The Differing Nature of Black-White Wage Inequality Across Occupational Sectors

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ABSTRACT

The nature of racial wage inequality appears to differ across occupation sectors. Specifically, I find that all of the racial wage inequality in the white-collar job sector can be accounted for by controlling for the academic skill level of each worker, but almost half of the overall racial wage inequality remains in the blue-collar sector after controlling for each worker's academic skill. Relatedly, after controlling for academic skill, I find that black workers are actually more likely to work in the white-collar sector than white workers. I show that these findings are consistent, and arguably directly implied by, both preference-based and statistical-based models of discrimination. However, omitted variable bias and measurement error also cannot be ruled out as possible explanations.

I. Introduction

It is well known that black Americans earn less than white Americans. In attempting to understand the underlying causes of such wage inequality, many economists have pointed to current and historical racial inequalities in schooling and the acquisition of academic skills. While there is little doubt that such racial differences in academic skills are a key factor contributing to continued wage differences between blacks and whites, the results of this paper suggest that such academic skill differences may not be the whole story. In particular, while racial differences in premarket academic skills appear to fully account for the current levels of wage inequality between black and white males in the white-collar job sector, racial wage inequality in blue-collar jobs may be substantially more complicated.

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He thanks James Andreoni, Meta Brown, Maria Cancian, Arnaud Chevalier, Tom Crossley, John Kennan, Lance Lochner, David Loughran, Derek Neal, Menesh Patel, Aloysius Siow, James R. Walker, the participants of the 2003 SOLE conference, the University of Toronto Applied Microeconomics Seminar, and RAND for helpful comments on earlier drafts. The data used in this paper can be obtained October 2007 through September 2010 from David Bjerk, RAND Corp. 1776 Main Street, P.O. Box 2138, Santa Monnica, CA 90407, <bjerkd@mcmaster.ca>
[Submitted January 2006; accepted July 2006]
ISSN 022-166X E-ISSN 1548-8004

As alluded to above, numerous authors have shown that racial differences in academic skills are a key factor for understanding racial wage inequality. For example, authors such as Welch (1973) and Card and Krueger (1992) provide convincing evidence that a significant fraction of the overall racial wage inequality observed in the United States throughout the 20th century can be attributed to dramatically unequal public schooling between blacks and whites, especially in Southern states, during in the earlier decades of the century. Further evidence of the continued importance of racial differences in academic skills in the context of racial wage inequality is presented by O'Neill (1990) and Neal and Johnson (1996). Indeed, Neal and Johnson (1996) show that of a roughly 25 percent gap in mean wages between white and black men in the early 1990s, almost three-fourths of it can be accounted for by racial differences in premarket academic skills (as measured by AFQT scores). In general, the evidence strongly suggests that educational discrepancies between whites and blacks have been an extremely important source of the observed racial wage inequality throughout U.S. history to the present day.

However, even in Neal and Johnson's (1996) analysis, there still remains a significant unexplained racial wage gap of roughly 7 percent. This paper looks more closely at this remaining unexplained gap. To do so, I first examine racial wage inequality separately by occupation, both overall and after conditioning on academic skill. The results that arise from dividing the labor market up in this manner reveal some interesting findings that are not apparent when examining the labor market as a whole. Specifically, overall racial inequality is substantially smaller in "white-collar" type occupations than in "blue-collar" type occupations. Moreover, all of the wage inequality in white-collar type occupations can be accounted for by racial differences in measured premarket academic skill, while only about half of the overall inequality in blue-collar type occupations can be accounted for by such measured academic skill differences. In other words, all of the racial wage inequality that remains in the overall labor market after controlling for premarket academic skill comes from workers working in blue-collar type occupations.

The second part of this paper considers what explanations may potentially account for these differing results across occupational sectors. The first explanation that I consider is discrimination. The second explanation I consider is the existence of an omitted variable bias. Finally, the third explanation I consider relates to the potential role played by measurement error.

The plausibility of a discrimination explanation comes directly from the fact that general academic skills are much more important for productivity in white-collar jobs than blue-collar jobs. Such differences in skill intensity across sectors suggest two reasons why discrimination might arise and persist in the blue-collar sector but not the white-collar sector. First, the weaker relationship between worker skill and productivity in the blue-collar sector implies that hiring a white worker over a more skilled black worker will generally result in smaller productivity losses at a blue-collar job than a white-collar job. This in turn means that it will generally be less costly for firms to engage in *preference-based* discrimination in the blue-collar sector than the white-collar sector (see Becker 1971 and Black 1995 for two examples of preference-based discrimination models). Second, differences in skill intensity across sectors may cause *statistical* discrimination to arise only in the blue-collar sector. More specifically, as shown by numerous authors, statistical discrimination can arise only when worker skill is not directly observed by employers (see for example Phelps 1972; Arrow 1974; Aiger and Cain 1977; Lundberg and Startz 1983; Coate and Loury 1993; Cornell and Welch 1996; Moro and Norman 2003; Antonovics 2004). However, as argued below, such imperfect information regarding worker skill is less credible when worker productivity depends dramatically on worker skill, as is true with most white-collar jobs, because in such cases firms have a strong incentive to invest in technologies that accurately reveal worker skill. Alternatively, in the blue-collar sector, where worker productivity is only slightly related to a worker's general academic skill, it may be more credible that firms often find it optimal to use race as a free signal of worker skill rather than invest in costly skill-assessment technology. Hence, imperfect information, and therefore statistical discrimination, is arguably more likely to arise and persist in the blue-collar sector.

A strong implication that arises from either of the above theories of discrimination is that after controlling for academic skill, black workers should be more likely than white workers of similar academic skill to work in the less discriminatory white-collar sector. I find strong empirical support for this implication. Moreover, as discussed more thoroughly below, for the *statistical* discrimination story to be true, it must also be the case that firms spend more resources on skill assessment when hiring for white-collar positions than for blue-collar positions, and the mean and variance of wages should be greater in the white-collar sector than the blue-collar sector, both overall and for each race separately. I also find these implications to be consistent with the empirical evidence.

As mentioned to above, however, the differences in the conditional racial wage gap across sectors also may be explained by a model of omitted variable bias or possibly differential measurement error across sectors. While neither of these explanation can be ruled out with certainty, and may at first both seem simpler than the discrimination explanations discussed above, I show both are not quite as straightforward as they might seem. In particular, for an omitted variable explanation to be correct, there must be a racial gap in some unobserved skill, and either this unobserved skill matters for productivity in the blue-collar sector but not the white-collar sector, or there must actually be a wage premium for black workers compared to equally skilled white workers in the white-collar sector (but not the blue-collar sector). On the other hand, while differential measurement error across sectors can quite plausibly account for the findings with respect to wage inequality across sectors, it cannot in and of itself account for the above results with respect to conditional differences between races with respect to sorting across sectors.

II. Empirically Examining Black-White Wage Inequality

In this section, I examine Black-White wage inequality over the labor market as a whole, as well as separately by occupation. The primary data for this analysis comes from the National Longitudinal Survey of Youth 1979 (NLSY79). The NLSY79 is a panel data set of 12,686 young people born between 1957 and 1964. These children were administered a survey every year after their initial interview to create a true panel data set covering their lives from the initial interview date in 1979 onward. The data set contains not only demographic information on each respondent, but also wage, education, and employment data throughout each respondent's life. The actual sample used in this analysis consists of male white and black workers, not in the low-income white or military oversamples, with valid AFQT test scores and educational attainment data, and having a valid CPS wage and occupation in at least one year between 1990 and 1992 panels inclusive. These particular years are chosen in order to make the results obtained here generally comparable to those in Neal and Johnson (1996).

A. *Black-White Wage Inequality in the Overall Labor Market*

To examine wage inequality across races, I run Random Effects Generalized Least Squares (GLS) regression specifications of the natural logarithm of each individual's wage from each year, on a race indicator dummy, as well as the individual's age in that year, and dummies for the year of observation. The results from this regression can be interpreted as capturing the magnitude of mean unconditional wage inequality between black and white males in their late twenties to mid-thirties during the early 1990s. Column 1 of Table 1 shows that the coefficient on the race dummy reveals that black male workers in this age group during this time period earned on average 28 percent less than their white male counterparts. These results are very similar to those obtained by Neal and Johnson (1996).

As discussed by Neal and Johnson (1996), much of this racial wage gap can be accounted for by racial differences in premarket academic skills. For example, the second column of Table 1 shows that if we control for completed years of education, the racial wage gap falls by roughly 25 percent, to a 22 percent differential. This result still likely understates the actual importance of academic skill differences, as completed years of education is likely a very noisy and racially biased measure of each individual's academic skill given variation in school quality across racial groups.

Neal and Johnson (1996) argue that an individual's score on the Armed Forces Qualification Test (AFQT) may provide a more precise and less racially biased measure of an individual's academic skill at the outset of his labor market activity than simply his years of completed schooling. The AFQT test is a combined measure of an individual's achievement on four academic skills tests: vocabulary, paragraph comprehension, arithmetic reasoning, and math knowledge. The AFQT is in no way meant to be a measure of inborn "intelligence" or innate potential for success in the labor market of any individual. Rather, the AFQT test is simply a measure used by the United States Military as a "measure of trainability and a primary criterion of enlistment eligibility" (Waters 1982). These scores are affected by many influences including age, school quality, parental and peer influence, and the effort an individual had previously exerted in obtaining these academic skills. Therefore, an individual's AFQT score should simply be interpreted as a noisy measure of the general academic skills the individual has acquired at the time of taking the test.[1]

1. It should be noted that Rodgers and Spriggs (1996) suggest that there may be a racial bias in the relationship between AFQT scores and wages since components to the AFQT test appear to have different returns across races. However, they do not control for occupation. As shown above, AFQT scores have very different returns across sectors, and blacks and whites may be distributed very differently across sectors. Moreover, other evidence has not suggested a significant racial bias on these dimensions (see Neal and Johnson 1996 and Waters 1982 for more in-depth discussion).

The third column of Table 1 shows that when AFQT scores are used instead of years of completed schooling to control each individual's academic skill, the black-white wage gap falls to only an 8 percent differential.[2] In other words, racial differences in academic skills as measured by AFQT scores explain over two-thirds of the unconditional racial wage gap. Once again, this result is almost identical to that found in Neal and Johnson (1996).

As emphasized by Neal and Johnson, this result suggests that the racial difference in academic skill acquired prior to the bulk of labor market activity is indeed a primary source of the overall wage inequality between black and white male workers, and that policies that help alleviate this academic skill gap are of utmost importance for lessening racial wage inequality. However, it is certainly not clear that this racial academic skill gap is the only source of the observed racial wage inequality that is of interest. After all, the coefficient on the black dummy variable remains negative and significant even after controlling for AFQT scores. Moreover, if we attempt to further control for academic skill by including each individual's years of completed schooling, the years of completed schooling for each individual's father and mother, as well as regional dummies (as black individuals disproportionately reside in southern states which may generally have lower performing schools), the coefficient on the black dummy variable remains negative and significant (and actually even increases in magnitude somewhat), as can be seen in Column 4 in Table 1.[3] Therefore, it is important to examine further what labor market forces may account for this unexplained portion of racial wage inequality.

B. Examining Black-White Wage Inequality Across Occupations

In order to understand further the portion of racial wage inequality left unexplained after controlling for academic skills, I begin by dividing the labor market into distinct occupational categories. Specifically, the NLSY79 uses the 1970 Census Occupational Classification System to classify reported occupations. These occupations are divided into several mutually exclusive categories, which include professional and technical occupations, managerial occupations, sales workers, clerical workers, craftsmen, operatives, laborers (nonfarm), and service workers.[4] Examples of job titles within each category are given in Table 2.[5]

Columns 1 and 2 of Table 3 show the results from Random Effects GLS log wage regression specifications identical to those reported in Columns 1 and 4 of Table 1, but done separately for professional/technical and managerial jobs, or "white-collar" occupations. The results reported in this table reveal several important patterns. First,

2. In order to renorm the test, the military administered the tests making up the AFQT to most of the NLSY79 respondents in 1980. Since individuals in the NLSY79 took the tests that make up the AFQT at different ages and scores clearly rise with age, scores are age adjusted, as well as normalized to have a mean of zero and a standard deviation of one.

3. Actual experience is not included in any of the specifications in this paper, as labor market discrimination may manifest itself through employers being less likely to hire black workers all else equal, which in turn lowers the reservation wage for black workers, which is then how such discrimination is revealed in wage regressions.

4. Armed Forces and Farm workers are excluded from this analysis because housing and food are often included as part of overall compensation for jobs in these categories.

5. For a complete list of jobs within each category, see NLSY79 Attachment 3.

Table 1
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	7,749			
Number of individuals	3,059			

Note: The sample used in this analysis comes from the NLSY79 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 having 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 indicated significance at 1 percent level.

the coefficients on the black dummy variable in Columns 1 and 3 show a significant unconditional racial wage gap in both of these occupational categories, but this gap is smaller than the unconditional gap in the labor market as a whole. Even more interestingly, after controlling for the measures of academic skill, the coefficients on the black dummy variable in Columns 2 and 4 are not significantly different from zero at any standard significance level. In other words, while black workers appear generally to be paid less than white workers in "white-collar" occupations, all of this racial wage inequality can be accounted for by racial differences in the academic skill variables used here. These general findings are summarized in Specifications 5 and 6, which pool all white-collar workers (that is, those working in Professional/Technical and Managerial Occupations).

The results in Table 4, however, which look at historically "blue-collar" occupations, lie in stark contrast to those presented in Table 3. Specifically, using analogous

Table 2
Examples of Jobs in Each Occupational Category

White Collar		Blue Collar				Other	
Professional (and Technical)	Managerial	Clerical	Craft	Operative	Laborer	Sales	Service
Computer Programmer	Bank Officer	Bank Teller	Baker	Assembler	Fisherman	Advertising Agent	Janitor
Chemical Engineer	Funeral Director	Cashier	Carpenter	Bottling Operative	Garbage Collector	Demonstrator	Cook
Actuary	Restaurant Manager	Mail Carriers	Brickmason	Garage Worker	Freight Handler	Hukster or Peddler	Waiter
Geologist	School Administrator	File Clerks	Crane Operator	Meat Cutter	Gardener	Insurance Agent	Dental Assistant
Physician	Sales Manager	Dispatchers	Dental Techncian	Furnaceman	Teamster	Newsboy	Stewardess
Registered Nurse	Buyer	Secretary	Jeweler	Riveter	Warehouseman	Stock and Bond Sales	Porter
School Teacher		Receptionist	Decorator	Knitter	Longshoreman	Sales Clerk	Hair Dresser
Pilot		Key Puncher	Electrician	Welder		Real Estate Agent	Fireman
Artist		Ticket Agent	Auto Mechanic	Drill Press			Policeman
		Stock Clerk	Roofer	Bus Driver			Detective
			Painter				Housekeeper
							Dishwasher

Note: Occupations categorized according to 1970 Occupational Classification System, as used by NLSY79.

Table 3
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 observations	1,225	1,225	386	386	2,029	2,029
Number of individuals	622	622	278	278	1040	1040

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

Table 4
Random Effects GLS Log Wage Regressions by Occupation Sector (Blue Collar Jobs)

Conditioning Variable	Specification									
	Clerical		Craftsmen		Operators		Laborers		Overall Blue Collar	
	(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***	−0.012***
	(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*	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.02***	0.01***
	(0.009)	(0.009)	(0.006)	(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)

Table 4 (*continued*)

Conditioning Variable	Specification									
	Clerical		Craftsmen		Operators		Laborers		Overall Blue Collar	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
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	1,667	1,667	1,475	1,475	911	911	5,720	5,720
Number of individuals	410	410	967	967	875	875	640	640	2,431	2,431

Note: The sample used is a subset of sample used for Table 1 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 5
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 1 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.

regression specifications to those used previously, Columns 1, 3, 5, and 7 show that unconditional racial wage inequality is quite large in each of these blue-collar occupations. Moreover, after controlling for the measures of academic skill, the specifications reported in Columns 2, 4, 6, and 8 reveal that black workers working in these blue-collar occupations still earn significantly less than white workers of similar measured academic skill in each of these occupations. Pooling all workers working in these blue-collar occupations, as done in Columns 9 and 10, reveal that only half of the overall racial wage inequality in blue-collar jobs can be accounted for by racial differences in the academic skill variables used here.

Table 5 shows analogous results to those presented above for workers working in sales and service occupations. As can be seen in Table 2, the types of jobs fitting into these to categories are quite heterogeneous, and cannot clearly be uniformly labeled white-collar or blue-collar in the traditional sense. Using analogous regression specifications as those above, Columns 1 and 2 in Table 5 show that black workers working in sales jobs earn about 32 percent less than white sales workers do, and only about half of this difference can be accounted for by racial differences in academic skill. Alternatively, Columns 3 and 4 show that black service workers earn about 24 percent less than white service workers, but all of this racial difference can be accounted for by racial differences in measured academic skill characteristics.

In general, the results in Tables 3–5 imply that all of the residual wage inequality that remains after controlling for measured academic skills in the labor market as a whole arises exclusively from significant racial wage inequality between workers of similar measured academic skill working in blue-collar and sales jobs. By contrast, racial differences in academic skill can account for all of the racial wage inequality among workers working in white-collar and service jobs.

C. Other Differences Across Occupational Sectors

The tables discussed above also reveal another key difference between occupational categories. Namely, academic skills appear to affect compensation more dramatically in the white-collar occupations than in the blue-collar occupations. This is most noticeable with respect to AFQT scores, where the coefficient on the AFQT score and AFQT score squared variables are substantially larger in white-collar occupations than in blue-collar occupations. Similarly, the coefficients on the education variables (especially 14 years or more and 16 years or more) are also substantially higher in the white-collar occupations than the blue-collar occupations.

Not surprisingly, these results suggest that academic skill may be more important for productivity in white-collar jobs than blue-collar jobs. This can be confirmed using data from the Multi-City Study of Urban Inequality (MCSUI). The MCSUI was designed to study how changing labor force dynamics, racial attitudes and stereotypes, and residential segregation affect urban inequality.[6] The MCSUI collected data on the frequency different tasks were used in the most recently hired position. The tasks examined here consist of ‘‘Write paragraphs or memos’’ (Writing), ‘‘reading instructions at least one paragraph in length’’ (Reading), ‘‘Do arithmetic or other computations’’ (Math). Performing these tasks certainly requires the use of the types of academic skills tested by the AFQT. Hence, the more often these tasks are performed, the more important academic skills are likely to be for worker productivity.

Table 6 confirms that each of these tasks were significantly more likely to be performed daily in white-collar jobs than blue-collar jobs. Alternatively, each of these tasks was significantly less likely never to be performed in white-collar jobs than

6. The data to be used for this analysis comes from the employer survey portion of the MCSUI, which was collected via a telephone survey of business establishments in Atlanta, Boston, Detroit, and Los Angeles carried out between the spring of 1992 and 1995. Two-thirds of the sample came from a size-weighted probability sample of regional employment directories, with the other third coming from the current or most recent employer reported in the household survey portion of the MCSUI.

Table 6
Academic Skills Used by Occupation

	Writing				Reading				Math or Arithmetic			
Occupation	Daily	Weekly	Monthly	Never	Daily	Weekly	Monthly	Never	Daily	Weekly	Monthly	Never
White collar	0.63	0.17	0.07	0.12	0.74	0.14	0.03	0.09	0.73	0.14	0.05	0.08
	(0.021)	(0.021)	(0.017)	(0.014)	(0.026)	(0.022)	(0.008)	(0.016)	(0.027)	(0.022)	(0.017)	(0.012)
Blue collar	0.31	0.16	0.09	0.43	0.53	0.21	0.07	0.19	0.61	0.14	0.05	0.20
	(0.016)	(0.011)	(0.008)	(0.015)	(0.016)	(0.012)	(0.008)	(0.013)	(0.016)	(0.012)	(0.006)	(0.013)
Sales	0.33	0.22	0.13	0.32	0.54	0.22	0.06	0.17	0.83	0.07	0.02	0.08
	(0.033)	(0.025)	(0.043)	(0.030)	(0.016)	(0.025)	(0.012)	(0.024)	(0.022)	(0.015)	(0.007)	(0.015)
Service	0.21	0.1	0.1	0.58	0.49	0.17	0.09	0.24	0.55	0.12	0.04	0.30
	(0.024)	(0.025)	(0.019)	(0.031)	(0.031)	(0.022)	(0.016)	(0.026)	(0.031)	(0.019)	(0.010)	(0.027)

Note: Data comes from MCSUI Employer sample, and includes all observations with valid occupational title. Statistics weighted to be "a representative sample of firms, such as would occur if a random sample of employed people were drawn from each city" (MCSUI Employer Telephone Survey Codebook, ICPSR 32535). Standard errors in parentheses.

in blue-collar jobs.[7] Given these results, for the remainder of the analysis I will refer to white-collar jobs as being in the "more academically skill-intensive" job sector, and blue-collar jobs as being in the "less academically skill-intensive" job sector, where the skill of interest is general academic proficiency.

Sales and service jobs are harder to characterize. As stated above, the types of jobs in each of these categories are quite heterogeneous. Table 5 shows that effect of AFQT scores on compensation in these two categories generally lies somewhere between white-collar jobs and blue-collar jobs. Moreover, Table 6 shows that while the frequency of reading and writing tasks in sales jobs is very similar to that in blue-collar jobs, the frequency of tasks involving math in sales jobs is more similar to white-collar jobs. On the other hand, tasks that require these academic skills are generally much more infrequent in service jobs than in any of the other categories.

III. What Can Account for these Cross-Occupational Differences in Conditional Wage Inequality?

What can explain these differing characteristics of measured racial wage inequality across occupations as detailed above? In this section, I examine three possible explanations: (i) differential discrimination across sectors, (ii) unobserved variable bias, and (iii) differential measurement error across sectors.

A. Labor Market Discrimination

Given the relative heterogeneity of jobs in the sales and service sectors, at this point, let us only consider how discrimination might explain the empirical results with respect to racial wage inequality in the white-collar and blue-collar sectors only (that is, the results shown in Tables 3 and 4). In particular, are there plausible reasons why black workers might be discriminated against in the blue-collar sector but not the white-collar sector?

Below, I consider both a preference-based discrimination explanation, as well as a statistical-based discrimination argument. As will be seen, both arguments are directly related to the discussion above suggesting that general academic skill is far more important for productivity in the white-collar job sector than the blue-collar job sector.

1. A Preference-based Discrimination Explanation

First, consider a simple model of preference-based discrimination along the lines of Becker (1971). In such a model, firms essentially have to pay a cost, in terms of lower profits, in order to act on their preference to employ white workers over black workers of similar or greater skill. Clearly, this cost will be greater, the greater the importance of each worker's skill to productivity. For example, say a racially biased firm chooses to hire a white truck driver over black truck driver with greater

7. It is important to note that the MCSUI uses a different occupational category system than the NLSY79. Specifically, instead of the 1970 Census Occupational Categories, the MCSUI uses the 1980 Standard Occupational Classification Manual. While the exact occupation categories are different across surveys, the occupational titles are similar enough across surveys such that the occupations I classify to be in the more general sector categories "white-collar," "blue-collar," "sales," and "service" are likely to be almost identical across surveys.

academic skill, or equivalently, consider a firm that offers black truckers much lower wages than equally skilled white truckers. If academic skill contributes to trucker productivity (for example, improves map reading proficiency, improves adaptability to new tasks and technology, improves ability to learn truck maintenance), then this racially biased firm will lose profits relative to its less racist competitor who hires the more academically skilled black trucker (at a similar or even lower wage). However, given academic skill is likely to be only marginally important for trucker productivity, then this cost of behaving in a racist manner will be relatively modest and the firm may be able to stay competitive through productivity gains in other areas (for example, higher effort put forth by other racist white employees).

On the other hand, consider a racist law firm that chooses to hire a white lawyer over a black lawyer with greater academic skill. Given academic skill is likely to have a very large influence on law firm profits, behaving in such a racist manner is likely to be extremely costly to the law firm, making it very hard for the law firm to stay competitive with the less racist law firms.

The above examples suggest that it is more likely that racist employers will be able to persist in the marketplace when these racist preferences are applied to hiring for less skill-intensive positions than for more skill-intensive positions. Hence, this story could certainly help explain the results in Tables 3 and 4. Racist employers simply cannot afford to act on their racist preferences when hiring for the highly academically skill-intensive white-collar jobs. However, when hiring for the less academically skill-intensive blue-collar jobs, racist employers are able to act on their racist preferences without large losses to their competitiveness.

2. *A Statistical Discrimination Explanation*

We can also consider whether a model of statistical discrimination can explain the empirical patterns in Tables 3 and 4, where employers discriminate not due to underlying racist preferences, but rather because such behavior is optimal from a profit-maximizing perspective. In general, models of statistical discrimination must assume firms have substantial uncertainty about worker skill. Under some circumstances, this uncertainty may then cause profit-maximizing employers to use race as a signal of skill, resulting in similarly skilled workers of different races being paid different wages.

Clearly, however, it is generally possible for firms to obtain quite precise information regarding the general skills of prospective workers. For example, they can extensively interview and test all applicants. While such investments in skill assessment are possible, they would be expensive. Therefore, it is likely that only when hiring for jobs where productivity is highly dependant on a worker's general academic skill will an employer make substantial investments in such skill-assessment technologies when making hiring and/or compensation decisions. On the other hand, in jobs where productivity is only slightly related to a worker's general academic skill, employers may find it optimal to avoid investing in costly skill-assessment technologies and simply use race as a free but noisy signal of an individual's academic skill.[8]

8. The racial gap in academic skill has been widely evaluated (see Jencks and Phillips 1998 for more extensive discussion and further citations). With respect to the racial gap in AFQT scores in the NLSY79 sample used here, there is a roughly one standard deviation gap in average scores between blacks and whites.

Given general academic skill appears to be much more important for productivity in the white-collar occupational sector than the blue-collar occupational sector, the above discussion suggests firms may find it optimal to invest much more heavily in assessing worker skill when hiring for white-collar positions than when hiring for blue-collar positions. Such differences in skill-assessment across sectors may then result in significant imperfect information regarding worker skill persisting in the blue-collar sector but not the white-collar sector, causing statistical discrimination to only arise and persist in the blue-collar sector. A formalized version of this argument is presented in the Appendix.

B. Evaluating the Discrimination Explanations

The above discussion argued that both preference-based and statistically based discrimination models could be straightforwardly adapted to explain why there exists substantial conditional wage inequality in the blue-collar sector but not the white-collar sector. To assess further whether either of these explanations is true, we can attempt to empirically evaluate whether any other implications that arise from these models also hold.

A strong implication arising from both of these discrimination models relates to differential sorting by race across sectors. Specifically, if discrimination against black workers arises in the blue-collar sector only (for either of the reasons discussed above), then *after conditioning on a noisy but racially unbiased measure of general academic skill*, black workers should be more likely than white workers to work in the more academically skill-intensive white-collar sector. The intuition behind this implication is quite straightforward—black workers have a greater incentive than white workers of similar academic skill to work in the more skill-intensive white-collar jobs if they will be paid less than their similarly skilled white counterparts if they choose to work in the blue-collar sector, but will be paid similarly if they choose to work in the white-collar sector. Note, however, discrimination in the blue-collar sector but not the white-collar sector does not necessarily imply that black workers should be *unconditionally* more likely than whites to work in the white-collar sector (this assertion is discussed more formally in model presented in Appendix).

Previous work on racial differences in occupational sorting has shown black workers are generally less likely to work in white-collar type occupations than white workers of similar age and years of education (Gill 1989; Gill 1994). However, as Gill (1989) acknowledges, similar years of schooling can mean quite different things across races if there are large racial differences in school quality, and therefore may be a somewhat racially biased measure of academic skill. Hence, Gill's findings may not provide a direct test of the implication discussed above.

To examine more precisely whether there appears to be such differential sorting across occupational sectors by race, we can once again use the NLSY79 sample from before, and control for academic skills using AFQT scores. Table 7 shows both the unconditional probability for workers of each race to work in the white-collar job sector, as well as the probability after roughly conditioning on where the worker lies in the AFQT score distribution, for each year separately from 1990–92. As can be seen in the top panel, consistent with Gill (1989), the unconditional probability that a black worker works in the white-collar sector is almost 50 percent less than the corresponding

Table 7
Probability of Working in White Collar Occupational Sector

	Black	White	Diff
Unconditional			
1990	0.15	0.32	−0.17***
	(0.012)	(0.011)	(0.016)
1991	0.16	0.32	−0.17***
	(0.012)	(0.012)	(0.017)
1992	0.16	0.32	−0.16***
	(0.012)	(0.012)	(0.017)
Conditional on location in AFQT distribution			
1990			
More than one standard deviation above mean AFQT	0.59	0.59	0.00
	(0.070)	(0.022)	(0.074)
Above the mean AFQT, but by less than one standard deviation	0.30	0.27	0.03
	(0.035)	(0.017)	(0.039)
Below the mean AFQT, but by less than one standard deviation	0.13	0.14	−0.01
	(0.019)	(0.020)	(0.028)
More than one standard deviation below mean AFQT	0.05	0.03	0.02
	(0.011)	(0.013)	(0.017)

Table 7 (*continued*)

	Black	White	Diff
1991			
More than one standard deviation above mean AFQT	0.64	0.59	0.05
	(0.066)	(0.022)	(0.069)
Above the mean AFQT, but by less than one standard deviation	0.31	0.28	0.03
	(0.036)	(0.017)	(0.040)
Below the mean AFQT, but by less than one standard deviation	0.14	0.13	0.01
	(0.020)	(0.019)	(0.028)
More than one standard deviation below mean AFQT	0.05	0.04	0.01
	(0.010)	(0.015)	(0.019)
1992			
More than one standard deviation above mean AFQT	0.66	0.60	0.06
	(0.065)	(0.022)	(0.069)
Above the mean AFQT, but by less than one standard deviation	0.35	0.29	0.06
	(0.037)	(0.018)	(0.041)
Below the mean AFQT, but by less than one standard deviation	0.16	0.12	0.04
	(0.021)	(0.018)	(0.028)
More than one standard deviation below mean AFQT	0.04	0.03	0.00
	(0.009)	(0.014)	(0.016)

Note: Sample same as used for Table 1. Standard errors in brackets.

probability for whites. However, consistent with the models of discrimination discussed above, the lower panels of Table 7 show that after controlling for where an individual lies in the AFQT distribution, black workers appear to be equally or more likely than white workers to work in the more academically skill-intensive white-collar sector.

Due to relatively small sample sizes within each of the above AFQT categories in any particular year, none of the differences in the conditional probabilities of working in the white-collar sector across races shown in Table 7 are significant. Therefore, Table 8 shows the results from several random effects probit specifications for the years 1990–92, where the dependant variable in each is a dummy variable equal to one if the individual works in the more highly skill-intensive white-collar sector.

In the first specification, the conditioning variables include a dummy variable equal to one if the respondent is black, the respondent's age, and the year of the observation. The results confirm that without conditioning on the academic skill of each worker, black workers are significantly less likely to work in the more highly skill-intensive white-collar sector than white workers. The second specification shows that while the gap shrinks somewhat, black workers are still less likely than white workers to work in the white-collar sector if we further control for parental education, whether each parent worked in a professional occupation, whether the respondent lived with both parents at age 14, and the region in which the respondent resides. However, the third specification shows that if we additionally control for premarket academic skills via AFQT scores, black workers are actually significantly *more* likely to work in the more highly skill-intensive white-collar job sector than their white counterparts. To give an indication of the magnitude of the coefficient estimates, if all other characteristics are held fixed at the population means, the results in Specification 3 imply that a black worker with an AFQT score one standard deviation above the population mean is about 30 percent more likely to work in the white-collar sector than a white worker with the same AFQT score.

It is important to note that each individual's own years of education were not controlled for in the first three probit specifications shown in Table 8 discussed above. The reason for this is that education beyond high school is generally a prerequisite for finding employment in a white-collar job, meaning an individual's decision regarding going to college is arguably almost equivalent to an individual's decision with respect to pursuing a white-collar career.[9] This means that further controlling for an individual's own level of education in the probit specifications discussed above would not necessarily reveal whether there is different sorting across occupation sectors by race (conditional on premarket academic skills), but rather would reveal whether there are racial differences in the ability to *obtain* a job in the white-collar sector conditional on premarket academic skills and years of education. Therefore, if indeed there is no discrimination in the white-collar sector then the coefficient on the black dummy variable in a probit specification analogous to the third specification in Table 8 but further controlling for years of own education should *not* be significantly different than zero. As shown in Specification 4 in Table 8, this is the case.

9. Indeed, after conditioning on AFQT scores, I find that black workers are also significantly more likely than their white counterparts to complete four or more years of post-high school education.

Table 8
Random Effects Probit Analysis of Probability of Working in White-Collar Occupation

	Dependent variable equals 1 if worker works in Professional or Managerial Occupation			
Conditioning Variable	[1]	[2]	[3]	[4]
Black	−1.35*** (0.010)	−0.51*** (0.114)	0.43*** (0.120)	−0.03 (0.111)
AFQT score	—	—	1.29*** (0.060)	0.61*** (0.060)
AFQT score squared	—	—	0.25*** (0.046)	0.07 (0.044)
Age	0.05*** (0.012)	0.05*** (0.013)	0.04*** (0.012)	0.03*** (0.012)
Lived with both parents at 14	—	0.12 (0.133)	0.08 (0.130)	0.04 (0.119)
Mother high school grad	—	0.77*** (0.121)	0.41*** (0.119)	0.27** (0.109)
Mother college grad	—	0.68*** (0.179)	0.37** (0.172)	0.08 (0.156)
Mother professional	—	0.48*** (0.149)	0.30** (0.144)	0.19 (0.130)
Father high school grad	—	0.74*** (0.122)	0.43*** (0.120)	0.29*** (0.110)
Father college grad	—	0.77*** (0.153)	0.47*** (0.148)	0.13 (0.134)
Father professional	—	0.95*** (0.129)	0.61*** (0.125)	0.38*** (0.114)
Controls for year of observation	yes	yes	yes	yes
Controls for region of country	no	yes	yes	yes
Controls for own years of education	no	no	no	yes
log likelihood	−4,740	−4,435	−4,162	−3,942

Note: Sample same as used for Table 1. Once again, only between subject variation is used for estimation. Standard errors in parentheses. One asterisk indicates significance at 10 percent level, two asterisks indicate significance at 5 percent level, three asterisks indicated significance at 1 percent level.

The model of statistical discrimination developed in the Appendix is even more specific regarding this racial difference in occupational sector sorting. Specifically, the model suggests that occupational selection for each race may be characterized by a skill threshold level for each race r, denoted θ_r^*, such that a worker from race r will choose to work in the more skill-intensive white-collar sector if and only if his general skill level exceeds this threshold θ_r^*. A direct implication of discrimination against blacks in the blue-collar sector but not the white-collar sector is that this threshold should be *lower* for blacks than whites. (See model in Appendix for formal proof of this assertion.) While not modeled explicitly, such a result could also certainly arise from a model of preference-based discrimination as described previously.

This suggests that a third way to evaluate whether there is differential occupational sorting across racial groups is to directly estimate the skill-sorting thresholds for each race and see if they differ. To do so, assume an individual i's AFQT score (denoted a_i) is a noisy measure of the individual's general academic skill θ_i, where $a_i = \theta_i + \varepsilon_i$ and ε_i is an i.i.d. mean zero normally distributed random variable. The probability that an individual i from race r works in the white-collar sector given his AFQT score a_i will then equal $\Phi(a_i - \theta_r^*)$, while the probability that an individual i from race r does not work in the H-sector given his AFQT score a_i equals $\Phi(\theta_r^* - a_i)$.[10] Therefore, to estimate the sorting threshold θ_r^* for racial group r, we can maximize the following log likelihood function with respect to θ_r^*:

$$\ln L = \Sigma_H \ln \Phi(a_i - \theta_r^*) + \Sigma_L \ln \Phi(\theta_r^* - a_i)$$

where Σ_H implies summation across all male workers of a particular race working in the more highly skill-intensive white-collar sector, and Σ_L implies summation across all male workers of a particular race not working in the white-collar sector.

Consistent with the discrimination stories discussed above, maximizing the above expression for each race separately for each year 1990, 1991, and 1992, suggests that indeed the skill-sorting threshold is lower for blacks than whites. Specifically, for 1990, the estimated skill-sorting threshold for whites is 1.07 (s.e. 0.036), while for blacks it is 0.67 (s.e. 0.057). The analogous results for 1991 are 1.06 (s.e. 0.036) for whites and 0.64 (s.e. 0.057) for blacks, while in 1992 the results are 1.05 (s.e. 0.036) for whites and 0.62 (s.e. 0.058) for blacks. All of these differences across races are significant at the 1 percent level.

The above results do suggest that black workers are more likely to work in the white-collar sector than white workers of similar premarket academic skill. Hence, at this point we cannot reject either the preference-based or statistical-based models of discrimination, where discrimination arises in the less academically skill-intensive blue-collar sector, but not the more skill-intensive white-collar sector. However, as discussed above, a necessary condition for the model of preference-based

10. To see this, recall that a worker i from race r chooses to work in the white-collar sector as long as his θ_i exceeds θ_r^*. Therefore, the probability a worker i from race r with AFQT score of a_i works in the H-sector is $\Pr(\theta_i > \theta_r^* | a_i) = \Pr(a_i + e_i > \theta_r^*) = \Pr(e_i > \theta_r^* - a_i)$. Given the distributional assumption regarding e_i, this equals $1 - \Phi(e_i > \theta_r^* - a_i)$, which in turn equals $\Phi(e_i > a_i - \theta_r^*)$. A similar procedure can be used to compute the likelihood for individuals choosing not to work in the white-collar sector.

discrimination to be true is that even though the more racist employers have lower skilled employees (or equivalently relatively higher labor costs) than the more race-neutral firms, market competition is not sufficiently strong to drive these less efficient racist firms out of business. While it was argued that this is more plausible with respect to the blue-collar labor market than the white-collar market, it is admittedly still a very strong assumption given the arguably very competitive global economy of the United States during the early 1990s.

The statistical-based discrimination argument is appealing in that the discrimination that arises in the blue-collar sector actually turns out to be optimal for profit-maximizing firms, even in a perfectly competitive economy. Moreover, the statistical-based discrimination argument provides us with other potentially refutable implications. Most notably, for the statistically based discrimination argument discussed above to be true, it clearly must be the case that we should see employers spending more resources when hiring for white-collar positions than when hiring for blue-collar positions, as such asymmetry in skill-assessment investments are required to drive the information differences across sectors necessary for discrimination to arise in the blue-collar sector but not the white-collar sector. Therefore, it is important to ask whether there is any evidence that such differential investment in skill-assessment across sectors is true.

To look at this question, I use data from The National Survey of Employers 1982 (NSE). This survey interviewed a nationally representative sample of 5,000 American for-profit employers and was a 1982 followup to the Employers Opportunities Pilot Project (EOPP) of 1980. In the course of this study, this survey collected data on wages of hired workers, employer, and most recently hired employee characteristics, and employer hiring practices including the number of hours spent "screening, interviewing, and testing" applicants for the most recently hired position.[11]

As with respect to the MCSUI, occupations in the NSE are not classified in exactly the same manner as in the NLSY79 (the NSE classifies occupations using the 1977 Dictionary of Occupational Titles). However, the categories in the two surveys are similar enough so that jobs can still be separated into white-collar or highly skill-intensive jobs (Professional, Technical, Managerial, and Supervisory jobs), and less skill-intensive or blue-collar jobs (Clerical, Processing, Machine Trades, Benchwork, Structural, and Miscellaneous jobs).[12] It is certainly possible that the different categorization systems used in the NSE and the NLSY79 may result in some jobs being categorized as being in different sectors in the NLSY79 data than the NSE data. While this may lead to some measurement error, such differing classifications are likely to be small in number given the broadness and generality of the white-collar and blue-collar categories that are examined. Sales and service jobs also can be distinguished in the NSE data.

11. The sample used in this paper restricts the data to only firms with valid answers to the key question regarding the number of hours spent "screening, interviewing, and testing" applicants during the course of hiring the most recently hired worker.

12. Amusement, recreation, motion picture, radio and television occupations (Category 96) and occupations in graphic art work (Category 97) are classified as Miscellaneous in the *Dictionary of Occupational Titles*, but are included in the highly skill-intensive sector in this analysis to correspond to where they are categorized in the Census Occupational Classification System that was used in the NLSY79.

Table 9
OLS Regressions of Log of Hours Spent Assessing Skill Per Hired Worker

	Specification		
Conditioning Variable	[1]	[2]	[3]
White collar job	0.50***	0.50***	0.48***
	(0.077)	(0.078)	(0.080)
Sales job	0.07	0.13	0.18*
	(0.096)	(0.098)	(0.101)
Service job	−0.34***	−0.32***	−0.29***
	(0.073)	(0.072)	(0.079)
Number of employees (in hundreds)	—	0.11***	0.11***
		(0.017)	(0.017)
Number of employees squared	—	−0.001***	−0.001***
		(0.0002)	(0.0003)
Age > 50	—	—	−0.16
			(0.123)
Age 30 – 50	—	—	0.07
			(0.061)
Female	—	—	0.13*
			(0.056)
Controls for industry	no	no	yes
R-squared	0.04	0.06	0.08
Number of observations	1,951		

Note: Sample taken from National Survey of Employers 1982. One asterisk indicates significance at 10 percent level, two asterisks indicate significance at 5 percent level, three asterisks indicate significance at 1 percent level. Standard errors in parentheses.

The NSE data shows that there do indeed exist substantial differences in the hours spent screening, interviewing, and testing job candidates for the most recently hired position (subsequently referred to as "hours assessing applicant skill") across occupational sectors. In particular, when hiring for white-collar positions, employers spent an average of 18.3 hours (s.e. 1.43) assessing applicant skill, compared to 10.5 hours (s.e. 0.46) for blue-collar positions. To confirm that these differences in hours assessing applicant skill across sectors are robust to controlling for a variety of employer and hired employee characteristics, Table 9 presents the results from several OLS regression specifications, where the dependant variable is the natural logarithm of hours spent assessing applicant skill. The first specification controls for the occupational sector of the hired position (the excluded category is blue-collar jobs). The subsequent specifications further control for the size of the hiring employer, the age of hired employee, the gender of hired employee, and the hiring employer's industry. As can be seen in the top row of Table 10, in all specifications, employers hiring for white-collar jobs spend roughly 50 percent more time

Table 10
Mean and Variance of Wages [Overall and by Occupational Sector]

	1990			1991			1992		
Group	Overall	White	Black	Overall	White	Black	Overall	White	Black
All occupations									
Mean	10.9	11.9	9.1	10.9	11.9	9.2	10.9	12.0	9.1
	(0.121)	(0.159)	(0.168)	(0.126)	(0.162)	(0.19)	(0.126)	(0.165)	(0.174)
Variance	38.3	42.0	27.1	41.0	33.7	42.6	40.5	28.4	44.2
	(4.00)	(5.54)	(4.90)	(5.06)	(7.12)	(6.80)	(3.71)	(4.63)	(5.08)
By sector									
White-collar									
Mean	14.2	14.5	12.8	14.0	14.5	12.0	14.5	14.9	13.2
	(0.249)	(0.282)	(0.524)	(0.246)	(0.279)	(0.498)	(0.263)	(0.287)	(0.63)
Variance	54.5	55.3	48.8	56.4	57.1	49.2	62.5	58.6	74.7
	(6.87)	(7.80)	(14.45)	(8.80)	(10.29)	(15.96)	(8.38)	(8.23)	(25.78)
Blue-collar									
Mean	9.8	10.7	8.5	9.7	10.5	8.5	9.7	10.7	8.3
	(0.121)	(0.167)	(0.164)	(0.123)	(0.162)	(0.181)	(0.121)	(0.170)	(0.152)
Variance	28.7	31.4	22.1	28.6	28.7	26.0	27.6	32.0	18.1
	(4.71)	(7.00)	(5.47)	(5.19)	(7.22)	(7.28)	(3.53)	(5.67)	(2.13)

Note: Sample same as used for Table 1. Standard errors in parentheses.

screening, interviewing, and testing job candidates than employers hiring for blue-collar sector jobs. In interpreting these results, however, it should be noted that employers may be assessing other skills besides academic skills.

Finally, it also is true that in this model where statistical discrimination arises in the blue-collar sector only, wages should exhibit a higher mean and variance in the white-collar sector than blue-collar sector, both overall and for each race separately. Intuitively, if firms have substantially imperfect information regarding blue-collar worker skill, there should be very little heterogeneity in wages in the blue-collar sector as workers cannot distinguish themselves by their skill. On the other hand, if firms have quite precise information regarding worker skill in the white-collar sector, white-collar wages will exhibit high variance, as such wages will reflect the heterogeneity in worker productivity associated with the heterogeneity in worker skill. Finally, mean wages will be higher in the white-collar sector than the blue-collar sector because workers only will choose to work in the white-collar sector if they can earn higher wages through revealing their skill in the white-collar sector than if they simply took the relatively more uniform wage available in the blue-collar sector. (These implications are also derived more formally in the model in the Appendix.)

To evaluate these implications, I once again use the NLSY79 sample used previously. Looking at Table 10, we can see that indeed wages in white-collar jobs exhibit a significantly greater mean and variance than in blue-collar jobs, both overall and for each race separately, in each of the panel years that were used for the earlier wage regressions. These results also generally hold true even if white-collar and blue-collar occupations are separated out into the more specific job categories used in Tables 3 and 4 (results available from author upon request).

C. Omitted Variable Bias

The subsections above showed that both preference-based and statistical-based discrimination stories can potentially explain the results highlighted in Tables 3 and 4, with Tables 6–10 presenting additional evidence consistent with these models. However, it should be noted that a variety of other stories also may be consistent with these findings. Moreover, considerable caution should certainly be taken before interpreting a negative coefficient on a black dummy variable to be indicative of discrimination, as regardless of the variables that are controlled for, it is likely that employers observe worker characteristics not available to the econometrician. If such an unobserved characteristic is correlated with race and is important for productivity, then the negative coefficient on the black dummy variable may simply be due to the omission of this variable from the regression specifications, not discrimination.

To see this formally, note that the regression specifications in Table 1 that control for academic skill were essentially of the following form

$$w_i = \alpha + \lambda_\theta \theta_i + \lambda_B B_i + \varepsilon_i \quad (1)$$

where w_i is the log of an individual's wage, θ_i is an individual's academic skill, B_i is an indicator for whether an individual is black, and ε_i is an independent random variable for individual i drawn from a normal distribution with mean zero, uncorrelated with race and academic skill. The main finding from Table 1 was that $\lambda_B < 0$.

The clear concern regarding the interpretation of this estimated coefficient is that Equation 1 may have omitted an important skill besides academic skill that also affects wages. In particular, consider a wage specification of the form

$$(2) \quad w_i = \delta + \pi_\theta \theta_i + \pi_s s_i + \pi_B B_i + e_i$$

where s_i is observed by employers but not available to the econometrician and e_i is an independent random variable for individual i drawn from a normal distribution with mean zero, uncorrelated with the other regressor variables. Moreover, assume that this unobserved skill s_i has the following relationship to academic skill and race

$$(3) \quad s_i = \rho + \mu_\theta \theta_i + \mu_B B_i + v_i$$

where v_i is an independent noise term. Substituting Equation 3 into Equation 2 and rearranging, we get

$$(4) \quad w_i = (\delta + \pi_s \rho) + (\pi_\theta + \pi_s \mu_\theta)\theta_i + (\pi_s \mu_B + \pi_B)B_i + (e_i + \pi_s v_i).$$

Relating the above equation to Equation 1 shows that $\lambda_B = \pi_s \mu_B + \pi_B$. This shows why it is generally difficult to distinguish between unobserved variable bias and discrimination—λ_B could be negative either because black workers are actually getting paid less than similarly skilled whites via discrimination (that is, $\pi_B < 0$), or because there is an unobserved skill that contributes positively to wages and there is a racial skill gap in this unobserved skill (that is, $\pi_s > 0$ and $\mu_B < 0$).

This omitted variable story is more complicated with respect to the results presented in Tables 3 and 4, however, as the coefficients in Equation 1 differed across sectors.[13] For ease of reference, let us refer to the more academically skill-intensive white-collar jobs as being in H-sector and the less academically skill-intensive blue-collar jobs as being in L-sector. Given this notation, the primary findings reported in Tables 3 and 4 can then be summarized as $\lambda_B^L < 0 = \lambda_B^H$, where the superscripts indicate sector. In words, after conditioning on academic skill, black workers are paid less than whites are in the blue-collar sector but not the white-collar sector.

Noting from above that for each Sector j, $\lambda_B^j = \pi_s^j \mu_B + \pi_B^j$, there are two ways in which an omitted variable bias, rather than discrimination against black workers, can account for this finding that $\lambda_B^L < 0 = \lambda_B^H$. First, it may be the case that $\pi_B^j = 0$ for $j = \{L, H\}$ but $\mu_B < 0$ and $\pi_s^L > 0 = \pi_s^H$. In words, there may be no explicit wage discrimination in either sector, but blacks have a lower average level of the omitted skill and this omitted skill only contributes to productivity in the less academically skill-intensive blue-collar sector. The second way in which the results in Tables 3 and 4 can be explained by an omitted variable is if $\mu_B < 0$ and $\pi_s^j > 0$ for $j = \{L, H\}$, but $\pi_B^H > 0 = \pi_B^L$. In words, blacks may have a lower average level of the omitted skill, and this skill may be important for productivity in both sectors, but black workers are actually paid more than their equally skilled white counterparts in the white-collar sector but not the blue-collar sector. The question then becomes, is there plausible justification for either of these hypotheses?

13. As before, given substantial amount of heterogeneity in the types of jobs classified as sales and service jobs, for time being, the let us focus primarily on the differences between the blue-collar sector and the white-collar sector. Discussion of sales and service jobs will follow.

Consider the first hypothesis, where there is no wage discrimination in either sector, but blacks have a lower average level of the omitted skill and this omitted skill only contributes to productivity in the blue-collar sector. In this case, it is important to consider what types of characteristics this unobserved skill may refer to. On the one hand, the unobserved characteristics may be what are sometimes termed soft skills, such as reliability, courteousness, or knowledge of workplace norms. Authors such as Wilson (1997) have suggested that because of isolation from jobs, quality schools, and adequate role models, many blacks who live in poor neighborhoods may indeed have acquired less such soft skills than their white counterparts (potentially accounting for why $\mu_B < 0$). While this may be true, one may argue that such soft skills are also valuable in white-collar jobs (meaning $\pi_s^H > 0$), making this explanation somewhat problematic.

On the other hand, the omitted skill may include nonacademic skill characteristics such as dexterity, mechanical intuition, physical strength, and endurance—attributes which certainly may affect productivity and wages in only the blue-collar sector (that is, $\pi_s^L > 0 = \pi_s^H$). However, there are few reasons to expect blacks to have lower average levels of many such nonacademic characteristics than whites have, especially with respect to characteristics such as physical strength and endurance. Moreover, the ASVAB test taken by members of the NLSY79 contains further tests beyond those used for calculating AFQT scores. These include a speed coding test where individuals are timed regarding how fast they can complete a simple matching task and a mechanical intuition test where individuals are shown pictures of basic machines such as pulleys, gears, and wedges, and then asked questions about how these objects would work together. While not perfect, the speed coding test was meant to measure general skills used by "clerks, coders, warehouse workers, filers, and bookkeepers," and the mechanical intuition test was meant to test general skills useful for subsequent work in "designing, manufacturing, or repairing machinery" (NORC 1981).[14] Including these test scores in a regression otherwise identical to that performed in the final column of Table 4 reduces the magnitude of the coefficient on the black dummy variable to -0.10 (s.e. 0.021), yet still reflects the existence of a relatively large and significant conditional racial wage gap in the blue-collar sector. Hence, while possible, it is certainly not obvious that the results presented in Tables 3 and 4 can be explained by the existence of omitted skill variables such that there is racial gap in these omitted skills and these omitted skills only contribute to productivity in the less academically skill-intensive blue-collar sector.

Now consider the second possibility, that blacks have a lower average level of an omitted skill that is important for productivity in both sectors, but black workers are actually paid more than their equally skilled white counterparts are in the white-collar sector. In other words, the results reported in Tables 3 and 4 may not be due to discrimination against black workers in the blue-collar sector, but rather a wage premium for blacks compared to whites in the white-collar sector. What might account for such a wage premium for blacks relative to whites in the white-collar sector? The most obvious candidate may be affirmative action. Namely, issues of diversity and

14. Other tests contained in the ASVAB beyond those used in the AFQT and listed above include tests on science knowledge, auto and shop knowledge, and electronics knowledge. All of these tests were meant to measure the very specific knowledge that comes from studying and receiving training in these fields.

affirmative action pressures may be much stronger with respect to white-collar jobs than blue-collar jobs, causing employers to bid-up salaries for the relatively scarce black white-collar workers relative to their white counterparts.

While this story is certainly plausible, I am currently not aware of studies showing direct evidence for (or against) this notion that affirmative action pressures are stronger in the white-collar job sector. Furthermore, such a story suggests that the return on academic skills should be greater for blacks than whites in the white-collar sector, as very high-skilled blacks would be the ones most sought after by firms looking to increase their diversity among their white-collar workers. We can directly examine this implication by estimating an equation similar to the one presented in the last column of Table 3 for workers working in white-collar jobs, but further including an interaction term between the black dummy variable and AFQT score. Strong affirmative action pressures in the white-collar sector suggest that the coefficient on this interaction term should be positive. Estimating this specification, I find that including this interaction term has no real impact on any of the other coefficients, and more importantly, the coefficient on this interaction term is very small in magnitude, not statistically significantly different than zero, and actually is negative in sign (-0.006 with a standard error of 0.040). Hence, this exercise does not provide any evidence that black workers incur a higher return on academic skills than whites in the white-collar sector. While this does not imply that the affirmative action story is necessarily incorrect, it certainly does not provide any evidence in support of such an argument.

In general, the above discussion reveals that the differential character of racial wage inequality across sectors arguably makes the omitted variable bias story somewhat less straightforward than usual.

D. Measurement Error

As discussed by Bollinger (2003), measurement error when skill is proxied for by AFQT scores may potentially lead to an overstatement of conditional racial wage inequality in regressions of the form estimated in Tables 1, 3, 4, and 5. Such measurement error may be particularly important with respect to the results presented here, as one could certainly argue that AFQT is a noisier measure of the "skills" relevant for productivity in the blue-collar sector than the white-collar sector. Hence, it is certainly very plausible that greater measurement error of skills in the blue-collar sector accounts for the relatively large in magnitude and significantly negative coefficient on the black dummy variable that remains after controlling for AFQT scores in the regressions presented in Table 4.

Although it once again must be emphasized that this explanation cannot be dismissed, it is not entirely free of concerns either. First, for this measurement error story to be correct, not only must both worker "skills" have a relatively strong effect on worker productivity in the blue-collar sector and AFQT be a noisier measure of these "skills" relevant for productivity in the blue-collar sector than the white-collar sector, but also it must be true that there is a significant racial gap in these "skills" most relevant for productivity in the blue-collar sector. However, as with the omitted variable explanation discussed above, if these skills relevant for productivity in the blue-collar sector generally differ from academic skills (which must be true for the AFQT to be a noisier skill measure in the blue-collar sector than the white-collar sector), it is not as clear that there is a large racial gap in such skills. Second, and maybe even more importantly, this measurement error hypothesis in and of itself does not account for the finding that black workers are more likely to choose to work in the white-collar sector than whites with similar AFQT scores, as shown in Table 8. In general, however, this issue of differential measurement error of skills across sectors is an important avenue for further inquiry with respect to the results presented in this paper.

IV. Discussion of Sales and Service Jobs

As mentioned above, Table 5 shows that conditional racial wage inequality among sales workers is similar to that of blue-collar workers (that is, only half of the overall inequality is explained by racial academic skill differences), while the conditional inequality among service workers is similar to that of white-collar workers (that is, all of it is explained by racial academic skill differences).

While these similarities are certainly of interest, it is not clear how to interpret these results with respect to the arguments discussed above. In particular, recall from above that while the NLSY79 data shows academic skills as measured by AFQT scores and years of schooling are monetarily rewarded similarly in service jobs to white-collar jobs, the MCUSI data as shown in Table 6 suggest that productivity in service jobs is the least tied to academic skills compared to all of the other occupational sectors examined in this paper. An analogous discrepancy across surveys occurs with respect to sales jobs, with the NLSY79 data showing that the degree to which academic skills are compensated in sales jobs is similar to how they are compensated in blue-collar jobs, but with the MCUSI data showing that the frequency with which academic skills are used in sales jobs is more similar to white-collar jobs.

Table 9 shows a related issue, that employers hiring for sales jobs spend more time assessing skills than employers hiring for blue-collar jobs, while employers hiring for service jobs spend less time assessing skills than employers hiring for blue-collar jobs do. Clearly, this finding is hard to reconcile with the hypothesis that better skill information in the service sector than the sales sector accounts for the much smaller conditional wage gap in the service sector (that is, the statistical discrimination story).

One explanation for these anomalies may be differences in the types of jobs being included in the sales and service sectors across the surveys, as well as a different distribution of jobs within each of these sectors across the surveys. For example, it may be the case that the service sector as defined using the NLSY79 data might have a higher fraction of academically skill-intensive jobs than the service sectors as defined using the MCSUI data or the NSE data. One reason for this may be that the MCSUI and the NSE only surveyed for-profit employers, and hence the service jobs covered in these surveys would not contain the possibly more highly skill-intensive government service jobs such as police officers and firefighters that are included in the NLSY79.

Another explanation with respect to the results regarding sales workers relates to the fact that productivity in sales jobs clearly depends substantially on the interaction between workers and customers. In particular, in such jobs productivity and compensation are often directly tied to how the worker interacts with his customers and clients. On the one hand, if customers are biased against black salesmen, then even if employers are not inherently discriminatory, black workers will end up earning less than whites with similar academic skill. On the other hand, because of the large amounts of customer interaction, it could also be the case that nonacademic skills such as knowledge of business etiquette and understanding dominant social norms are particularly important in sales jobs for productivity. Hence, if there is any racial gap in such skills, failing to empirically account for these skills could lead to a substantial omitted variable bias with respect to the coefficient on the race dummy.

V. Summary and Conclusion

The first part of this paper showed that racial wage inequality has quite different characteristics across occupational sectors. Specifically, while there exists significant overall wage inequality in all occupations, this inequality is lesser in white-collar occupations than in blue-collar occupations. Moreover, all of the racial wage inequality in white-collar occupations can be accounted for by racial differences in academic skill at the outset of each worker's career, while only just over half can be accounted for by racial differences in academic skill for workers in blue-collar occupations.

I then discussed several potential explanations for these findings. The first two considered different forms of discrimination, and why such discrimination may arise only in the blue-collar sector. The key to both of these arguments centered around the fact that general academic type skills are much more important for productivity in the white-collar sector than in the blue-collar sector. With respect to preference-based discrimination, such smaller variability in productivity due to academic skill in the blue-collar sector means that competitive pressures to eradicate racist hiring practices will not be as strong in the blue-collar sector as in the white-collar sector. Hence, preference-based discrimination may be more able to persist in the less academically skill-intensive blue-collar sector.

Alternatively, with respect to the statistical discrimination argument, the strong dependence of productivity on academic skill in the white-collar sector suggests that firms will likely find it optimal to spend substantial resources assessing applicant skill when hiring for white-collar positions. However, the relatively weak dependence of productivity on academic skill in the blue-collar sector suggests that when hiring for blue-collar positions, firms may choose to use the applicant's race as a free, albeit noisy signal of an applicant's skill, as opposed to investing in costly skill assessments. This difference in skill information gathering across sectors may then cause statistical discrimination to only arise in the less academically skill-intensive blue-collar sector.

A key implication of both of these discrimination arguments is that conditional on premarket academic skill, black workers should be more likely to work in the white-collar sector than white workers. This implication was confirmed empirically using several different statistical methods, revealing, for example, that among individuals with relatively high AFQT scores, black workers are about 30 percent more likely than their white counterparts to work in the white-collar sector. Two further implications also come from the model of statistical discrimination arising only in the blue collar sector. First, firms should spend significantly fewer resources assessing applicant skill when hiring for a blue-collar job than a white-collar job, and second, the mean and variance of wages should be greater in the white-collar sector than the blue-collar sector, both overall and for each race separately. Both of these implications were also strongly confirmed by the data.

Neither of these discrimination arguments are definitive, however. Other possible explanations for the differences in the conditional wage gap across sectors include an omitted variable bias and differential measurement error across sectors. While these explanations cannot be ruled out, they either require additional assumptions for which there currently exists very little confirmatory evidence, or they do not account for other results presented in this paper—notably that black workers appear to be more likely to work in the white-collar sector than white workers with similar AFQT scores.

In general, the results of this analysis suggest that it is important not to treat the labor market as one homogeneous entity when analyzing racial wage differences in the economy, as the racial wage gap may be fundamentally different with respect to less academically skilled workers than the labor market for higher skilled workers. Future research is still necessary to pin down exactly what mechanism or mechanisms are behind these differences across sectors. However, the findings of this paper suggest that policies that make discrimination more difficult and/or that provide incentives for employers to invest greater resources in assessing the general academic skills of workers and applicants, may be more effective methods for decreasing racial wage inequality when targeted at employers hiring for the less academically skill-intensive blue-collar jobs than white-collar jobs.

Appendix

A Model of Differential Statistical Discrimination Across Occupational Sectors

Consider an economy with a large number of workers, where each worker can be characterized by his general academic skill level denoted θ. Let θ be a random variable drawn from a cumulative distribution F defined over an unbounded support with a well-defined expectation $E[\theta]$, where $\theta' - E[\theta | \theta < \theta']$ is strictly increasing in θ', but goes to zero as θ' goes to negative infinity.[15] Furthermore, assume each worker knows his general-skill level prior to entry into the labor market.

Let the demand side of the labor market be made up of employers in two labor market sectors, referred to as the *H*-sector and the *L*-sector, with two identical firms in each sector.[16] Assume each firm is able to hire an infinite number of workers, and the value product produced by each worker depends on the general-skill level of the worker. In particular, let the value product of a worker of skill level θ in a j-sector firm be given by the function $v_j(\theta) = \alpha_j + \beta_j\theta$. Assume the technology in the two sectors differs in that $\alpha_L > \alpha_H$ and $\beta_L < \beta_H$.[17] Hence, the *H*-sector firms can be

15. Note that this is not a very restrictive assumption as many common distributions meet these criteria, including the normal (and the uniform when the support is bounded).

16. *H*-sector and *L*-sector are used rather than *W*-sector and *B*-sector to avoid confusion with "white" and "black." Moreover, two employers in each sector is used for convenience only. More generally, the model will hold for any number of employers greater than one.

17. Assuming $\alpha_L > \alpha_H$ simply assures that some individuals will find it optimal to work in the *L*-sector. Intuitively, very low skilled individuals are assumed to be more productive in the *L*-sector than the *H*-sector, as low-skilled workers may actually have negative productivity in very complicated tasks.

thought of as hiring for the more highly skill-intensive white-collar jobs, while the L-sector firms can be thought of as hiring for the less skill-intensive blue-collar jobs.

While general skill is important for productivity in each sector, assume that employers cannot observe each worker's general skill directly. Rather, an employer can only observe a worker's θ if it invests in a skill-assessment technology at a cost of $c > 0$ per worker.

Finally, define θ^* to be such that $\alpha_H + \beta_H\theta^* - c = \alpha_L + \beta_L E[\theta|\theta < \theta^*]$.[18] Given this definition, assume that the returns to general skill are sufficiently high in the H-sector and sufficiently low in the L-sector such that

$$\text{(A1)} \quad \frac{1}{\beta_L} > \frac{\theta^* - E[\theta|\theta < \theta^*]}{c} > \frac{1}{\beta_H}$$

Intuitively, Equation A1 assumes that there is a significant difference in the productivity return to skill across sectors, the cost of investing in skill-assessment technology is not exceedingly high nor exceedingly low, and the distribution of θ is relatively smooth and diffuse.

Given this environment, the objective of each worker is to maximize his expected wage by choosing which employer to work for, while the objective of each employer is to choose whether to invest in the skill-assessment technology for each worker and the wage schedule to offer to maximize expected profits and stay in business. In order to stay in business, each employer cannot lose money or fail to attract any workers in the long run, and, finally, assume new employers can freely enter either sector using the same technology as the incumbent firms.

A. Equilibrium

Equilibrium in this economy will occur when all workers and employers act optimally given the behavior of the others, no employer goes out of business, and no new employers have an incentive to enter either sector. The following behavior constitutes such an equilibrium:

(i) the H-sector employers invest in the skill-assessment technology and offer a wage schedule given by

$$\text{(5)} \quad \omega_H^*(\theta) = \alpha_H + \beta_H\theta - c,$$

(ii) the L-sector employers do not invest in the skill-assessment technology and offer a wage equal to

$$\text{(6)} \quad \omega_L^* = \alpha_H + \beta_H E[\theta \mid \theta < \theta^*],$$

and (iii) workers with a skill level greater than θ^* choose randomly between the H-sector employers, while workers with a skill level less than θ^* choose randomly between the L-sector employers.

18. Such a θ^* can be easily shown to exist via the assumptions made previously and application of the Intermediate Value Theorem.

To prove that the behavior described above constitutes an equilibrium in this environment, first note that the definition of θ^*, the fact that $\theta' - E[\theta|\theta < \theta']$ is increasing in θ', and Assumption A1, the following inequalities can easily be shown to hold true:

(7) $\alpha_H + \beta_H\theta' - c > \alpha_L + \beta_L E[\theta|\theta < \theta']$ *if* $\theta' > \theta^*$,

(8) $\alpha_H + \beta_H\theta' - c < \alpha_L + \beta_L E[\theta|\theta < \theta']$ *if* $\theta' < \theta^*$,

(9) $\alpha_H + \beta_H\theta' - c > \alpha_H + \beta_H E[\theta|\theta < \theta']$ *if* $\theta' > \theta^*$,

(10) $\alpha_L + \beta_L\theta' - c < \alpha_L + \beta_L E[\theta|\theta < \theta']$ *if* $\theta' < \theta^*$.

Now, let θ^e be the efficient sorting skill threshold, such that workers with a skill level above θ^e are more productive in the *H*-sector and workers with a skill level less than θ^e are more productive in the *L*-sector (specifically, $\alpha_H + \beta_H\theta^e = \alpha_L + \beta_L\theta^e$). Note that it will also be true that $\theta^* > \theta^e$, or the sorting threshold under imperfect information will be higher than the sorting threshold under perfect information. To see why this is true, note that if $\theta^* \leq \theta^e$, then Equation 7 implies that $\alpha_H + \beta_H\theta^e - c \geq \alpha_L + \beta_L E[\theta|\theta < \theta^e]$. Using the definition of θ^e, the previous expression implies $\alpha_L + \beta_L\theta^e - c \geq \alpha_L + \beta_L E[\theta|\theta < \theta^e]$, which in turn implies $\theta^e - E[\theta|\theta < \theta^e \geq c/\beta_L$. This however contradicts Assumption A1, meaning it cannot be true that $\theta^* \leq \theta^e$.

Given the inequalities in Equations 7-10, I can now confirm that worker behavior, *H*-sector employer behavior, and *L*-sector employer behavior, as defined in the proposed equilibrium, are optimal.

1. Worker Behavior

Optimal worker behavior is to work for the employer that offers the highest wage for his given skill level. Given the wage schedules in the proposed equilibrium, a worker *i* will optimally choose to work for an *H*-sector employer if and only if his skill level θ_i is such that

(11) $\alpha_H + \beta_H\theta_i - c \geq \alpha_L + \beta_L E[\theta \mid \theta < \theta^*]$.

From Equations 7 and 8 we know that Condition 11 will hold if and only if a worker has a skill level $\theta_i > \theta^*$. Therefore, given the employer behavior described by the proposed equilibrium, worker behavior as described by the proposed equilibrium is optimal.

2. H-Sector Employer Behavior

Next, we must confirm that no *H*-sector employer has an incentive to deviate from the proposed equilibrium behavior, given workers and the other employers behave in accordance with the proposed equilibrium. To do so, first note that by investing in the skill-assessment technology and offering a wage schedule equal to $\omega_H^*(\theta) = \alpha_H + \beta_H\theta - c$, the *H*-sector employers will not lose money, since this wage equals a worker's value product net of the skill-assessment investment.

Now, say one of the *H*-sector employers decides to invest in the skill-assessment technology, but offers a lower wage than the proposed equilibrium wage to any particular skill level. Such a wage offer would mean all workers of that skill level would choose to work for either the other H-sector employer (for workers with $\theta > \theta^*$) or for one of the L-sector employers (for workers with $\theta < \theta^*$). Similarly, if this employer invests in the skill-assessment technology, but offers a wage higher than $\omega_H^*(\theta)$ to any skill level, then it will surely lose money on each worker of that skill level it hires since it is paying that worker more than his value product. Hence, there is no incentive for an H-sector employer to make either of these deviations.

Alternatively, say an H-sector employer does not invest in the skill-assessment technology. By not investing in the skill-assessment technology, the employer cannot distinguish between workers and therefore must offer every worker the same wage, which will be denoted ω_H^d. If this wage ω_H^d is lower than ω_L^*, then this firm will go out of business because it will not be able to attract an workers.

On the other hand, say this noninvesting H-sector employer offers a wage ω_H^d higher than ω_L^*. This would immediately mean that all workers with $\theta < \theta^*$ would choose to work for this deviating H-sector firm, since their best other option is ω_L^*. Moreover, define θ^d to be such that $\alpha_H + \beta_H\theta^d - c = \omega_H^d$, making $\alpha_H + \beta_H\theta^d - c > \omega_L^*$. Recalling the definitions of ω_L* and θ^*, we then know $\alpha_H + \beta_H\theta^d - c > \alpha_H + \beta_H\theta^* - c$. This in turn implies $\theta^d > \theta^*$ and $\omega_H^d > \omega_H^*(\theta)$ for all workers with $\theta < \theta^d$. Hence, all workers with $\theta \in [\theta^*, \theta^d)$ would also choose to work for this deviating employer.

Given all workers with $\theta < \theta^d$ work for this deviating employer, the expected productivity of each worker working for this employer will be $\alpha_H + \beta_H E[\theta|\theta < \theta^d]$. However, given $\theta^* < \theta^d$, our definition of θ^d, and Equation 9, we know

$$\omega_H^d = \alpha_H + \beta_H\theta^d - c > \alpha_H + \beta_H E[\theta \mid \theta < \theta^d].$$

Therefore, the wage paid by this deviating employer, ω_H^d, is greater than the expected productivity of its workers. Hence, neither H-sector employer has an incentive to deviate from investing in the skill-assessment technology and paying each worker the value of his productivity minus the cost of the skill-assessment technology.

3. L-sector Employer Behavior

Finally, let us examine the L-sector employers. As shown above, if all employers behave according to the proposed equilibrium, all workers with $\theta < \theta^*$ will choose to work for an L-sector employer. Therefore, in equilibrium, L-sector employers will not lose money in the long run by offering all workers a wage of $\omega_L^* = \alpha_L + \beta_L [\theta|\theta < \theta^*]$.

If an L-sector employer deviated from this proposed equilibrium by offering a wage less than ω_L^*, no workers would choose to work for this deviating employer since they could all make more money by working for the other L-sector employer offering ω_L^*.

Alternatively, say an L-sector employer offered a wage ω_L^d greater than ω_L^*. This would once again cause all workers with $\theta < \theta^*$ to work for this deviating employer since their previous best other option is ω_L^*. If we now define θ^d to be such that $\omega_L^d = \alpha_H + \beta_H\theta^d - c$, then because $\omega_L^d > \omega_L^*$, and the definitions of ω_L^* and θ^*, we know $\alpha_H + \beta_H\theta^d - c > \alpha_H + \beta_H\theta^* - c$, meaning $\theta^d > \theta^*$ and $\omega_L^d > \omega_H^*(\theta)$ for all $\theta < \theta^d$. Therefore, all workers with $\theta < \theta^d$ would choose to work for this deviating employer.

Because all workers with $\theta < \theta^d$ would choose to worker for this deviating employer, the value of the expected productivity for workers working for this deviating employer would equal $\alpha_L + \beta_L E[\theta|\theta < \theta^d]$. However, since $\theta^d > \theta^*$, Equation 7 implies

$$\omega_L^d = \alpha_H + \beta_H\theta^d - c > \alpha_L + \beta_L E[\theta \mid \theta < \theta^d].$$

Therefore, an L-sector employer has no incentive to deviate from the proposed equilibrium by offering a wage greater than $\omega_L^* = \alpha_L + \beta_L E[\theta|\theta < \theta^*]$, since by doing so it will pay a wage to each worker higher than the value of his expected productivity.

The other deviation an L-sector employer can make is to invest in the skill-assessment technology. If an L-sector employer invests in the skill-assessment technology and offers a wage schedule that pays a worker of skill level θ *a* wage greater than $\alpha_L + \beta_L\theta - c$ it will lose money, giving no incentive for either L-sector firm to behave in this manner.

Alternatively, if an L-sector firm deviates by investing in the skill-assessment technology and offers a wage less than or equal to $\alpha_L + \beta_L\theta - c$ for any skill level θ, it will not be able to attract any workers. To see why, note that Equation 10 implies that for all $\theta < \theta^*$,

$$\alpha_L + \beta_L\theta - c < \alpha_L + \beta_L E[\theta \mid \theta < \theta^*] = \omega_L^*.$$

Therefore, no workers with $\theta < \theta^*$ would choose to work for an L-sector employer that invests in the skill-assessment technology and offers a wage less than or equal to $\alpha_L + \beta_L\theta - c$, since they could earn more by working for the other L-sector employer. Furthermore, since $\theta^* > \theta^e$ (the efficient sorting cutoff), we know that for all $\theta' > \theta^*$

$$\alpha_L + \beta_L\theta' - c < \alpha_H + \beta_H\theta' - c = \omega_H^*(\theta).$$

Therefore, no workers with $\theta > \theta^*$ would choose to work for such a deviating L-sector employer since they could make more with and H-sector employer. This confirms that neither L-sector employer has an incentive to deviate from the proposed equilibrium of not investing in the skill-assessment technology and offering each worker a wage equal to $\omega_L^* = \alpha_L + \beta_L E[\theta|\theta < \theta^*]$. Hence, the proposed equilibrium ensures each worker and employers acts optimally given the behavior of the others, confirming the proposed equilibrium.

B. Adding Two Distinguishable Racial Groups

Now, assume that workers can be divided into two costlessly distinguishable racial groups, denoted group w and group b. Assume that general skill is distributed normally for both groups, where both groups have the same variance in general skill but group w has a higher mean skill level than group b (specifically, $\mu_b < \mu_w$ where μ_r is the mean skill level for group r).[19] In words, for reasons not modeled here, assume workers from group b have generally acquired a lower level of general skills prior to entering the labor market than workers from group w.[20] The key implication of this difference across

19. The assumption that the variance in general skill is the same across groups is not necessary for the results of the model, but does simplify the analysis substantially.

20. Clearly, a number of factors could account for this, including segregated and unequal public schools, credit constraints impacting race b more than race w, or differing "social capital" across racial groups. Clearly, endogenizing skill would substantially complicate the model, and is not the focus of this analysis.

groups is that, given the normal distributions, it will be true that $E[\theta|\theta < \theta', \mu_r]$ is increasing in μ_r meaning $E[\theta|\theta < \theta', \mu_w] > E[\theta|\theta < \theta', \mu_b]$ for any θ'.[21]

This difference in premarket skill distributions across groups will mean that the θ_r^* that solves

$$\alpha_L + \beta_L E[\theta \mid \theta < \theta_r^*, \mu_b] = \alpha_H + \beta_H \theta_r^* - c,$$

will differ by group r.[22] In particular, $\theta_b^* < \theta_w^*$.

1. Implications

The first implication to note is that conditional on general skill, group b workers will be paid the same as group w workers in the H-sector, but be paid less than group w workers in the L-sector. To see this, simply note that from Equation 5, a worker of skill level θ will be paid $\omega_H{}^*(\theta) = \alpha_H + \beta_H\theta - c$ in the H-sector, which is obviously the same across races. On the other hand, from Equation 6, we know that a worker of skill level θ from race r will be paid $\omega_L^* = \alpha_L + \beta_L E[\theta|\theta < \theta_r^*, \mu_r]$ in the L-sector. Since $E[\theta|\theta < \theta_w^*, \mu_w] > E[\theta|\theta < \theta_b^*, \mu_b]$, it is straightforward to see that group b workers will be paid less than group w workers of similar general skill in the L-sector.

The second implication is that, conditional on a noisy measure of general skill, black workers should be more likely than white workers to work in the more skill-intensive H-sector. To formally prove this implication is true, first assume that premarket general skills as measured by the econometrician are captured by $\eta = \theta + \varepsilon$, where ε is a mean zero i.i.d. random variable drawn from the distribution G. This means the probability that a worker from race r with a measured skill level of η chooses to work in the H-sector is equal to $\Pr(\theta > \theta_r^*|\eta)$, or equivalently $\Pr(\eta - \theta_r^* > \varepsilon) = G(\eta - \theta_r^*)$. Because $\theta_b^* < \theta_w^*$, it is true that $G(\eta - \theta_b^*) > G(\eta - \theta_w^*)$, meaning for any observed skill level η, a worker from group b will be more likely to work in the H-sector than a worker from group w.

Note that this implication does not necessarily imply that group b workers are *unconditionally* more likely to work in the H-sector than group w workers. The unconditional probability that a group b worker chooses to work in the H-sector is given by $1 - F_b(\theta_b^*)$, while the unconditional probability that a group w worker chooses to work in the H-sector is given by $1 - F_w(\theta_w^*)$, (where F_b and F_w are the premarket general skill distributions for members of race b and race w respectively). Therefore, if F_b is sufficiently greater than F_w near θ_b^*, then even though $\theta_b^* < \theta_w^*$, it may still be the case that $1 - F_b(\theta_b^*) < 1 - F_w(\theta_w^*)$.

The third and final implication of this model is that the mean and variance of wages should be higher in the H-sector than the L-sector, both overall and for each racial group. The higher mean wage in the H-sector is a direct result of sorting being determined by the threshold θ_r^*, which causes all individuals who work in the H-sector earn more than all individuals from the same racial group working in the L-sector.

21. The normal distribution is used here for convenience, but the results will hold for any two distributions such that $E[\theta|\theta < \theta', \mu_w] > E[\theta|\theta < \theta', \mu_b]$ for any θ'.

22. It is assumed that β_L is sufficiently lower than β_H such that Assumption A1 holds for both the group's general skill distributions.

The higher variance is a direct result of the fact that everyone of the same race gets paid the same in the L-sector via Equation 6, but wages vary by general skill level in the H-sector via Equation 5.

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