the interaction between the linear term of potential experience and black remains statistically significant at 5%.

[5] See Machado and Silva 2013 with reference to clustered standard errors imputations found in Parente and Santos Silva 2016.

	(1) median log wages	(2) median log wages
Black	-0.187***	-0.0692**
	(0.0289)	(0.0333)
Potential Experience	0.0685***	0.0693***
	(0.00591)	(0.00574)
Potential Experience^2	-0.00134***	-0.00142***
	(0.000182)	(0.000148)
Potential Experience * Black	-0.0144***	-0.00986**
	(0.00391)	(0.00479)
Potential Experience^2 * Black	0.000137	0.000193
	(0.000106)	(0.000135)
AFQT		0.0768***
		(0.0175)
AFQT^2		-0.0439***
		(0.0112)
Potential Experience * AFQT		0.00568**
		(0.00243)
Potential Experience^2 * AFQT		-0.0000112
		(0.0000685)
Constant	6.521***	6.863***
	(1.346)	(1.072)
R^2	0.09	0.14
N	28,866	28,866

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 1: Gap in Median wages over the life-cycle

Part D of the Appendix presents the estimates from the previously defined specifications for every percentile from the median to the 98^{th}. The main takeaway is that the raw gap grows over the life-cycle for any percentile below the 80^{th}, while at higher percentiles the gap seems to remain stable at a cost of a higher constant gap. The labor market entry wage gap adjusted for measures of cognitive skills is much smaller, and not statistically significant at 5% for some of the percentiles. Similarly, except for the median, none of the wage gap growth or reduction is statistically significant. This is again attributable to the positive effect of AFQT on wage growth. However, this also shows that the median should be considered as a special case in this specification, but as shown in the next subsections, addressing some specification concerns leads to more consistent growth of the gap for percentiles above the median. Finally, Figure 9 in the Appendix shows a similar pattern. The only additional feature that stands out is that the growth of wages at the upper end of the wage distribution is considerably affected by social skills. In other words, individuals with higher social skills see their wages grow faster if they are at the upper end of the wage distribution to begin with.

6.2 Model Mis-specification and Small Sample Size

This section discusses a few concerns related related to the specification of the model and to the way observations at the beginning and the end of the experience-wage cycle might be affecting the results.

The first concern is that AFQT may play a more important role in wage growth in the very first years after entering the labor market, and then the impact of AFQT on wage growth could remain constant. This is motivated by the concept of employer learning that has been shown to play an important role in the wage growth of high school graduates (Arcidiacono, Bayer, and Hizmo 2010), and arguably, the impact of employer learning on wage growth is likely to be most pronounced during the first years of employment. The risk in that situation is that the naive interaction between AFQT and a quadratic in potential experience will understate the effect of AFQT on the wage growth during the first years of labor market experience, and overstate it for later years. This may hide a widening of the wage gap over the life-cycle because if the effect of AFQT is underestimated for the first years of the labor market experience, the black-white wage gap adjusted for AFQT is overestimated during that period. Similarly, if the AFQT is reported to have a higher effect than it actually has during the later years of the labor market experience, the wage gap adjusted for AFQT is underestimated. As a result, these to features together lead two an underestimation of the widening of the wage gap between black and white workers.

A second concern is that wages as a function of potential experience are mis-specified. In fact, while the squared specification does a better job at approximating the gap over the life cycle than a linear specification, it might still fail to properly describe the pattern observed in the data, thus increasing the standard errors due to the higher variance of the residuals. One alternative is to use a cubic or quartic function. Another is to focus on a period of time over which experience-wage profiles behave most like a quadratic function.

A final concern is the low levels of employment in the first and last years of the life cycle. For the first years after high school graduation, especially because it has been documented that black workers have a harder time finding a job, it is possible that a) black workers start with jobs that are below their potential wages or b) they stay out of the labor force until they find something that matches their profile and skill set. Both cases would lead to an overestimation of the wage gap in the first years after graduation. The other end of the potential experience-wage profile can also be problematic. For example, if individuals leave the labor market once they have earned enough, we would witness larger decreases in employment from the upper end of the wage distribution, which can lead to an underestimation of the actual gap in the growth of potential wages. However, if individuals leave the labor market because they have health concerns, and individuals with the lowest potential wages are most likely to get health issues, the regression to the median would capture that.

6.3 Specification-Adjusted Results

Table 2 presents the results from specifications that account the issues mentioned previously. The first column presents the same results as above which are used as a reference point. In column (2) I allow AFQT to affect wage growth differently during the first 12 years after graduation. This choice of years is motivated by the fact that Arcidiacono, Bayer, and Hizmo 2010 used 12 years as the threshold for their analysis of employer learning. In fact, given that employer learning takes place, the effect of AFQT on wage growth is likely to be magnified during this period. Additionally, they argued that this is also the period during which the relationship between wages and the interaction between AFQT and potential experience is linear. This motivates the inclusion of the interaction AFQT and potential experience. We see that wage growth is indeed more affected by differences in AFQT in the first 12 years, but the coefficient is only significant at a 10% level. Moreover, there appears to be no effect on the coefficient for the interaction between potential experience and black.

Column (3) specifies wages as a cubic function of potential experience adding an interaction between a cubic in potential experience and AFQT. The results suggest a stronger relationship between wage growth and AFQT in the first years after graduation than the baseline model suggested. However, while it also suggests a larger widening of the black-white wage gap during the first years after graduation, the coefficient is no longer significant even at a 10% level. Most of this is driven by the high standard errors associated with the estimate. In fact, while adding higher degrees of the polynomial provides a better fit for what is observed in the data, and thus reduces the standard errors due to misspecification, it also increases the standard errors due to a higher level of colinearity between the different covariates. The effect of the latter seems to outweigh the effect of the former. Table 6 in the Appendix reports the results from a quartic specification. The main patterns remain similar: the point estimates indicate a higher growth in the wage gap during the first years after high school graduation, but the coefficients are again statistically insignificant.

	(1) Baseline	(2) First 12 Years	(3) Cubic	(4) Quadratic, PE<=25
Black	-0.0692**	-0.0673**	-0.0526	-0.0289
	(0.0333)	(0.0338)	(0.0414)	(0.0357)
Potential Experience	0.0693***	0.0700***	0.0849***	0.0847***
	(0.00574)	(0.00589)	(0.00786)	(0.00693)
Potential Experience^2	-0.00142***	-0.00143***	-0.00248***	-0.00214***
	(0.000148)	(0.000149)	(0.000374)	(0.000219)
Potential Experience * Black	-0.00986**	-0.0101**	-0.0153	-0.0207***
	(0.00479)	(0.00483)	(0.00978)	(0.00643)
Potential Experience^2 * Black	0.000193	0.000196	0.000593	0.000694***
	(0.000135)	(0.000137)	(0.000642)	(0.000239)
AFQT	0.0768***	0.0651***	0.0360*	0.0556***
	(0.0175)	(0.0183)	(0.0207)	(0.0180)
AFQT^2	-0.0439***	-0.0441***	-0.0428***	-0.0416***
	(0.0112)	(0.0114)	(0.0110)	(0.0104)
Potential Experience * AFQT	0.00568**	0.00592**	0.0167***	0.0103***
	(0.00243)	(0.00247)	(0.00509)	(0.00330)
Potential Experience^2 * AFQT	-0.0000112	-0.00000722	-0.000695**	-0.000181
	(0.0000685)	(0.0000696)	(0.000330)	(0.000123)
Potential Experience * AFQT * FY		0.00177*		
		(0.000981)		
Potential Experience^3			0.0000189***	
			(0.00000701)	
Potential Experience^3 * Black			-0.00000773	
			(0.0000121)	
Potential Experience^3 * AFQT			0.0000114*	
			(0.00000629)	
Constant	6.863***	6.988***	6.790***	9.870***
	(1.072)	(1.082)	(1.130)	(1.482)
Pseudo - R^2	0.14	0.14	0.14	0.16
N	28,866	28,866	28,866	21,938

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Functional Form Adjusted Results

Column (4) addresses two issues at once. By only keeping the observations with potential experience lower or equal to 25 years, it improves the quality of fit of the quadratic form presented in the main specification. Note that a similar argument has been made by Arcidiacono, Bayer, and Hizmo 2010 when they chose to focus on workers with less than 12 years of potential experience because the relationship between wages and potential experience is linear for that period. Additionally, and arguably most importantly, after 25 years of potential experience, employment rates drop drastically leading to employment rates of roughly 60-65% for Black workers. As a result, given the uncertainty related to the reasons why individuals exit the labor force at this time and the implications it can have for the accuracy of our point estimates, it seems appropriate to estimate a model for observations that have not yet reached a point where many stop receiving wages.

As we can see from the results in column (4), the coefficient on the interaction between experience and black is highly significant. Moreover, as reported in the Appendix, this significance remains for most percentiles between the median and the 75^{th} percentile. The coefficient on the interaction between AFQT and potential experience is much steeper than in the baseline specification, further supporting the findings from a cubic specification. Table 7 reports the results for the same sample without and with controls for AFQT.
The last specification is, according to the author, the most credible estimate of the difference in wage growth between black and white high-school graduates because the sample considered is best approximated by the functional form defined in the methodological section.

7 Robustness checks

7.1 Age at the time of AFQT testing

This part conducts a robustness check that controls whether the gap in median wages grows faster for the group who took the test before or at the age of 18, or vice-versa. One would expect that, if discrimination affects skill accumulation by providing less opportunities to the discriminated group, the inclusion of individuals who have labor market experience would capture some of the labor market discrimination, and provide biased results. In particular, if black high school graduates have less learning opportunities once they enter the labor market, their stock of cognitive skills would depreciate at a faster rate than the stock of white graduates, therefore widening the gap in cognitive skills. As a result, one would also expect that including individuals who have already entered the labor market would reduce the unexplained portion of the wage gap, and the unexplained portion of the gap in wage growth.

An alternative narrative would suggest that, when faced with labor market discrimination, black individuals decide to further invest in their skills to gain an edge over currently similar white individuals. According to this narrative, the AFQT gap for those already in the labor market would be smaller than for those who have not entered the labor market yet. In that case, we would be understating the widening of the wage gap for those who are not yet in the labor market, because they have not yet made the additional investments in their cognitive skills. As a result, we would observe a larger widening of the wage gap for those already in the labor market and who have thus already invested in additional skills than for those who have not entered it yet and thus have not invested yet.

To test these hypothesis, I repeat the specification used in this analysis is the same as in Column (4) from Table 2, but allow the gap to grow differently between those who took the test at or before 18, and those who took it after 18. Interestingly, my point estimate leans more towards the second hypothesis, although the difference in growth is statistically highly insignificant with a p-value on the linear interaction term of 0.27.

From these results, there appears to be little reason to not include the sample of individuals who took the AFQT test after graduating from high school. As shown in the Table 6 from the Appendix and in Table 3, the gap in AFQT does not seem to grow once individuals enter the labor market, and this can in part explain why we do not observe a smaller widening of the gap for the population who took the test after entering the labor market. In fact, their inclusion is beneficial for statistical power purposes, as otherwise one might fail to draw some of the conclusions drawn in this paper due to a lack of statistical power because of the limited sample size.

	(1) Quadratic, PE<=25	(2) Quadratic, PE<=25 & Age-test Interaction
Black	-0.0289	-0.0328
	(0.0357)	(0.0351)
Potential Experience	0.0847***	0.0864***
	(0.00693)	(0.00745)
Potential Experience^2	-0.00214***	-0.00211***
	(0.000219)	(0.000248)
Potential Experience * Black	-0.0207***	-0.0158**
	(0.00643)	(0.00692)
Potential Experience^2 * Black	0.000694***	0.000561**
	(0.000239)	(0.000258)
AFQT	0.0556***	0.0554***
	(0.0180)	(0.0180)
AFQT^2	-0.0416***	-0.0404***
	(0.0104)	(0.0106)
Potential Experience * AFQT	0.0103***	0.0103***
	(0.00330)	(0.00326)
Potential Experience^2 * AFQT	-0.000181	-0.000184
	(0.000123)	(0.000123)
Potential Experience * Black * Post 18		-0.00707
		(0.00641)
Potential Experience^2 * Black * Post 18		0.000159
		(0.000276)
Constant	9.870***	9.905***
	(1.482)	(1.749)
Pseudo - R^2	0.16	0.16
N	21,938	21,938

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Growth in gap of median wages between blacks and whites, by age at the time of AFQT test

7.2 Parental Education as a covariate

The NLSY79 dataset unfortunately does not contain information on parental income. However, it does contain information on parental education. As a result, I conduct my analysis by allowing parental education to affect experience-wage trajectories. As shown in Table 4, there does not seem to be any effect of parental education on wages and wage trajectories. Similarly, the coefficient on Potential Experience * Black does not seem to have changed considerably. More data, notably data from NLSY97, would allow to explore the role of parental income on the wage trajectories of their children.

8 Conclusion

This paper documents how the gap in median wages between black and white high school graduates evolves over the life cycle. In order to solve the potential bias introduced by the gap in employment, I assign the wages of those not employed to 0 and apply Quantile Regression as this method is unaffected by outliers. There are 3 main results. First, I find that, without controlling for measures of cognitive skills, the gap in median wages between black and white high school graduates widens throughout the entire life cycle. Second, I find that individuals with higher

	(1) Baseline	(2) Education*Experience	(3) Education*Experience^2
Black	-0.0289	-0.0274	-0.0226
	(0.0357)	(0.0418)	(0.0428)
Potential Experience	0.0847***	0.0805***	0.0914***
	(0.00693)	(0.00900)	(0.0189)
Potential Experience^2	-0.00214***	-0.00221***	-0.00268***
	(0.000219)	(0.000247)	(0.000660)
Potential Experience * Black	-0.0207***	-0.0208***	-0.0221***
	(0.00643)	(0.00726)	(0.00750)
Potential Experience^2 * Black	0.000694***	0.000678**	0.000742***
	(0.000239)	(0.000264)	(0.000270)
AFQT	0.0556***	0.0572***	0.0552***
	(0.0180)	(0.0203)	(0.0205)
AFQT^2	-0.0416***	-0.0410***	-0.0405***
	(0.0104)	(0.0124)	(0.0124)
Potential Experience * AFQT	0.0103***	0.00922**	0.00966**
	(0.00330)	(0.00381)	(0.00378)
Potential Experience^2 * AFQT	-0.000181	-0.000189	-0.000201
	(0.000123)	(0.000138)	(0.000139)
Father Highest grade		0.00485	0.00487
		(0.00563)	(0.00624)
Mother Highest grade		-0.00120	0.00227
		(0.00778)	(0.00888)
Mother grade * Potential Experience		0.0000906	-0.000903
		(0.000529)	(0.00170)
Father grade * Potential Experience		0.000635*	0.000709
		(0.000360)	(0.00119)
Mother grade * Potential Experience^2			0.0000444
			(0.0000633)
Father grade * Potential Experience^2			-0.00000512
			(0.0000435)
Constant	9.870***	10.86***	10.88***
	(1.482)	(1.694)	(1.700)
Pseudo - R^2	0.16	0.16	0.16
N	21,938	18,052	18,052

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Adjusting for parental education

cognitive skills enjoy steeper experience-wage profiles, and experience-wage profiles appear to be more sensitive to differences in AFQT during the first 12 to 25 years of potential experience than after 25 years of potential experience. Finally, this paper presents evidence that the wage gap between black and white high school graduates grows over the life cycle even after equalizing the level of pre-market cognitive skills individuals have upon entering the labor market.

The last finding is important. It suggests that comparing wage gaps between two cohorts at different points during their life-cycle might lead to misleading conclusions as the wage gap conditional on skills grows over the life-cycle. In particular, this limits the inference one can draw from the comparison made by G Jr 2011 between the NLSY79 and the NLSY97 cohorts, who looked at the wage gap observed in 2006 for each cohort. In 2006, as reported in his paper, NLSY79 individuals are aged 42-44, while the NLSY97 individuals are aged 21-27. This paper provides support to the theory that the gap in raw wages is smaller for the NLSY97 cohort because they are younger and because white workers experience steeper wage profiles. However, the author also reports that the wage gap conditional on cognitive skills is the same for the two cohorts. In light of the findings of this paper, notably the fact that, conditional on cognitive skills, the gap in median wages grows over the life-cycle, it seems reasonable to be more cautious about the conclusions one draws from this kind of comparison, especially when it comes to claiming that the significance of discrimination has declined between the two cohorts. Nonetheless, it must be acknowledged that my analysis focuses on the gap in median wages among high school graduates, and relies on the assumption that those not employed have lower potential wages than the median conditional on their cognitive skills. It differs from the analysis run by G Jr 2011, where no employment correction has been implemented, and the analysis was focusing on the gap in mean wages for the entire sample of employed individuals. However, to the extent that the assumptions made in this paper hold, and that the widening of the gap in median wages (and for this matter other percentiles until the 80^{th}) is not offset by a convergence in wages at other percentiles, the widening in median wages should translate into a widening in mean wages. However, this question is left for future research.

This paper also sheds light onto a couple of topics that are worth further investigation. First, it would be interesting to conduct a similar analysis on the experience-wage profiles of college graduates, and see how it differs from the findings reported in this paper. In particular, having a better understanding of experience-wage profiles for both high school graduates and college graduates by race would help understand how different groups choose to self-select into a college degree, and how this affects the black-white wage gap when technological change or other factors induce more students to attend college. Second, this paper provides some weak support for the theory of employer learning, and suggests that the dynamics and determinants of wage growth over the life-cycle could be explored further. Third, Figure 9 suggests that, social skills are a determinant of wage growth at the upper end of the wage distribution. It would be interesting to explore what explains this pattern, and how this could be linked to the work conducted by Deming on the role of social skills in the labor markets. Finally, it would be worth investigating how black and white college students differ in their non-cognitive skills.

References

Altonji, Joseph G, Prashant Bharadwaj, and Fabian Lange (2012). "Changes in the characteristics of American youth: Implications for adult outcomes". In: *Journal of Labor Economics* 30.4, pp. 783–828.

Arcidiacono, Peter, Patrick Bayer, and Aurel Hizmo (2010). "Beyond signaling and human capital: Education and the revelation of ability". In: *American Economic Journal: Applied Economics* 2.4, pp. 76–104.

Becker, Gary S (2010). *The economics of discrimination*. University of Chicago press.

Bohren, J Aislinn et al. (2023). "Inaccurate statistical discrimination: An identification problem". In: *Review of Economics and Statistics*, pp. 1–45.

Butler, Richard and James J Heckman (1977). "The government's impact on the labor market status of black Americans: A critical review". In: *National Bureau of Economic Research Working Paper Series* w0183.

Deming, David J (2017). "The growing importance of social skills in the labor market". In: *The Quarterly Journal of Economics* 132.4, pp. 1593–1640.

G Jr, Fryer Roland (2011). "Racial inequality in the 21st century: The declining significance of discrimination". In: *Handbook of labor economics*. Vol. 4. Elsevier, pp. 855–971.

Hansen, Bruce (2022). *Econometrics*. Princeton University Press.

Heckman, James J, Jora Stixrud, and Sergio Urzua (2006). "The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior". In: *Journal of Labor economics* 24.3, pp. 411–482.

Karageorge, Eleni (2017). "The unexplainable, growing black-white wage gap". In: *Monthly Lab. Rev.* 140, p. 1.

Kline, Patrick, Evan K Rose, and Christopher R Walters (2022). "Systemic discrimination among large US employers". In: *The Quarterly Journal of Economics* 137.4, pp. 1963–2036.

Lang, Kevin and Michael Manove (2011). "Education and labor market discrimination". In: *American Economic Review* 101.4, pp. 1467–1496.

Machado, José AF and JMCS Silva (2013). "Quantile regression and heteroskedasticity". In: *Unpublished manuscrip, Department of Economics, University of Essex, available at.*

Neal, Derek A and William R Johnson (1996). "The role of premarket factors in black-white wage differences". In: *Journal of political Economy* 104.5, pp. 869–895.

O'Gorman, Melanie (2010). "Educational disparity and the persistence of the black–white wage gap in the US". In: *Economics of Education Review* 29.4, pp. 526–542.

Parente, Paulo MDC and João MC Santos Silva (2016). "Quantile regression with clustered data". In: *Journal of Econometric Methods* 5.1, pp. 1–15.

Reardon, Sean F and Kendra Bischoff (2011). "Income inequality and income segregation". In: *American journal of sociology* 116.4, pp. 1092–1153.

Western, Bruce and Becky Pettit (2005). "Black-white wage inequality, employment rates, and incarceration". In: *American Journal of Sociology* 111.2, pp. 553–578.

Appendix

A Quantile Regression - Theory

Here I reproduce the derivations from Hansen 2022, and add some comments and examples to match the context of this work. The reason to present this is to better understand the idea behind quantile regression, especially because some results rely on regressions for quantiles beyond the median.

Let $\tau \in [0,1]$, q_τ represents the τ^{th} quantile of Y i.e., $P[Y \leq q_\tau] = \tau$. Define the quantile operator $\mathbb{Q}_\tau[Y]$ as the solution to the equation:

$$P[Y \leq \mathbb{Q}_\tau[Y]] = \tau.$$

In our case, taking $\tau = 0.5$, $q_{0.5}$ is the median of the distribution of wages over the entire population. Similarly, define the conditional quantile of Y given X = x as $q_\tau(x)$ such that:

$$P[Y \leq q_\tau(x)|X = x] = \tau$$

Where $q_\tau(x)$ is the quantile regression function. It reports the value of the τ^{th} quantile of Y for a given X = x. The conditional quantile operators that will generate this value are represented by $\mathbb{Q}_\tau[Y|X = x]$ for a given X = x, and $\mathbb{Q}_\tau[Y|X]$ for the entire random variable X. In our example, $q_{0.5}(1)$ will represent the median of the distribution of black wages, thus satisfying the condition that $P[Y \leq q_{0.5}(1)|\text{Black} = 1] = 0.5$. Notice that X can be a vector of random variables, while x is a vector of realizations of these random variables. For example, we can have $q_{0.5}(1, 0, 10)$ representing the median of the distribution of wages of black workers with a (standardized) AFQT equal to 0 (the average value) and 10 years of potential experience. This in turn would satisfy the condition $P[Y \leq q_{0.5}(1, 0, 10)|(\text{Black, AFQT, Potential Experience}) = (1, 0, 10)] = 0.5$.

More generally, one can define a quantile regression model as:

$$Y = q_\tau(X) + e$$
$$\mathbb{Q}_\tau[e|X] = 0$$

Where the second expression indicates that the τ^{th} quantile of the errors given X is equal to 0[6]. This is one of the key elements that differentiates quantile regression from OLS, and this is the element that is leveraged to perform the analysis found in Figures 7, 8, 9 and 10. First, the way it makes quantile regression differ from OLS is that mechanically it finds $q_\tau(x)$ that leads a proportion τ of the errors to be negative, and a proportion $1 - \tau$ of the errors to be positive. This nests the special case of the median, where $q_{0.5}(x)$ represents a function such that half of the errors are below 0, half above, and $\mathbb{Q}_{0.5}[e|X] = 0$. This is where setting unadjusted wages to 0 kicks in. If $e_i|X = x_i < \mathbb{Q}_\tau[e|X = x_i] = 0$, then by setting unadjusted wages to 0, wages adjusted for experience, AFQT and race will fall far below 0. This will lead $e_{i,wage=0}|X = x_i < \mathbb{Q}_\tau[e|X = x_i] = 0$, which in turn will make the condition $\mathbb{Q}_\tau[e|X = x_i] = 0$ remain valid. This works because the QR minimization problem cares only about the sign of the deviation. As a result, setting wages to 0 makes this inference strategy valid under the assumption that, conditional on X, wages of those not employed would fall below the percentile considered anyway.

Finally, this condition foreshadows the minimization problem analogous to the minimization of squared errors in the OLS model. The QR minimization problem assigns equal weights to each error and tries to find $q_\tau(x)$ such that a proportion τ of the errors is negative, and a proportion $1 - \tau$ of the errors is positive. In the case of median

[6]Note that this mirrors the argument made in the main text whereby $\mathbb{Q}_\tau[e|X] = 0$ by definition of $q_\tau(X)$.

regression, this means that the minimization problem will lead to half of the errors being positive, and half negative. For a regression to the τ^{th} quantile, it means that a proportion τ will remain negative, and $1-\tau$ positive.

A linear quantile regression model can be defined as:

$$
\begin{aligned}
Y &= X'\beta_\tau + e \\
\mathbb{Q}_\tau[e|X] &= 0
\end{aligned}
$$

Where the coefficients on X differ by quantile considered. Here again, $\mathbb{Q}_\tau[e|X] = 0$ is an assumption, and it fails under mis-specification. Now turning to the specification of the loss function, we have that the value the loss function $\rho_\tau(.)$ takes is defined as:

$$
\begin{aligned}
\rho_\tau(e) &= \begin{cases} -e(1-\tau) & e < 0 \\ e\tau & e \geq 0 \end{cases} \\
&= e[\tau - \mathbb{1}\{e < 0\}].
\end{aligned}
$$

As we can see, at higher quantiles the loss function penalizes positive e's more than it does for negative e's. To understand why it is constructed this way, we should take the derivative of the loss function for x $\neq 0$. This gives us $\Psi(e) = \frac{d}{de}\rho_\tau(e) = \tau - \mathbb{1}\{e < 0\}$. Intuitively, this suggests that the loss function is minimized when the penalty for positive errors is equal to τ, and the penalty for negative errors is equal to $1-\tau$. Let us assume that we want to focus on the 75^{th} percentile of wages conditional on some characteristics X. In order to do this, we want to penalize each positive deviation from the $X'\hat{\beta}_\tau$ by 3 times as much as we do for each negative deviation. This will lead us to have 3 times as many negative deviations as we have positive deviations, leading negative deviations to represent 75% of the population versus 25% for positive deviations. This in turn is the definition of the 75^{th} percentile of the conditional wages. Notice that for the median the loss function is:

$$
\begin{aligned}
\rho_\tau(e) &= \begin{cases} -\frac{1}{2}e & e < 0 \\ \frac{1}{2}e\tau & e \geq 0 \end{cases} \\
&= e[\frac{1}{2} - \mathbb{1}\{e < 0\}].
\end{aligned}
$$

In the population, the conditional quantile $q_\tau(X)$ satisfies:

$$\mathbb{E}[\Psi_\tau(Y - q_\tau(X))|X] = \mathbb{E}[\Psi_\tau(e)|X] = 0$$

Finally, for linear conditional quantile regression models with finite mean for the dependent variable, we have that

$$\beta = \underset{b}{\operatorname{argmin}} \mathbb{E}\left[\rho_\tau\left(Y - X'b\right)\right].$$

And the first order conditions imply that:

$$\mathbb{E}\left[X\Psi_\tau(e)\right] = 0$$

Finally, using the sample analog principle, one obtains:

$$M_n(\beta;\tau) = \frac{1}{n}\sum_{i=1}^{n}\rho_\tau\left(Y_i - X_i'\beta\right)$$
$$\hat{\beta}_\tau = \underset{\beta}{\operatorname{argmin}} M_n(\beta;\tau)$$

Where the sample analog of the first order condition implies that

$$\frac{1}{n}\sum_{i=1}^{n} X_i\psi_\tau\left(\widehat{e}_i(\tau)\right) \simeq 0$$

B AFQT gap and age at the time of the test

	(1)	(2)
	AFQT, age test <= 18	AFQT, age test > 18
age_test	0.0197	-0.000506
	(0.0394)	(0.0362)
black	0.186	-1.066
	(0.976)	(1.079)
black_age_test	-0.0746	-0.00803
	(0.0588)	(0.0530)
Constant	0.104	0.460
	(0.655)	(0.740)
r2	0.27	0.35
N	740	673

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: AFQT gap and testing age

C Educational distribution

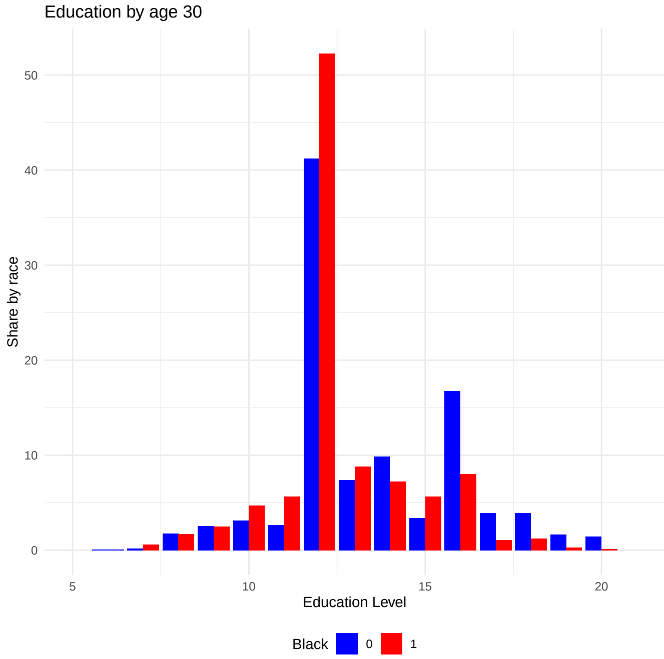

Figure 5: Education and college premium

Note: The plot presents the distribution of the highest education recorded by the age of 30 for white and black males in the entire NLSY79 sample. Source: U.S. Bureau of Labor Statistics, NLSY79.

D Attrition rates

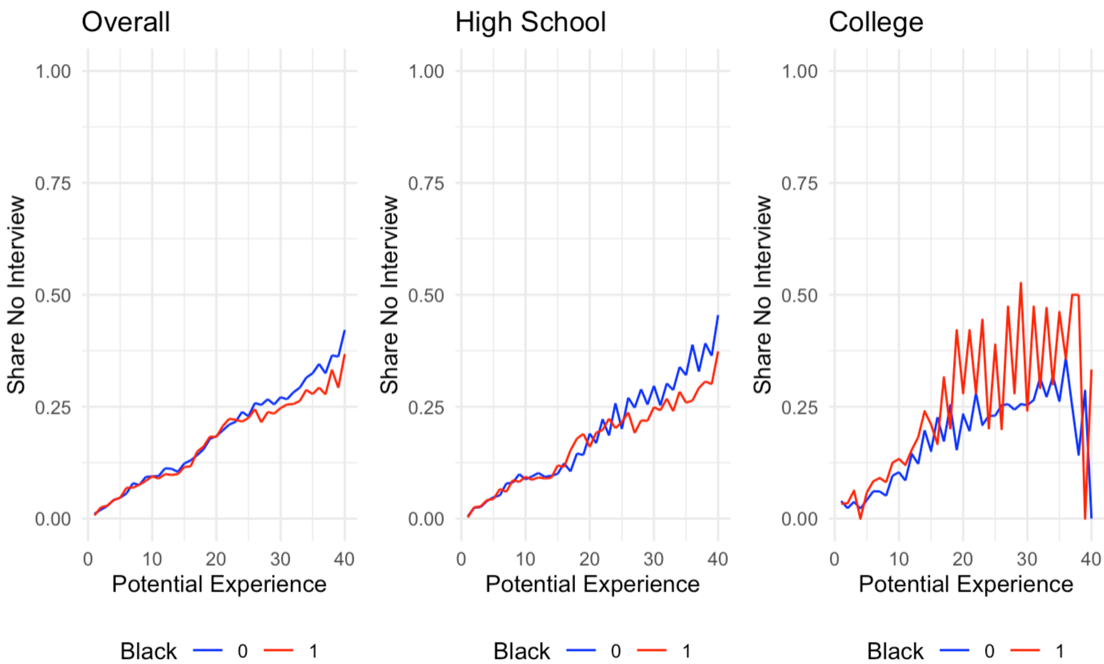

Figure 6: Attrition

Note: Each line presents the share of individuals without interview for each year of potential experience for black and white males. Potential experience is recovered as the number of years since the last change in the years of education. Source: U.S. Bureau of Labor Statistics, NLSY79.

E Results by quantile

E.1 Baseline Specification

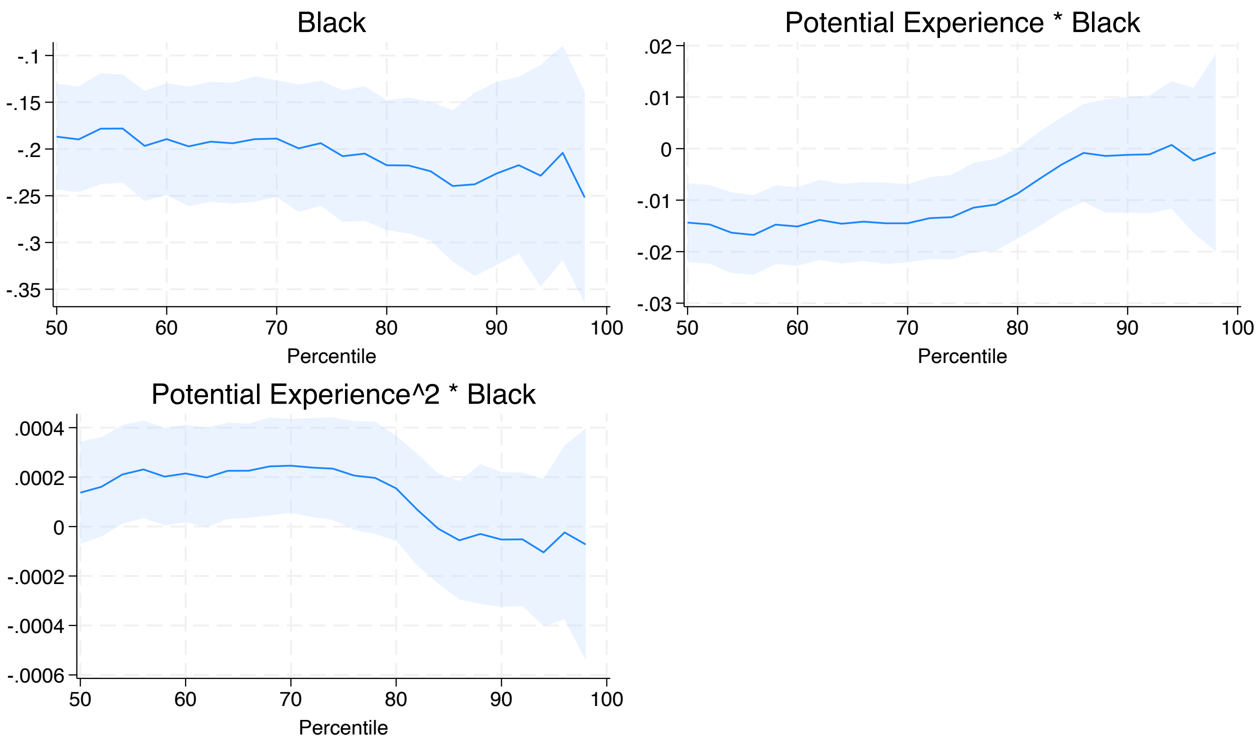

Figure 7: Raw Gap

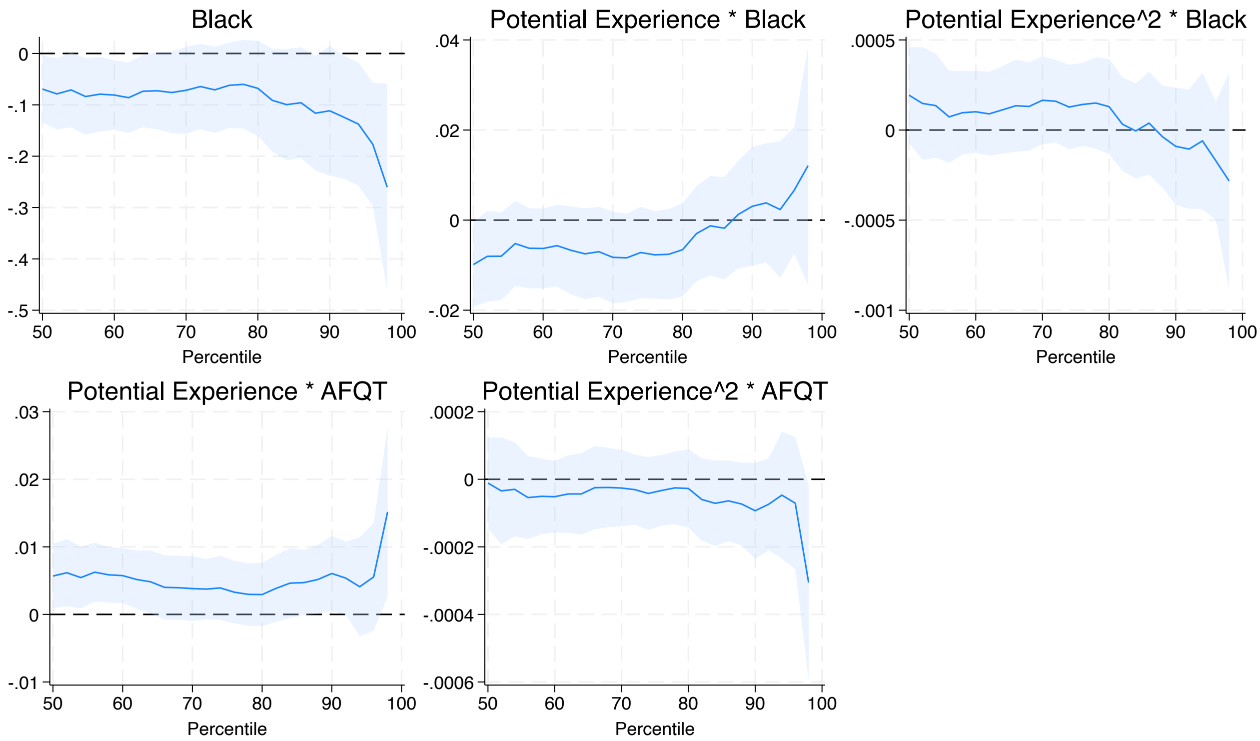

Figure 8: Adjusted Gap

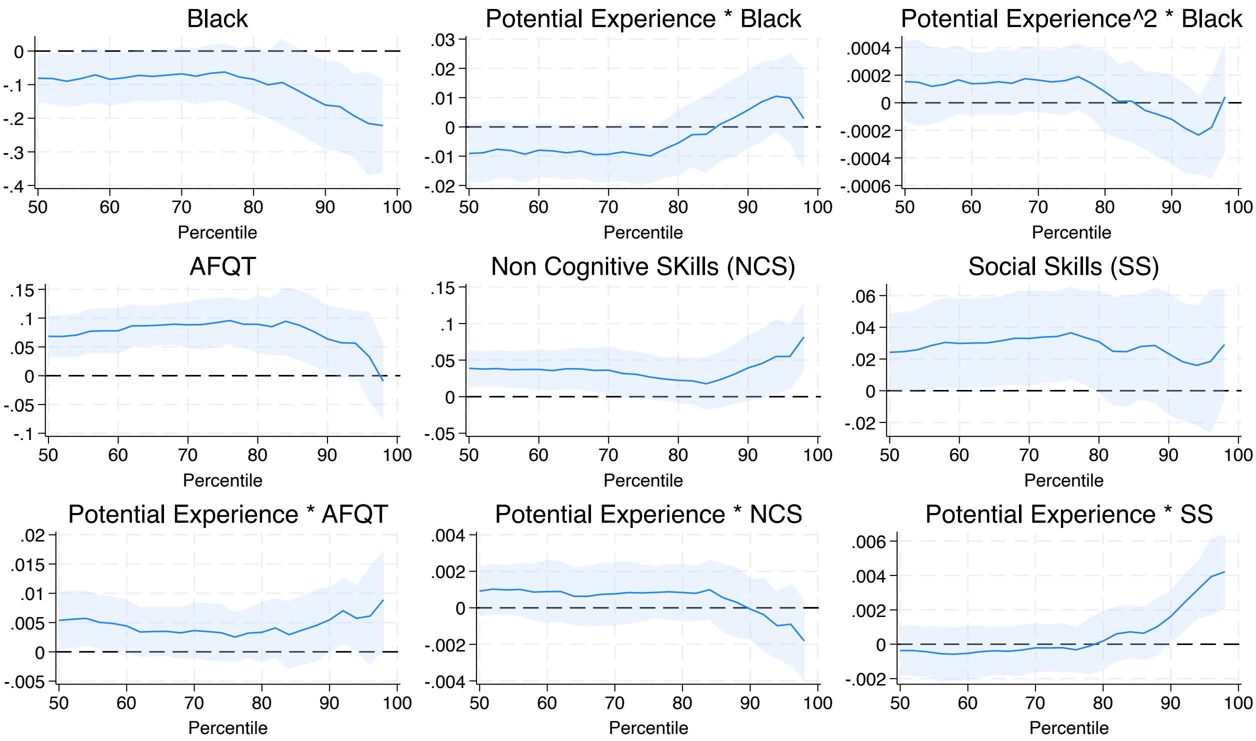

Figure 9: Fully Adjusted Gap

F Additional Results - Quartic in experience

	(1) Baseline	(2) Cubic	(3) Quadrtic
Black	-0.0692**	-0.0526	-0.0264
	(0.0333)	(0.0414)	(0.0463)
Potential Experience	0.0693***	0.0849***	0.105***
	(0.00574)	(0.00786)	(0.0102)
Potential Experience^2	-0.00142***	-0.00248***	-0.00486***
	(0.000148)	(0.000374)	(0.000952)
Potential Experience * Black	-0.00986**	-0.0153	-0.0277
	(0.00479)	(0.00978)	(0.0170)
Potential Experience^2 * Black	0.000193	0.000593	0.00209
	(0.000135)	(0.000642)	(0.00191)
AFQT	0.0768***	0.0360*	0.0228
	(0.0175)	(0.0207)	(0.0218)
AFQT^2	-0.0439***	-0.0428***	-0.0424***
	(0.0112)	(0.0110)	(0.0110)
Potential Experience * AFQT	0.00568**	0.0167***	0.0228***
	(0.00243)	(0.00509)	(0.00814)
Potential Experience^2 * AFQT	-0.0000112	-0.000695**	-0.00135
	(0.0000685)	(0.000330)	(0.000894)
Potential Experience^3		0.0000189***	0.000118***
		(0.00000701)	(0.0000385)
Potential Experience^3 * Black		-0.00000773	-0.0000702
		(0.0000121)	(0.0000782)
Potential Experience^3 * AFQT		0.0000114*	0.0000368
		(0.00000629)	(0.0000363)
Potential Experience^4			-0.00000130**
			(0.000000509)
Potential Experience^4 * Black			0.000000833
			(0.00000104)
Potential Experience^4 * AFQT			-0.000000317
			(0.000000485)
Constant	6.863***	6.790***	6.582***
	(1.072)	(1.130)	(1.127)
Pseudo - R^2	0.14	0.14	0.14
N	28,866	28,866	28,866

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Quartic in Experience

	(1) Pre 25	(2) Pre 25
Black	-0.116***	-0.0289
	(0.0310)	(0.0357)
Potential Experience	0.0908***	0.0847***
	(0.00684)	(0.00693)
Potential Experience^2	-0.00239***	-0.00214***
	(0.000209)	(0.000219)
Potential Experience * Black	-0.0320***	-0.0207***
	(0.00563)	(0.00643)
Potential Experience^2 * Black	0.000900***	0.000694***
	(0.000208)	(0.000239)
AFQT		0.0556***
		(0.0180)
AFQT^2		-0.0416***
		(0.0104)
Potential Experience * AFQT		0.0103***
		(0.00330)
Potential Experience^2 * AFQT		-0.000181
		(0.000123)
Constant	10.38***	9.870***
	(1.364)	(1.482)
Pseudo - R^2	0.11	0.16
N	21,938	21,938

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Wage-experience profiles for those with less than 25 years of potential experience

F.1 Specification 4 by percentile

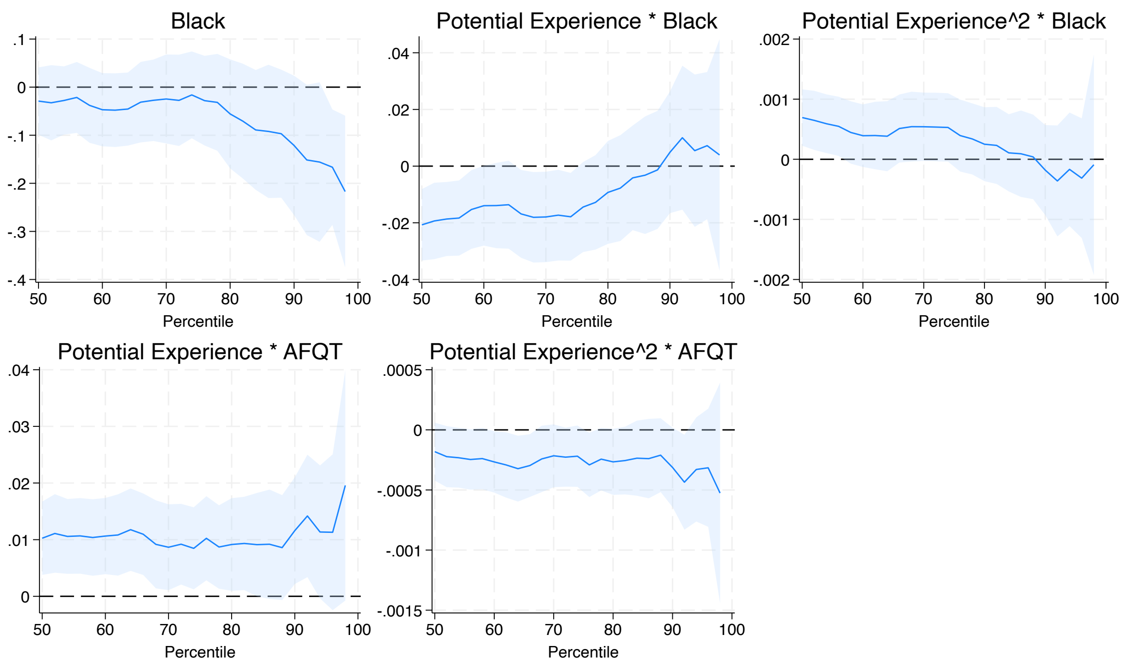

Figure 10: Fully Adjusted Gap - Preferred Specification