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The Evolution of Black-White Wage Inequality across Occupational Sectors in the US since the 1990s

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Abstract

This paper updates the current knowledge about Black-White wage inequality in the US male labor market by using the NLSY97 sample. Compared with the results obtained from the NLSY79 cohort, I find that the unconditional racial wage inequality is smaller today, but after controlling for premarket academic skills, the conditional racial wage gap remains roughly the same as it was twenty years ago. After dividing the labor market by occupational categories, I find that in the white collar sector, the racial wage gap has largely disappeared even without controlling for academic skills. In the blue collar sector, academic skills can fully account for the unconditional racial wage gap among clerical jobs but there still remains a substantial conditional racial wage gap among craftsman and laborer jobs. I show that clerical jobs are more similar to white collar jobs than blue collar jobs today. The racial wage inequality also has disappeared among the operative workers, probably due to omitted variable bias. For the remaining racial wage gap in the craftsman and laborer jobs, both preference-based and statistical models of discrimination are consistent with the findings.

I. Introduction

The black-white wage gap has declined substantially from 1940s to 1980s (Smith & Welch, 1986). There are many explanations for this convergence: relative increase in quantity and quality of education, black migration out of the South, Federal civil rights policies, and declining labor force participation of low-skilled blacks (Smith & Welch, 1986; Donohue & Heckman, 1991). However, the improvement stagnated after 1980s and a substantial racial wage gap persists into 21st century (black men on average earn around 75% as white men do). While factors such as migration and Federal policies played important roles in the convergence before 1980s, their impacts are less obvious after 1980s. Many theories argued that the earning inequality today is largely due to the differences in education attainment and academic skills acquisition. Neal and Johnson (1996) found that premarket academic skills, as measure by AFQT scores, could account for three quarters of the black-white wage gap. Bjerk (2007) divided the labor market into blue collar sector and white collar sector and found that while the differences in academic skills could fully account for the racial wage gap in white-collar jobs, they only account for half of the wage gap among blue-collar jobs. Therefore, he argued that the observed racial wage gap in the market is mainly due to the inequality in the blue-collar sector.

The main purpose of this paper is to update the current knowledge about the effects of premarket academic skills on racial wage inequality in the US labor market by using the most recent data from NLSY97. Most existing literatures about the racial inequality in labor market used the sample from NLSY79. As the individuals in the NLSY97 cohort reached their late 20s or early 30s in the latest round of interview (round 15), they were at the same age as the individuals in Neal and Johnson (1996) and Bjerk (2007) papers using the NLSY79 sample. By comparing my results from the NLSY97 cohort with the results obtained by previous studies from the NLSY79 cohort, I'm able to find the changes occurred in the US labor market over the last 20 years.

Due to the complexity in the female job market, I only focus on the earning differences between black and white males in this paper. Similar to Bjerk (2007), I not only examine the labor market as a whole but also divide the market into two occupational sectors (white-collar and blue-collar) and look at several subgroups in each of these sectors. Compared with the older cohort in NLSY79, I find that the unconditional wage gap between black and white male workers further narrowed down in the last 20 years. Black men on average earned 22% less than white men in 2009 compared to 28% less in early 1990s. After controlling for premarket academic skills, as measured by AFQT scores, the wage gap among white-collar jobs disappears; but for the blue-collar sector as a whole, academic skills only account for one-third of the wage inequality, with a 13% conditional wage gap unexplained. Interestingly, among the subgroups in blue-collar sector, the wage inequality in the clerical and operative jobs disappears while the gap remains significant and substantial for craftsmen and laborers. This might suggest that the nature of clerical and operative jobs has changed from 20 years ago and their work resembles those of white-collar jobs more than those of blue-collar jobs. And all of the racial wage inequality in the US male labor market comes from craftsman and laborer jobs.

The rest of the paper is structured as follows: Section II summarizes the previous literature about labor market racial inequality; Section III introduces the data and methods I use in this study; Section VI summarizes the results from regressions; Section V discusses the potential explanations for the different wage inequality across occupational sectors; Section VI discusses the problem of labor market participation; Section VII concludes.

II. Related Literature

While the racial difference in years of schooling has declined considerably during the 20th century, there still remained large differences in the actual academic achievement (usually measured by achievement scores). O'Neill (1990) argued that the decline in the racial difference in schooling together with the migration of blacks out of the South contributed to the narrowing of racial wage gap before 1980s, and the remaining wage gap to a large extent comes from the differences in academic achievement. Using AFQT scores as the measure of academic skills, he found that skills were highly correlated with future earnings and accounted for a substantial fraction of the black-white wage inequality.

Neal and Johnson (1996) pointed out that a problem with many studies on labor market inequality is that they included endogenous variables such as postsecondary education and work experience in their models, which are the choices made by the individuals and could be affected by market discrimination, and therefore their results were biased. By controlling only for the premarket factors, they found that academic skills could explain three-quarters of the black-white wage gap. One policy implication from this study is that improving black students' academic skills can narrow down the unconditional racial wage gap. But the question is how. One might argue that improving the school quality will help, especially the quality of those schools with predominantly black students. However, Grogger (1996) found that the inputs usually thought to be related to school quality, such as student-teacher ratio, class size and term length, have little effect on wages. Discrimination at school is also a big concern. Figlio (2005) found that teachers have lower expectations for students with distinctive black names and these in turn negatively affect students' cognitive performance and test scores.

Depending on the authors' belief about how long the premarket factors will matter into the labor market and how long discrimination will persist on the job, different papers choose different age groups to look at. On the one hand, as statistical discrimination models suggest, some employers use characteristics such as education and race as proxies of certain variables related to ability but unobservable during the hiring process, such as certain test scores (Altonji & Pierret, 2001). Therefore, estimating the effect of academic skills on wages when the employees have just entered their jobs could be biased and underestimate the effect of skills. On the other hand, if we look at the wages of employers when they have been in the labor market for a very long time, we might be testing the effect of trainings and experiences rather than the premarket skills. What's more, one could assume that some discrimination is based on prejudice and is quite persistent. If it is the case, the older age group we look at, the larger wage inequality we will see because discrimination can be a self-fulfilling prophecy which affects the group being discriminated against increasingly negatively as time goes by. According to Farber and Gibbons (1991), as observations of actual performance and ability accumulate, the impact of schooling on employers' inference process decreases. However, the effect of schooling on wages is independent of market experiences. More importantly, they found that time invariant variables related to ability but unobservable by employers (such as AFQT scores) are increasingly correlated with wages as experience accumulates. Therefore, it's reasonable to examine the effect of academic skills on the wage gap when the workers are roughly 10 years into the labor market, as Neal and Johnson (1996) and Bjerk (2007) did in their papers.

III. Data

D. NLSY97

The primary labor market and demographic data used in this analysis come from the National Longitudinal Survey of Youth 1997 (NLSY97). The NLSY97 sample is a panel data of 8,984 individuals born between 1980 and 1984. They received the first interview in 1997 at an age of 12 to18 and a survey was administrated each year after that to create a true panel data set. At the time of their round 15 interviews (the most recent survey), the individuals aged from 26 to 32, making the sample comparable to the NLSY79 cohort used in former studies by Neal and Johnson (1996) and Bjerk (2007). The types of information gathered in the two surveys and the interview methods are largely similar, making the data comparable between the two cohorts. The NLSY97 sample consists of a cross-sectional sample of 6,748 respondents and a supplement sample of 2,236 respondents to oversample Hispanic or Latino and black people. My analysis combines the white and black males in the cross-section sample and the black males in the supplemental sample. The dataset contains a large amount of information one each respondent. In my analysis, I only use the data on education, demographics, income and employment for each individual. And my sample only includes the respondents with valid AFQT test scores, educational attainment data, and valid wage and occupation data in at least one year between 2008 and 2010. The time interval is chosen to make my age group comparable to that in Bjerk (2007).

I limit my sample to individuals under 18 years old when they took the AFQT test at 1998. I'm interested in the effect of human capital on future wages. Postsecondary education and job experience will surely enhance skills. But as Neal and Johnson (1996) pointed out, these variables are endogenous. In other words, going to college or obtaining trainings are the choices made by individuals and they are affected by discrimination. If I include these as regressors, my results will be biased. By restricting my sample to respondents aged 18 or younger by the time they took the test, I can make sure most of them hadn't entered the job market or started postsecondary education and therefore their scores were not affected by discrimination.

B. AFQT Score

In 1998, most NLSY97 respondents (79.3%) participated in the administration of the computer-adaptive form of the Armed Services Vocational Aptitude Battery (CAT-ASVAB), a military enlistment test battery. The CAT-ASVAB consists of ten power and two speeded subtests that measure different vocational aptitude, among which four subtests: Mathematical Knowledge (MK), Arithmetic Reasoning (AR), Word Knowledge (WK), and Paragraph Comprehension (PC), were used to create a summary percentile score variable. The formula to generate this variable is similar to the AFQT score generated by the Department of Defense for the NLSY79 cohort. However, the two test scores are different in several ways. Firstly, the NLSY79 cohort took the paper and pencil test while the new ASVAB test was administrated on computer. Secondly, each of the NLSY97 participants was assigned a percentile score between 0 and 99 among each three-month age group. Therefore, I don’t need to adjust the scores for the age. Thirdly, the new variable is neither generated nor endorsed by the Department of Defense. For these reasons, the test scores of the two cohorts are not directly comparable. But since they are both measuring the same thing (academic skills or vocational aptitude), the effect of the scores on wages should still be comparable. And since the new test score is calculated in a similar way as AFQT, for simplicity, I’ll just refer to this variable as AFQT score in this paper. I normalize the test scores in order to use them in my regressions.

Neal and Johnson (1996) argued that AFQT is a racially unbiased measure of basic skills. But Bjerk (2007) pointed out that although it's better than years of schooling, it is still affected by many other factors such as parents' education and school quality. Therefore it is a noisy measure of academic skills. But it's a reasonable one to use in my analysis. My results can be interpreted as the proportion of the wage gap that can be explained by the difference in premarket academic skills.

C. Occupational Sectors

In order to examine the wage inequality in more detail, I follow Bjerk (2007) methodology by dividing the overall labor market into several mutually exclusive occupational categories including professional and technical occupations, managerial occupations, clerical workers, craftsmen, operatives, laborers, sales workers, and service workers based on job titles. NLSY97 uses the 2002 Census Industrial & Occupational Classification Codes to classify occupations, which is different from the NLSY79 cohort which used the 1970 Census Occupational Classification System. Although the coding systems are different, the resulting categories are largely similar. Bjerk (2007) classified each occupational category into either white collar sector or blue collar sector based on the frequency different tasks were performed on the job using data from the Multi-City Study of Urban Inequality (MCSUI). Specifically, professional workers and managerial workers were significantly more likely to perform tasks that require academic skills, including writing, reading and math, on a daily basis than clerical workers, craftsmen, operatives and laborer. Therefore, he referred to professional and managerial occupations as white collar jobs, or “more academically skill-intensive” jobs, and clerical occupations, craftsmen, operatives and laborers as blue collar jobs, or “less academically skill-intensive” jobs. Sales workers and services workers were discussed separately because the jobs in these two categories are quite heterogeneous and could not be labeled as “white-collar” or “blue-collar” easily. I assume the nature of these jobs didn’t change dramatically in the last 20 years and use the same classification as Bjerk (2007). In Results section, I will show that this assumption is largely correct except for the clerical jobs. The examples of job titles within each category using the 2002 Census Industrial & Occupational Classification Codes are given in Table 1.

D. Wage and Control Variables

My dependent variable is the natural logarithm of each individual’s average wage during the 3-year period between 2008 and 2010. One potential problem of this method is that it results in a smaller sample size, especially after dividing the overall sample into the distinct categories. A small sample size could lead to non-significant results and make the interpretation of my results more complicated.

To avoid the endogeneity problem with respect to education, I only generate a dummy for 12 years or more of education to control for years of schooling. Other control variables include AFQT score, AFQT score squared, age, region of the country, and parent’s education.

Table 1

Examples of Jobs in Each Occupational Category

White Collar		Blue Collar				Other	
Professional & Technical	Managerial	Clerical	Craft	Operative	Laborer	Sales	Service
Computer Scientist	Chief Executive	Telephone Operator	Carpenter	Assembler	Animal Breeder	Cashier	Cook
Mathematicians	General and Operations Manager	Bill and Account Collector	Electrician	Machine Setter, Operator, and Tender	Fisher	Retail Salesperson	Waiter and Waitress
Biological Scientist	Financial Manager	Hotel, Motel, and Resort Desk Clerk	Painter, Construction and Maintenance	Model Maker and Patternmaker	Hunter	Insurance Sales Agent	Detective and Criminal Investigator
Economist	Education Administrator	Secretary	Construction and Building Inspector	Tailor, Dressmaker, and Sewer	Bus Driver	Travel Agent	Fire Fighter
Lawyers	Funeral Director	Dispatcher	Earth Driller	Computer Control Programmer	Sailor and Marine Oiler	Real Estate Brokers and Sales Agents	Janitor and Building Cleaner
School Teachers	Purchasing Agents and Buyers	Postal Service Clerk	Electrical and Electronics Repairer	Jeweler and Precious Stone Worker	Truck and Tractor Operator	Telemarketer	Funeral Service Worker
Actors	Legislator	Computer Operator	Automotive Repairer	Medical, Dental Laboratory Technician	Cleaner	Model, Demonstrator, and Product Promoter	Barber
Physician and Surgeon	Marketing and Sales Manager	Data Entry Keyer	Baker	Furnaceman	Freight, Stock, and Material Mover	News and Street Vendor	Tour and Travel Guide

Note: Occupations categorized according to 2002 Census Industrial & Occupational Classification Codes, as used by NLSY97

IV. Results[1]

A. Examining Wage Inequality in the Overall Labor Market

I first examine the unconditional wage inequality between black and white workers in the overall labor market by running the Ordinary Least Squares (OLS) regression of natural logarithm of each individual's average wage between 2008 and 2010 on a race indicator dummy and the individual's age in year 2009. The coefficient on the race dummy in Column 1 of Table 2 shows that black male workers on average earn 22 percent less than their white peers in their late twenties. The unconditional wage gap obtained from this regression is substantially smaller than the one obtained by Bjerk (2007), who found a 28 percent gap between the two races using the NLSY79 cohort. This change suggests that the wage gap between black and white male workers in the overall labor market has further narrowed down in the last twenty years. In other words, the convergence has resumed after a stage of stagnation between 1980s and early 2000s. Column 2 of Table 2 shows that after controlling for the years of education and region of residence, there still remains a 20 percent wage gap across the races. The small change doesn't mean that education plays a minor role in future earnings. But it confirms Neal and Johnson's (1996) critics that years of schooling is a very noisy measure of education attainment and itself is affected by discrimination and therefore it underestimates the real effect of academic skills.

In specification 3, I further control for AFQT scores as the measure of

[1] For reference, results obtained by Bjerk (2007) using NLSY79 can be found in Appendix.

Table 2
OLS Log Wage Regressions (Whole Labor Market)

	Specification			
Conditioning Variable	(1)	(2)	(3)	(4)
Black	-0.22***	-0.20***	-0.12***	-0.11***
	(0.031)	(0.030)	(0.033)	(0.034)
AFQT score	—	—	0.11***	0.08***
			(0.016)	(0.018)
AFQT score squared	—	—	-0.03**	-0.03*
			(0.016)	(0.016)
Age	-0.06***	-0.06***	-0.06***	-0.06***
	(0.012)	(0.012)	(0.012)	(0.012)
12 years or more of education	—	0.17***	—	0.09***
		(0.031)		(0.033)
Controls for region of country	No	yes	yes	yes
Controls for parent's education	No	no	no	yes
Number of observations	2144			

Note: The sample used in this analysis comes from the NLSY97 and consists of observations in the years 2008-2010, for male white and black workers in both the cross-section sample and black oversample, with valid ASVAB test scores, and a valid wage and occupation. AFQT scores are normalized to have a population mean of zero and standard deviation of one. Standard errors are in parentheses. One asterisk indicates significance at 10 percent level, two asterisks indicate significance at 5 percent level, three asterisks indicate significance at 1 percent level.

academic skills instead of years of schooling in my regression. As shown in Column 3 of Table 2, the wage differential falls to 12 percent. After further controlling for regions and parents' level of education completed, the gap further decreases to 11 percent, as shown in Column 4 of Table 2. This means the racial differences in pre-market human capital accumulation as measured by AFQT scores can explain half of the earning gap between blacks and whites. The result of conditional racial wage gap is very similar to the one obtained by Bjerk (2007) as shown in Table 8 in the Appendix. However, the fraction of wage differential that can be explained by differences in pre-market academic skills is smaller in my study. This does not mean that education plays a less important role today or those policies that aim to alleviate academic skill gap and therefore reducing the wage gap are less useful. Note that the wage gap after controlling for test scores is similar to the results obtained by previous studies. It is the unconditional wage gap being smaller that leads to the smaller proportion that can be explained by academic skills. Therefore, we should interpret this change as a good sign because it implies that there is better education equality today.

After controlling for academic skills, there still exists a substantial 12 percent racial wage gap. To examine this unexplained portion of wage gap, I follow Bjerk's (2007) methodology to divide the labor market into mutually exclusive occupational sectors as I explained in the Data section. This helps me better understand the causes of labor market discrimination and enables me to compare the changes occurred in different occupational categories during the last twenty years.

B. Wage Inequality in the White Collar Sector

Table 3 shows the results from OLS log wage regressions for the white collar sector. The independent variables in the two columns under each sub-category are the same as those in Column 1 and 4 in Table 2. Results in Column 5 and 6 show that the black white collar workers today only earn slightly less (6 percent) than the white workers, and the difference is not statistically significant. After controlling for academic skills, the coefficient before the black dummy variable indicates that the black workers are not earning any less than their equally skilled white counterparts, if not more. The coefficient on AFQT scores is positive and

Table 3

OLS Log Wage Regressions by Occupation Sector (White-collar Jobs)

	Specification					
	Professional		Managerial		Overall White Collar	
Conditioning Variable	(1)	(2)	(3)	(4)	(5)	(6)
Black	-0.02	0.10	-0.12	-0.01	-0.06	0.06
	-0.084	(0.095)	(0.128)	(0.144)	(0.070)	(0.079)
AFQT score	—	0.08	—	0.08	—	0.09*
		(0.055)		(0.086)		(0.046)
AFQT score squared	—	0.02	—	-0.01	—	0.01
		(0.042)		(0.069)		(0.036)
Age	-0.02	-0.03	-0.10**	-0.10**	-0.05**	-0.06**
	-0.029	(0.029)	(0.044)	(0.044)	(0.024)	(0.024)
12 years or more of education	—	-0.04	—	-0.40***	—	-0.17*
		(0.113)		(0.153)		(0.091)
Controls for region of country	no	yes	no	yes	no	yes
Controls for parent's education	no	yes	no	yes	no	yes
Number of observations	348	348	161	161	509	509

Note: The sample used is a subset of sample used for Table 2 results. Standard errors are in parentheses. One asterisk indicates significance at 10 percent level, two asterisks indicate significance at 5 percent level, three asterisks indicate significance at 1 percent level.

significant, suggesting that academic skills are important in accounting for the wage differential between black and white white-collar workers. The results for unconditional log wage regressions show that for both professional and managerial jobs, the coefficients before the race indicator dummy are much smaller than it is in the whole labor market sample and they are not statistically significant anymore. The unconditional racial wage gap in managerial jobs (12%) is relatively larger than that in professional jobs (2%) in magnitude, but academic skills can fully account for this racial gap. For professional jobs, I'm interested in why the racial wage gap has essentially disappeared even before controlling for academic skills. My first hypothesis is that today the black male professional workers on average have acquired the same level of premarket academic skills as white professional workers. If this is the case, we will be happy because it suggests the racial inequality in education has narrowed in the past 20 years. Unfortunately this is not the case. Data analysis shows that for those working in the professional occupations, black male workers on average scored 1.04 standard deviations below their white counterparts in the AFQT test and the difference is highly significant, suggesting there remains a quite large racial gap in education today. After I control for test scores, the coefficient on black indicator variable turns positive and relatively large in magnitude (0.10), but it is not significant. This cannot be interpreted as evidence that black professional workers are paid higher than their equally skilled white colleagues, but together with the finding that the academically disadvantaged black professional workers are earning as much as their white colleagues, they suggest that black professionals might have gained bigger bargaining power in wage setting relative to the whites in the last 20 years.

One potential explanation for this change is the increasing demand for black workers in the professional field. A considerable proportion of professional workers work for academia, research institutes, different levels of government, or highly specialized entities such as law firms and hospitals. Most of these places have equal employment policies and many of them, universities for example, have explicit emphasis on ethnic diversity. While there is a demand for black workers in the professional occupations, the supply of black workers can be limited because of the highly technical and skill-intensive nature of the jobs and the fact that black people on average have lower skills and less professional trainings than white people. As a result, qualified black workers' bargaining power increases. But again, since the positive coefficient found in professional jobs is statistically insignificant, we shouldn't put too much emphasis on it until more concrete results are found. The important point is that there is no significant racial wage inequality in the white collar sector, both before and after controlling for academics skills.

In the NLSY79 cohort, significant and substantial unconditional wage gaps still existed in the professional and managerial occupations, as well as in the overall white collar sector, although smaller than the gap in the overall labor market. The gap disappeared only after AFQT score was controlled for (Bjerk, 2007).

C. Wage Inequality in the Blue Collar Sector

The results for the blue collar jobs are summarized in Table 4. The coefficients on the black dummy variable in Column9 and 10 show that there still exists significant unconditional racial wage inequality in the blue collar sector, and academic skills can only account for roughly one-third of this earning gap. The overall conditional racial wage gap is 13%, which is similar to the result obtained by Bjerk (2007) in NLSY79 cohort. The results for each sub-category are more mixed. Column 3 and 7 show that there are large unconditional income gaps in craftsmen and laborer jobs, larger than the gap in the overall labor market. Controlling for AFQT scores narrows down the gaps, but they still remain significantly large, meaning black workers earn significantly less than the similarly academically skilled white workers in these occupational categories and the inequality is substantially big. The coefficient before the black dummy in Column 1 indicates that there is a significant unconditional racial wage gap in clerical jobs. However, the gap disappears after controlling for premarket academic skills. The coefficient before the black dummy in Column 2 is very small and not significantly different from zero, while the coefficient before AFQT scores in the same column is positive and highly significant. This means all of the wage inequality in the clerical jobs can be explained by the racial difference in the premarket academic skills attainment. Surprisingly, the results for operative occupations are quite similar to those for professional occupations. Column 5 shows that there is essentially no unconditional wage gap between black and white workers. After controlling for academic skills, the coefficient on the black

Table 4

OLS Log Wage Regressions by Occupation Sector (Blue-collar Jobs)

	Specification									
	Clerical		Craftsmen		Operators		Laborers		Overall Blue Collar	
Conditioning Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Black	-0.14**	-0.03	-0.28***	-0.19**	-0.03	0.12	-0.23**	-0.17*	-0.20***	-0.13***
	(0.063)	(0.069)	(0.075)	(0.083)	(0.101)	(0.122)	(0.092)	(0.099)	(0.041)	(0.045)
AFQT score	—	0.09***	—	-0.02	—	0.10	—	0.01	—	0.03
		(0.036)		(0.040)		(0.072)		(0.059)		(0.024)
AFQT score squared	—	0.01	—	-0.09**	—	-0.04	—	-0.015**	—	-0.07
		(0.034)		(0.041)		(0.065)		(0.061)		(0.024)
Age	0.00	-0.01	-0.09***	-0.08***	-0.03	-0.01	0.00	0.00	-0.04**	-0.04**
	(0.027)	(0.027)	(0.026)	(0.026)	(0.043)	(0.046)	(0.039)	(0.040)	(0.017)	(0.017)
12 years or more of education	—	0.18**	—	0.15**	—	-0.06	—	0.13	—	0.09**
		(0.078)		(0.064)		(0.110)		(0.098)		(0.042)
Controls for region of country	no	yes	no	yes	no	yes	no	yes	no	yes
Controls for parent's education	no	yes	no	yes	no	yes	no	yes	no	yes
Number of observations	192	192	390	390	157	157	237	237	976	976

Note: The sample used is a subset of sample used for Table 2 results. Standard errors are in parentheses. One asterisk indicates significance at 10 percent level, two asterisks indicate significance at 5 percent level, three asterisks indicate significance at 1 percent level.

dummy turns positive and relatively large in magnitude, but not statistically significant, suggesting black operators are earning at least as much as their similarly skilled white counterparts, if not more.

In the results from the NLSY79 cohort, there were unconditional racial income gaps in all occupational categories in the blue collar sector and all the gaps remained significant after controlling for academic skills (Bjerk, 2007). Compared with my study, although the big picture in the blue collar sector seems not have changed that much, the patterns in each subcategory are quite different from 20 years ago. The racial wage inequality disappears in the clerical and operative jobs after taking academic skills into account. But in the craftsman and laborer jobs, the racial wage gaps grow even larger than they were twenty years ago.

One potential explanation for the change in the racial wage inequality among clerical and operative occupations is that their work might require a higher level of academic skills than 20 years ago, making them more similar to those jobs classified as white collar jobs. One direct way to test this hypothesis is to examine the frequency of academic skills used by clerical and operative workers and compare them to the data of white collar workers. But unfortunately, such a study as MCSUI is not conducted recently. Therefore, I look at the schooling data and test scores to make comparisons across occupational categories. Firstly, note that the coefficient before AFQT scores for clerical jobs is 0.09 and statistically significant, which is the same as the coefficient for white collar jobs. By contrast,

Table 5

Test Scores and Years of Education by Occupational Category

Occupational Category	AQFT score	Years of Education
Clerical	0.17	12.85
	(0.073)	(0.308)
Operative	-0.38	10.89
	(0.070)	(0.337)
Craftsmen+Laborers	-0.31	10.70
	(0.035)	(0.166)
White Collar	0.68	14.58
	(0.040)	(0.214)
Clerical-(Craftsmen+Laborers)	0.47***	2.16***
	(0.081)	(0.350)
Clerical-White Collar	-0.52***	-1.73***
	(0.083)	(0.375)
Operative-(Craftsmen+Laborers)	-0.07	0.19
	(0.078)	(0.376)
Operative-White Collar	-1.06***	-3.69***
	(0.080)	(0.400)

Note: The sample used in this analysis comes from the NLSY97 and consists of observations in the years 2008-2010, for male white and black workers in both the cross-section sample and black oversample, with valid ASVAB test scores, and a valid wage and occupation. AFQT scores are normalized to have a population mean of zero and standard deviation of one. Standard errors are in parentheses. One asterisk indicates significance at 10 percent level, two asterisks indicate significance at 5 percent level, three asterisks indicate significance at 1 percent level.

the same coefficients for craftsman and laborer jobs are only -0.02 and 0.01 respectively and are statistically insignificant. This suggests that the academic skills play a more important role in clerical jobs than other blue collar jobs today and they fully explain the racial wage gap among clerical occupations. For operative jobs, although the coefficient on AFQT score is comparable to those on white collar jobs in magnitude, it is statistically insignificant.

Secondly, data on the years of schooling show that clerical jobs today resemble white collar jobs more than other blue collar jobs. As shown in Table 5, clerical workers receive significantly more years of education than craftsmen and laborer. Although they also receive significantly fewer years of education than white collar workers, the difference between clerical workers and white collar workers is smaller the difference between clerical workers and other blue collar workers. By contrast, the difference in the quantity of education between operative workers and white collar workers is larger than the difference between clerical workers and white collar workers. And operative workers' years of education received are not significantly different from the amount received by craftsmen and laborers. Thirdly, data on AQFT scores show a similar pattern. Both clerical and operative workers achieve worse in academic skills than white collar workers, but the difference is smaller for clerical workers than operative workers. Clerical workers' test scores are significantly higher than craftsmen and laborers, while operative workers' scores are no different from other two groups. All these results confirm that today clerical jobs are more similar to white collar jobs than to blue collar jobs in terms of the employees' educational background and academic skills. However, this is not the case for operative jobs.

It's hard to see why the results for operative jobs show a similar pattern as professional jobs. One interesting finding in the operative category is that the black workers in a specific subcategory, assembling jobs, are enjoying a significant wage premium over their similarly skilled white counterparts. There might be some omitted variable that can potentially explain this odd phenomenon, but since the sample size in this subgroup is very small, I cannot rule out the possibility of measurement error.

D. Wage Inequality in Sales and Service Jobs

Due to the heterogeneity among sales and service jobs, these two categories are discussed separately. The results of OLS log wage regressions are shown in Table 6. Column 1 shows that there is a 22 percent unconditional racial wage gap between black and white sales workers. However, most of this inequality can be accounted for by premarket academic skills. The coefficient before the black dummy in Column 2 is still negative, but statistically insignificant. There is a racial wage gap, unconditional and conditional, in the service occupations, but the differences are not significant. In the NLSY79 cohort, a substantial racial wage inequality existed in sales jobs even after controlling for academic skills. One potential explanation for the disappearance of that wage inequality in my study is the decrease in customer discrimination over the last twenty years. Because the nature of the sales jobs, if the customers are strongly discriminating against the black workers, we can expect the black wages to be negatively affected by this discrimination. The results in my study suggest that unless the employers are compensating black sales workers for some reason, the effect of customer discrimination is small either because the customers no longer discriminate against black workers or because the black workers can avoid facing the prejudiced customers directly by making the sales through the phone or online, for example.

In general, the results in Table 3-6 show that racial wage inequality has largely disappeared in the white collar sector. All of the racial wage gap in the

Table 6

OLS Log Wage Regressions by Occupation Sector (Sales and Service Jobs)

	Specification			
	Sales		Service	
Conditioning Variable	(1)	(2)	(3)	(4)
Black	-0.22***	-0.09	-0.10	-0.08
	(0.074)	(0.080)	(0.074)	(0.084)
AFQT score	—	0.10***	—	0.00
		(0.040)		(0.050)
AFQT score squared	—	-0.10**	—	-0.05
		(0.038)		(0.049)
Age	-0.05	-0.06**	-0.08**	-0.09**
	(0.030)	(0.029)	(0.034)	(0.034)
12 years or more of education	—	0.19**	—	0.08
		(0.081)		(0.079)
Controls for region of country	no	yes	no	yes
Controls for parent's education	no	yes	no	yes
Number of observations	214	214	395	395

Note: The sample used is a subset of sample used for Table 2 results. Standard errors are in parentheses. One asterisk indicates significance at 10 percent level, two asterisks indicate significance at 5 percent level, three asterisks indicate significance at 1 percent level.

labor market after controlling for premarket academic skills comes from two subcategories in the blue collar sector, specifically, craftsmen and laborers. There is unconditional racial wage inequality among clerical and sales jobs, but academic skills can account for all the wage gaps in these categories. The racial wage gap in operative jobs has also disappeared today, but the reason for that is unclear.

V. Explanations for Different Wage Inequality across Occupational Categories

As I show in the previous section, academic skills can fully account for the racial wage gap among clerical jobs and clerical jobs resemble white collar jobs more than other blue collar jobs. Therefore, I group clerical jobs together with white collar jobs in this section and label them as “skill-intensive” jobs. By contrast, I label craftsmen and laborers as “labor intensive” jobs. I show that both models of preference-based discrimination and statistical discrimination can explain the difference in racial wage inequality between these two occupational categories. Other explanations for the cross-occupational difference are briefly discussed in the end.

A. Theories of Labor Market Discrimination

One common explanation for the racial wage inequality is the labor market discrimination. There is a substantial collection of literature showing that discrimination widely exists in the labor market. For example, Bertrand and Mullainathan (2003) conducted an audit study and showed that individuals with distinctive black names receive fewer responses from employers than those with distinctive white names, while everything else on their resumes are equal. If discrimination is the cause of racial wage inequality, there must be some reason that discrimination can only persist in craftsman and laborer jobs, since conditional racial gaps are only observed among these two occupational categories but not others. Both the Preference-based Discrimination and the Statistical Discrimination models are consistent with my findings.

For preference-based discrimination to persist, the labor market must satisfy one of the two conditions: (1) the market is not very competitive, or (2) the benefit loss for a firm to act on prejudice is small. If a firm acts on its racial prejudice by hiring a white worker over a black worker with similar or better skills, it will suffer a profit loss. Unless the firm has large market power, such as in the case of monopoly or oligopoly, so that there are enough profits remaining for the firm to survive, it must be the case that the profit loss from acting on bias is negligible for the company. Otherwise the firm won't be able to maintain its position in the market and will be driven out by its more profitable competitors.

Due to the broad range of job titles within each occupational category, as can be seen in Table 1, I argue that the market for each category is reasonably competitive. Therefore, I will focus on the second condition. In skill-intensive jobs, productivity is highly associated with academic skills. Therefore, if the firm acts on its racial bias by hiring white employees over black people with similar or greater skills, it will suffer a large profit loss due to the lower productivity, which makes the firm hard to survive in the competition. However for the labor-intensive jobs, the skills are only weakly related to productivity. Therefore, it's not very costly for firms to act on their racial bias and they are still able to stay relatively competitive in the market. As a result, the preference-base discrimination explains why the conditional racial inequality exists in the labor-intensive jobs but not in the skill-intensive jobs.

A Statistical Discrimination theory can also explain the observed differences in wage inequality across different categories. This theory argues that the employers are not biased, but are using race, correctly, as a convenient and cheap proxy of certain hardly obtainable characteristics in the hiring process for the profit maximization reason. For example, Holzer, Raphael, and Stoll (2006) found that without background checks, certain employers use race as a signal of criminality and statistically discriminate against black people. This results from imperfect information. Employers are always trying to find the true level of skills of the applicants. However, besides easily observable variables such as years of education, there are some variables related to academic skills that are available to economists but not to employers, such as AFQT scores. The employers can use other techniques to obtain more accurate information on the job-seekers' skills, such as interviews and company-administrated tests. But these techniques are usually costly and time-consuming. Therefore, from the profit-maximization perspective, it's only worth spending the time and money on the candidates applying for jobs on which skills are highly important. For the labor-intensive jobs, academic skills are only weakly associated with productivity and therefore it's not very helpful and worthwhile to put time and money in assessing the precise level of skills of the candidates. Since race is usually correlated with skills and is easily observable, certain profit-maximizing employers will use race as a proxy of skill. On average black people have poorer academic skills than white people. As a result, black workers on average receive lower wages than their similarly skilled white counterparts in labor-intensive jobs but not in the skill-intensive jobs.

The statistical discrimination model is more relevant during the hiring process. But as the employees start working, the learning models argue that the employers will gradually get a better picture of the workers' actual skills as observations accumulate and as a result the wages will be more and more correlated with academic skills (Farber & Gibbons, 1996; Altonji & Pierret, 2001). However, labor-intensive jobs usually have a high turnover rate as many workers work for employers only for a short term and will change to another employer once the current project or contract is over. As a result, it's hard for employers to collect observations on the workers' skills and these workers are more likely to become the victims of statistical discrimination when they change jobs. What's more, the economic downturns, such as the Great Recession experienced by the individuals in my sample, could also somewhat encourage the statistical discrimination. As the needs to save costs and stay alive increased drastically during the Great Recession, employers are more likely to use race as a cheap signal of skills when hiring for labor-intensive jobs.

B. Other Explanations

Besides the preference and statistical discrimination models, omitted variable bias and measurement error can also lead to different racial wage inequality across occupational categories. AFQT score is the only measure of premarket academic skills I use in my study. It is a noisy measure of skills. If there are some other variables that are correlated with race and productivity, especially when they are more important in the labor-intensive jobs than in the skill-intensive jobs, for instance some nonacademic skills, the omission of such variables, or using AFQT score as the only proxy of skills in the regressions can lead to the observed racial wage inequality.[2]

Both the preference-based and statistical models of discrimination cannot explain the wage pattern observed in operative jobs very well. The operative workers share similar characteristics with craftsmen and laborers in terms of their academic skills and education attainment. It's hard to see what makes operative job market different from craftsman and laborer job markets. One can study the competitiveness in these markets. If the operative job market is more competitive than other blue collar job markets, then the preference-based discrimination model is consistent with my findings. Just based on my sample, the observed wage pattern among operative jobs is very likely due to omitted variable bias or measurement error.

Due to the heterogeneity among Sales and Service jobs, I leave them out in this section. In the future, researchers can look further into these two occupations by dividing each of them into more specific categories.

VI. Labor Market Participation

Labor market participation is an important issue that should be taken into account when interpreting my results. Joining or leaving the labor market can be a choice that is affected by discrimination. If some black people choose to quit the labor market because they are facing racial discrimination on the job in the form

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[2] For details on the effects of omitted variable bias and measurement error on racial wage inequality, see Bjerk (2007).

of unreasonably low wages, by only considering those who are currently employed, my results will overstate the median wage of the blacks relative to the whites, therefore underestimating the actual degree of racial inequality. What's more, it's argued that many labor market drop-outs are poorly skilled blacks and if they had jobs, they would likely receive wages lower than the mean black wages. If this is the case, my results also underestimate the actual racial wage gap by not including these low-skill black drop-outs.

As shown in Table 7, black males constitute a significantly larger proportion of the population among the unemployed than employed during the period 2008-2010. This statistic alone doesn't tell us much information because there can be many reasons that one chooses not to have a job. The results in the second row show that black labor market non-participants have lower test scores than those black participants and the difference is significant. By contrast, there is no significant difference in the test scores between white non-participants and participants. These results confirm that black men without earnings are more likely to be those with poor academic skills. If these black non-participants had been working, on average they would have received lower wages than an average black worker. As the result of not taking these people into account, my results underestimate the actual racial wage inequality. The time period of the data collected in this study coincides with the Great Recession. During the recession, the unemployment rate in the US increased drastically, and those workers with lower skills were more likely to be fired. Since black males are more likely to be poorly skilled than white males, they were disproportionally hit by the recession.

Table 7

Characteristics of Labor Market Participants vs Non-Participants

	Participants			Non-Participants			Non participants-Participants		
Characteristics	Black	White	Overall	Black	White	Overall	Black	White	Overall
Black Proportion	—	—	0.28	—	—	0.33	—	—	0.05*
			(0.010)			(0.023)			(0.025)
AFQT scores	-0.61	0.27	0.02	-0.72	0.23	-0.09	-0.11*	-0.04	-0.11**
	(0.031)	(0.025)	(0.022)	(0.061)	(0.057)	(0.048)	(0.068)	(0.062)	(0.053)

Note: The sample used in this analysis comes from the NLSY97 and consists of observations in the years 2008-2010, for male white and black workers in both the cross-section sample and black oversample, with valid ASVAB test scores. AFQT scores are normalized to have a population mean of zero and standard deviation of one. Standard errors are in parentheses. One asterisk indicates significance at 10 percent level, two asterisks indicate significance at 5 percent level, three asterisks indicate significance at 1 percent level.

The exit of these people narrowed down the actual racial wage gap in my study for the reasons I discussed above. One way to get a more precise picture of the racial wage inequality in the US is to examine the wage gap with new data after the distorting effects of the Great Recession are gone.

VII. Conclusion

In this paper I examined the wage inequality between male black and white workers using the most recent labor market data. I found that the unconditional racial wage gap is smaller than it was twenty years ago. Differences in premarket academic skills can account for roughly half of the unconditional wage gap but the black workers on average still earn 11 percent less than their comparable white counterparts, and the conditional wage gap is roughly the same as it was twenty years ago. After further dividing the labor market into white collar and blue collar sectors, I found that all of the conditional wage inequality comes from the craftsman and laborer jobs under the blue collar sector. Academic skills can fully account for the unconditional racial wage gap in the white collar jobs and clerical jobs. My results showed that today the clerical workers are more similar to white collar workers than blue collar workers in terms of their academic skills and education attainment. The racial wage gap in operative jobs has also disappeared, but the reason is unclear. Measurement error and omitted variable bias are two possible explanations.

I discussed why conditional racial wage inequality persists in labor-intensive jobs (Craftsman and Laborer), but not in skill-intensive jobs (White

Collar Jobs plus Clerical Jobs). Both the preference-based discrimination and statistical discrimination theories can explain the observed wage difference across occupational sectors. The key assumption for both theories is that academic skills are highly related with productivity in skill-intensive jobs but only weakly related with productivity in labor-intensive jobs. The preference-based discrimination theory shows that acting on prejudice by hiring white workers over equally or better skilled black workers will only lead to small profit loss for a labor-intensive company and therefore the company can still survive in the competition. On the contrary, acting on prejudice will lead to a large profit loss for a skill-intensive company, making the company more likely to be driven out by more profitable competitors. As a result the preference discrimination only persists in the labor-intensive jobs. The statistical discrimination is based on the assumption of imperfect information. It's possible but expensive to find out the accurate level of skills of a job candidate. While employers in the skill-intensive market will try their best to uncover the true skills of a candidate, it's not worthwhile for the employers of labor-intensive jobs to invest heavily in skill assessment since skills are only weakly related to productivity in labor-intensive jobs. Instead they use race as a cheap and convenient proxy of skills. As a result, the blacks in labor-intensive jobs are paid less than the comparable whites. Besides the discrimination models, omitted variable bias and measurement error can lead to different racial wage inequality across occupational categories.

My results are limited by sample size. The number of observations in each of my occupational categories ranges from 157 to 390, which limits the statistical power of my model to find significance in the results. Therefore, except for the results for Overall White Collar, Overall Blue Collar, Overall Labor Market, results for other categories should be interpreted with caution.

My results are likely to underestimate the actual black-white wage gap in the US. Poorly skilled black people are more vulnerable to economic shocks and more likely to be unemployed. When they have jobs, they are likely to receive wages lower than the median black wage. By excluding such black labor market dropouts in my analysis, I underestimated the actual wage gap.

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Appendix

Results Obtained by Bjerk (2007) Using the NLSY79 Cohort

There are two major differences between Bjerk's (2007) methods and mine. One, Bjerk (2007) obtained wage data of the individuals for each year of observation between 1990 and 1992 and ran Random Effects Generalized Least Square (GLS) regressions, while I take the average of each individual's wage over the three year period 2008-2010 and run Ordinary Least Square (OLS) regressions. Two, Bjerk (2007) included 14 years or more of education and 16 years or more of education as two additional control dummy variables in some of his regressions, but I only include 12 years of more of education in my regressions.

Table 8

Random Effects GLS Log Wage Regressions (Whole Labor Market)

	Specification			
Conditioning Variable	(1)	(2)	(3)	(4)
Black	-0.28***	-0.22***	-0.08***	-0.10***
	(0.017)	(0.016)	(0.018)	(0.019)
AFQT score	—	—	0.19***	0.09***
			(0.009)	(0.011)
AFQT score squared	—	—	0.01**	-0.01*
			(0.007)	(0.008)
Age	0.02***	0.02***	0.02***	0.02***
	(0.004)	(0.003)	(0.004)	(0.003)
12 years or more of education	—	0.16***	—	0.07***
		(0.022)		(0.023)
14 years or more of education	—	0.15***	—	0.08***
		(0.020)		(0.020)
16 years or more of education	—	0.23***	—	0.17***
		(0.023)		(0.024)
Controls for year of observation	yes	yes	yes	yes
Controls for region of country	no	yes	yes	yes
Controls for parent's education	no	no	no	yes
Number of observations	7749			
Number of Individuals	3059			

Note: The sample used in this analysis comes from the NLS79 and consists of observations in the years 1990 to 1992, for male white and black workers, not in the low-income white or military oversamples, with valid ASVAB test scores, and a valid CPS wage and occupation. AFQT scores are age-adjusted and normalized to have a population mean of zero and standard deviation of one. Standard errors are in parentheses. One asterisk indicates significance at 10 percent level, two asterisks indicate significance at 5 percent level, three asterisks indicate significance at 1 percent level.

Table 9

Random Effects GLS Log Wage Regressions by Occupation Sector (White Collar Jobs)

	Specification					
	Professional		Managerial		Overall White Collar	
Conditioning Variable	(1)	(2)	(3)	(4)	(5)	(6)
Black	-0.14***	0.01	-0.16**	0.01	-0.17***	-0.01
	-0.045	(0.050)	(0.067)	(0.072)	(0.035)	(0.038)
AFQT score	—	0.09**	—	0.16***	—	0.11***
		(0.037)		(0.042)		(0.024)
AFQT score squared	—	0.03	—	0.02	—	0.01
		(0.025)		(0.033)		(0.017)
Age	0.02**	0.02***	0.06***	0.04***	0.03***	0.03***
	(0.009)	(0.008)	(0.012)	(0.012)	(0.007)	(0.006)
12 years or more of education	—	0.24*	—	-0.01	—	0.08
		(0.140)		(0.138)		(0.088)
14 years or more of education	—	0.1	—	0.05	—	0.11***
		(0.062)		(0.067)		(0.041)
16 years or more of education	—	0.20***	—	0.09	—	0.17**
		(0.045)		(0.070)		(0.035)
Controls for year of observation	yes	yes	yes	yes	yes	yes
Controls for region of country	no	yes	no	yes	no	yes
Controls for parent's education	no	yes	no	yes	no	yes
Number of obsevations	1225	1225	386	386	2029	2029
Number of Individuals	622	622	278	278	1040	1040

Note: The sample used is a subset of sample used for Table 8 results. Standard errors are in parentheses. One asterisk indicates significance at 10 percent level, two asterisks indicate significance at 5 percent level, three asterisks indicate significance at 1 percent level.

Table 10

Random Effects GLS Log Wage Regressions by Occupation Sector (Blue Collar Jobs)

	Specification									
	Clerical		Craftsmen		Operators		Laborers		Overall Blue Collar	
Conditioning Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Black	-0.26***	-0.12**	-0.24***	-0.09**	-0.17***	-0.08**	-0.18**	-0.09**	-0.24***	-0.12***
	(0.042)	(0.052)	(0.03)	(0.034)	(0.028)	(0.034)	(0.035)	(0.043)	(0.018)	(0.021)
AFQT score	—	0.11**	—	0.06***	—	0.01	—	0.02	—	0.07***
		(0.030)		(0.019)		(0.021)		(0.031)		(0.012)
AFQT score squared	—	-0.05**	—	-0.03*	—	-0.03**	—	-0.04**	—	-0.03***
		(0.024)		(0.015)		(0.015)		(0.020)		(0.009)
Age	0.03**	0.02*	-0.09***	0.02***	0.02**	0.02***	0.02***	0.02***	0.02***	0.01***
	(0.009)	(0.009)	(0.026)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.004)	(0.004)
12 years or more of education	—	0.1	—	0.10***	—	0.10***	—	0.07	—	0.07***
		(0.089)		(0.037)		(0.036)		(0.044)		(0.023)
14 years or more of education	—	0.05	—	0.04	—	0.04	—	0.07	—	0.07***
		(0.048)		(0.034)		(0.04)		(0.056)		(0.022)
16 years or more of education	—	0.04	—	0.07	—	0.01	—	-0.06	—	0.04
		(0.056)		(0.067)		(0.082)		(0.102)		(0.034)
Controls for year of observation	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls for region of country	no	yes	no	yes	no	yes	no	yes	no	yes
Controls for parent's education	no	yes	no	yes	no	yes	no	yes	no	yes
Number of observations	622	622	1667	1667	1475	1475	911	911	5720	5720
Number of observations	410	410	967	967	875	875	640	640	2431	2431

Note: The sample used is a subset of sample used for Table 8 results. Standard errors are in parentheses. One asterisk indicates significance at 10 percent level, two asterisks indicate significance at 5 percent level, three asterisks indicate significance at 1 percent level.

Table 11
Random Effects GLS Log Wage Regressions by Occupation Sector (Sales and Service Jobs)

	Specification			
	Sales		Service	
Conditioning Variable	(1)	(2)	(3)	(4)
Black	-0.32***	-0.18**	-0.24***	-0.03
	(0.073)	(0.087)	(0.040)	(0.046)
AFQT score	—	0.07	—	0.11***
		(0.049)		(0.028)
AFQT score squared	—	0.01	—	0.01
		(0.037)		(0.019)
Age	0.03**	0.03**	0.01	0.01*
	(0.014)	(0.014)	(0.009)	(0.008)
12 years or more of education	—	-0.01	—	0.01
		(0.186)		(0.050)
14 years or more of education	—	0.13	—	0.18***
		(0.088)		(0.047)
16 years or more of education	—	0.21***	—	0.08
		(0.080)		(0.067
Controls for year of observation	yes	yes	yes	yes
Controls for region of country	no	yes	no	yes
Controls for parent's education	no	yes	no	yes
Number of observations	418	418	930	930
Number of Individuals	259	259	515	515

Note: The sample used is a subset of sample used for Table 8 results. Standard errors are in parentheses. One asterisk indicates significance at 10 percent level, two asterisks indicate significance at 5 percent level, three asterisks indicate significance at 1 percent level.