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

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Abstract

This paper argues that the underlying causes of racial wage inequality may differ across labor market sectors. In particular, because employers hiring for jobs in the more highly skill-intensive sector have a greater incentive to accurately assess worker skill than employers hiring for jobs in the less skill-intensive sector, these more skill-intensive employers also have incentives to invest more in skill revealing technology, and thereby obtain more precise information regarding worker skill, than less skill-intensive employers. Under some technologies, these cross sector information differences will lead to several implications regarding racial wage inequality. Most notably, (i) after controlling for worker skill, very little racial wage inequality should remain in the highly skill-intensive sector, yet substantial racial wage inequality may remain in the less skill-intensive sector, and (ii) workers from the relatively worse paid group should be more likely than similarly skilled workers from the better paid group to work in the highly skill-intensive sector. Using data from the NLSY, I find empirical support for these implications. Specifically, after controlling for pre-market academic skills, the entire racial wage gap disappears in the highly skill-intensive sector, but almost half of the unconditional gap remains in the less skill-intensive sector. Furthermore, I find that black workers are roughly

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25 percent more likely than similarly skilled white workers to work in the highly skill-intensive sector.

1 Introduction

Previous empirical work on racial wage inequality has shown that over two-thirds of the overall racial wage gap can be attributed to racial differences in pre-market academic skills [Neal and Johnson, 1996]. However, the underlying reasons for the remaining portion of the wage gap are less clear. Several current theoretical models suggest that one possible explanation for this remaining wage inequality is statistical discrimination on the part of employers, due to imperfect information regarding some aspects of each worker's general skills [Phelps, 1972; Arrow, 1974; Aiger and Cain, 1977; Lundberg and Startz, 1983; Coate and Loury, 1994; Cornell and Welch, 1996; Norman and Moro, 2003].

While such imperfect information is plausible for employers hiring for jobs where an individual's general skills, such as academic proficiency, contribute little to productivity, such an assumption may not be realistic for employers who hire for jobs where such skills have a large influence on productivity. More specifically, it is certainly possible for all employers to obtain very precise information concerning the academic skills of applicants and workers by either devising exams to test such skills directly, or by performing extensive background checks into each applicant's academic history. However, designing and administering an academic skills test and/or researching the academic background of all applicants is likely to be very costly. Hence, employers hiring for jobs where academic skills contribute only marginally to productivity (e.g. clerical, blue-collar) may not find it cost effective to make such investments. On the other hand, employers hiring for highly skill-intensive jobs (e.g. professional, managerial, sales) generally have very large incentives to differentiate between workers on the basis of academic skill, meaning such employers may often find such investments to be worthwhile.

This paper investigates the consequences of such differing incentives for investing in skill assessment technology across the labor market, specifically with respect to racial wage inequality. I begin the analysis by developing and examining the implications of a simple model of the labor market where assessing the general skills of each worker is costly to an employer, and there exist two distinct sectors of employers—those that hire for highly skill-intensive jobs ("H-sector jobs") and those that hire for less skill-intensive jobs ("L-sector jobs").

Because skill has a greater importance for production in the H-sector, employers hiring for H-sector jobs will generally choose to invest greater resources in the skill revealing technology than employers hiring for L-sector jobs. This causes employers hiring for H-sector jobs to have more accurate information concerning the general skills of each worker than employers hiring for L-sector jobs. Under a variety of technology assumptions, such cross sectoral informational differences will cause wages in the L-sector to depend more on the average skill level of workers of the same race than wages in the H-sector. I then show that when this is the case, and if white workers enter the labor market having acquired greater general skills on average than black workers, then the following implications should hold concerning race and the labor market. First, the mean and variance of wages should be higher in the H-sector, both overall and for each race separately. Second, black workers should be paid equally to similarly skilled white workers in the H-sector, but be paid substantially less than white workers of similar skill levels in the L-sector. Third, black workers should be more likely than white workers with similarly measured skill to choose to work in the H-sector. Fourth, black workers should be under-represented among the most skilled workers in both sectors relative to the overall racial composition in each sector.

Using data from the National Longitudinal Survey of Youth 1979 I find evidence consistent with each of these implications. Most notably, in support of the second implication, I find that the entire racial wage gap in the H-sector (professional-technical-managerial-sales jobs) disappears after accounting for racial differences in pre-market academic skill, yet almost half of the gap remains in the L-sector (all other jobs) after controlling for pre-market academic skills. Moreover, in support of the third implication, black workers appear to respond to this differing treatment across sectors in the manner described by the model by being roughly 25 percent more likely to work in the H-sector than white workers of similar pre-market academic skill.

The empirical findings described above, as well as further empirical findings supporting the remaining two implications from the model, reveal the model to be consistent with real world data. This suggests that the underlying causes of racial wage inequality may differ significantly across labor market sectors. Namely, while most of the wage inequality in the highly skill-intensive job sector appears to be due to a racial gap in the acquisition of pre-market academic skills, the inequality in the less skill-intensive job sector may be the product of both a racial gap in pre-market academic skills as well as statistical discrimination on the part of employers.

The remainder of the paper is organized as follows. Section 2 presents a model of the labor market with two technology sectors and costly skill assessment. I then examine this model in the context of race, deriving implications regarding racial wage inequality and racial differences in sector choice. In Section 3, I evaluate the model and its implications empirically using data from The Multi-City Study of Urban Inequality, The National Survey of Employers 1982, and The National Longitudinal Survey of Youth 1979. Section 4 discusses some alternative theories for the findings presented in Section 3, and finally, Section 5 summarizes and concludes.

2 Theoretical Framework

This section presents a simple model of a labor market with two sectors, where the general skill of a worker has a greater influence the productivity of the worker in one sector than the other. After describing the equilibrium of the model, I show what implications this equilibrium has for understanding and assessing the underlying nature of racial wage inequality.

2.1 Model of a Two Sector Labor Market

Consider an economy with a large number of workers, where each worker can be characterized by his general skill level denoted θ.[1] Let θ be a random variable drawn from a distribution F defined over an unbounded support with a well defined expectation $E[\theta]$, where $\theta' - E[\theta|\theta \leq \theta']$ is strictly increasing in θ', but goes to zero as θ' goes to negative

[1] "General skills" refer to skills that affect a worker's productivity in all firms in the labor market. In others words, these are not firm or task specific skills. In the empirical portion of the paper to follow, "general skills" are assumed to be academic skills, such as reading comprehension, vocabulary, and arithmetic skills.

infinity.[2] 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 L-sector, with two identical firms in each sector.[3] 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 $\beta_L < \beta_H$. In other words, a worker's general skill level affects productivity more in the H-sector than the L-sector. 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 (i.e. $\alpha_H + \beta_H\theta^e = \alpha_L + \beta_L\theta^e$).

Furthermore, assume a firm can only observe a worker's θ if it invests in a skill assessment technology at a cost of $c > 0$ per worker. Given the technology differences across sectors, H-sector employers have a stronger incentive than L-sector employers to make this investment in the skill assessment technology.

Finally, define θ^* to be such that $\alpha_H + \beta_H\theta^* - c = \alpha_L + \beta_L E[\theta|\theta < \theta^*]$.[4] Given this definition, assume that the returns to general skill are sufficiently greater in the H-sector than the L-sector such that

$$\frac{c}{\beta_H} < \theta^* - E[\theta|\theta < \theta^*] < \frac{c}{\beta_L}. \qquad (A1)$$

Figure 1 summarizes this assumption graphically. The shape of $\theta' - E[\theta|\theta < \theta']$ in Figure 1 is derived by assuming θ is distributed normally.

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 or not to invest in the skill assessment technology for each worker

[2]Note that this is not a very restrictive assumption as many common distributions meet these criteria, including the normal and the uniform distributions. For the normal distribution in particular, $\theta' - E[\theta|\theta \leq \theta']$ will be an increasing convex function of θ'. This is depicted in Figure 1.

[3]Two employers in each sector is used for convenience only. More generally, the model will hold for any number of employers greater than one.

[4]Existence and uniqueness of θ^* is proved in the Appendix.

and the wage schedule to offer so as 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 new employers can freely enter either sector using the same technology as the incumbent firms.

2.2 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. My assertion is that the following behavior constitutes an equilibrium:
(i) the H-sector employers invest in the skill assessment technology and offer a wage schedule given by

$$\omega_H^*(\theta) = \alpha_H + \beta_H\theta - c,$$

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

$$\omega_L^* = \alpha_L + \beta_L E[\theta|\theta < \theta^*],$$

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

(iv) workers with a skill level less than θ^* choose randomly between the L-sector employers.

To confirm this is an equilibrium, first note that the definition of θ^*, the fact that $\theta' - E[\theta|\theta \leq \theta']$ is increasing in θ', and assumption (A1), we know the following inequalities will hold true:

$$\alpha_H + \beta_H\theta' - c > \alpha_L + \beta_L E[\theta|\theta < \theta'] \quad \text{if } \theta' > \theta^*, \tag{1}$$

$$\alpha_H + \beta_H\theta' - c < \alpha_L + \beta_L E[\theta|\theta < \theta'] \quad \text{if } \theta' < \theta^*, \tag{2}$$

$$\alpha_H + \beta_H \theta' - c > \alpha_H + \beta_H E[\theta|\theta < \theta'] \quad \text{if } \theta' > \theta^*, \tag{3}$$

$$\alpha_L + \beta_L \theta' - c < \alpha_L + \beta_L E[\theta|\theta < \theta'] \quad \text{if } \theta' < \theta^*. \tag{4}$$

Further 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 $\theta^e \geq \theta^*$, then equation (1) 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 $\theta^e - E[\theta|\theta < \theta^e] \geq \frac{c}{\beta_L}$. This however contradicts assumption (A1), meaning it cannot be true that $\theta^e \geq \theta^*$.

Given the inequalities in equations (1)-(4), I can now confirm that worker behavior, H-sector employer behavior, and L-sector employer behavior, as defined in the proposed equilibrium, are optimal.

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 will optimally choose to work for an H-sector employer if and only if his skill level θ is such that

$$\alpha_H + \beta_H \theta - c > \alpha_L + \beta_L E[\theta|\theta < \theta^*]. \tag{5}$$

From equations (1) and (2) we know that condition (5) will hold if and only if a worker has a skill level $\theta > \theta^*$. Therefore, given the employer behavior described by the proposed equilibrium, worker behavior as described by the proposed equilibrium is optimal.

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.

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 non-investing H-sector employer offers a wage ω_H^d higher than ω_L^*. This would immediately mean that all workers with $\theta \leq \theta^*$ 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 $\theta^d > \theta^*$, our definition of θ^d, and equation (3), we know

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

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.

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 $\omega_L^* = \alpha_L + \beta_L E[\theta|\theta < \theta^*]$.

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.

Since 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 (1) implies

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

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 (4) implies that for all $\theta < \theta^*$,

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

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 $\theta^* > \theta^e$ (i.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.

2.3 Adding Two Distinguishable Racial Groups

In the equilibrium described and confirmed above, the wages in the H-sector depend only on a worker's pre-market skill level and are given by the function $\omega_H^*(\theta) = \alpha_H + \beta_H\theta - c$. Alternatively, wages in the L-sector depend only on the mean skill level of all workers in the L-sector and are given by $\omega_L^* = \alpha_L + \beta_L E[\theta|\theta < \theta^*]$. These wage schedules show that while wages in the H-sector depend only on worker skill, wages in the L-sector depend on the distribution of skill level in the population and the skill level threshold θ^* that determines who works in the L-sector.

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 (i.e. $\mu_b < \mu_w$). In words, for reasons not modelled 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. The key implication of this difference across groups is that, given the normal distributions, $E[\theta|\theta < \theta', \mu_j]$ is increasing in μ_j, meaning $E[\theta|\theta < \theta', \mu_w] > E[\theta|\theta < \theta', \mu_b]$ for any θ'.[5]

This difference in pre-market skill distributions across groups will mean that the θ_j^* that solves

$$\alpha_L + \beta_L E[\theta|\theta < \theta_j^*, \mu_j] = \alpha_H + \beta_H \theta_j^* - c,$$

will differ by group j.[6] In particular, $\theta_b^* < \theta_w^*$.

Because employers can costlessly distinguish between groups, it will be true that equilibrium wages for any worker in the L-sector will depend only the mean skill level for L-sector workers of that worker's group. However, since H-sector employers invest in the skill assessment technology, H-sector workers are still compensated only according to their own skill level. Figure 2 graphically depicts how the equilibrium wage schedules will differ across sectors and across races, as well as why $\theta_b^* < \theta_w^*$.

2.4 Implications of the Model

The primary implications of this model can now be explicitly stated.

Implication 1 Wages in the H-sector will have a higher mean and exhibit greater variation than wages in the L-sector, both overall and by group.

This first implication is a straightforward from the fact that, in equilibrium, the wage schedule in the L-sector is constant for all workers of the same racial group, while the wage schedule in the H-sector varies across workers according to general skill level of the worker, and that workers only choose to work in the H-sector if they can earn a higher wage in the H-sector. A corollary implication to this result is that the wage distribution will be right-skewed—a fact that has been documented numerous times in the empirical literature.

[5]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 all θ'.

[6]It is assumed that β_L is sufficiently lower than β_H such that Assumption (A1) holds for both the black and white general skill distributions.

Implication 2 Group b workers will be paid lower wages than similarly skilled group w workers in the L-sector, but will be paid equally to similarly skilled group w workers in the H-sector.

This implication comes from fact that in L-sector, a worker of skill level θ from group b will be paid $\omega_L^*(b) = \alpha_L + \beta_L E[\theta|\theta < \theta_b^*, \mu_b]$, while a similarly skilled worker from group w will be paid $\omega_L^*(w) = \alpha_L + \beta_L E[\theta|\theta < \theta_w^*, \mu_w]$. Since $\theta_w^* > \theta_b^*$, and $E[\theta|\theta < \theta', \mu_w] > E[\theta|\theta < \theta', \mu_b]$ for any $\theta' \in [0, \overline{\theta}]$, it will be true that $\omega_L^*(w) > \omega_L^*(b)$. Hence, an L-sector worker from group w is paid more than an L-sector worker from group b, regardless of skill level θ. Alternatively, an H-sector worker of skill level θ will be paid a wage equal to $\omega_H^*(\theta) = \alpha_H + \beta_H\theta - c$, regardless of which group the worker is from.

This implication does not necessarily imply that the unconditional racial wage gap should be larger in the L-sector than the H-sector. To see why, first note that the unconditional racial wage gap in the L-sector is given by $\beta_L(E[\theta|\theta < \theta_w^*, \mu_w] - E[\theta|\theta < \theta_b^*, \mu_b])$, and the unconditional racial wage gap in the H-sector is given by $\beta_H(E[\theta|\theta \geq \theta_w^*, \mu_w] - E[\theta|\theta \geq \theta_b^*, \mu_b])$. Hence, the unconditional racial wage gap in each sector depends both on the difference between θ_w^* and θ_b^*, as well as the difference in general skill distributions across the two groups. Therefore, even though there is no racial wage gap in the H-sector after conditioning on skill level, it is theoretically possible for there to be a larger wage gap in the H-sector than the L-sector without conditioning on skill level.

Implication 3 Conditional on a noisy measure of general skill, group b workers will be more likely than group w workers to work in the H-sector.

To see why this is true, first assume that pre-market general skills can only be measured with noise by the econometrician, meaning measured pre-market general skills are captured by $\eta = \theta + \epsilon$, where ϵ is a mean zero i.i.d. random variable drawn from the distribution G. This means the probability that a worker from group j with a measured skill level of η chooses to work in the H-sector is equal to $Pr(\theta > \theta_j^*|\eta, \theta_j^*)$, or equivalently $Pr(\eta - \theta_j^* > \epsilon|\eta, \theta_j^*) = G(\eta - \theta_j^*)$. 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 pre-market general skill distributions of the b group and w group 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 $1 - F_b(\theta_b^*) < 1 - F_w(\theta_w^*)$.

Before stating the fourth implication, define the "most skilled" workers in the j-sector (for j = H, L) to be all workers in that sector with a skill level greater than some cutoff S_j. Given this definition, the fourth and final Implication can be stated.

Implication 4 If the skill threshold for choosing to work in the H-sector is sufficiently high for each group such that more than half of the workers from each group choose to work in the L-sector, and if S_L is sufficiently strict such that more than half of group w workers have a skill level below this cutoff, and $S_L < \theta_b^* < \theta_w^* < S_H$, then it is necessarily the case that workers from group b will make up a smaller fraction of the *most skilled* workers in the each sector than they make up of each sector as a whole.

In simpler terms Implication 4 states that, under certain reasonable conditions, group b workers will be under-represented among the most skilled workers in each sector relative to their overall fraction of each sector.[7] The proof of this Implication is relegated to the Appendix, but the intuition is relatively straightforward. Namely, one of the forces leading to this result is the fact that because group b workers have a lower skill threshold to overcome to work in the H-sector, group b workers who could be among the most skilled members of the L-sector, choose instead to work as one of the least skilled members of the H-sector. This brings down the fraction of group b workers who would be among the most skilled members of the L-sector, and brings up the fraction of group

[7] Note that $F_w(S) \geq 1/2$ is a sufficient condition for group b to be under-represented among the most skilled members of the L-sector, but is not necessarily required.

b workers who will not be among the most skilled members in the H-sector.

3 Discussion and Possible Extensions to the Model

At this point, it is worth briefly comparing the implications presented above to what would arise from a model with complete information. With complete information, all workers would be paid according to their productivity, causing workers to work in the H-sector as long as their skill level exceeded the efficiency cutoff θ^e defined at the beginning of the model. While this wage structure would still imply that mean wages would be greater in the H-sector than the L-sector, it would not necessarily be the case that the variance of wages would be greater in the H-sector than the L-sector, as variance of wages in the H-sector could be greater or smaller than in the L-sector depending on the variance of the skill distributions and the value of θ^e. Moreover, in contrast to Implications 2 and 3 coming from this model, complete information implies that racial wage inequality should disappear in both sectors after controlling for skill level, and both groups should be equally likely to work in the H-sector after conditioning on a noisy measure of skill. Finally, under complete information, it will still generally be true that group b workers should be under-represented among the most skilled members of each sector.[8] However, the degree of this under-representation should be much larger under imperfect information, as the degree of under-representation among the most skilled in each sector is extenuated by the differential sorting thresholds across sectors by races as described above. Therefore, finding that a less-skilled group is not significantly under-represented among the most skilled in each sector would be even stronger evidence against the model with imperfect information in the L-sector than a model of complete information.

It is also worth noting that the model presented above can be easily extended so that it is not necessarily true that employers can more accurately predict the future productivity of a new entrant to the H-sector than the future productivity of a new entrant to the L-sector. Specifically, say productivity in each sector j is captured by $v_j(\theta) = \alpha_j + \beta_j \theta + \epsilon_j$, where ϵ_j is an occupation specific skill of each worker at each firm in

[8] Specifically, if general skill is distributed normally for each group, with a similar variance and $\mu_b < \mu_w$, and more than half of each racial group has a general skill level less than θ^e.

sector j. If ϵ_j is an independent random variable across individuals, is unknown to both workers and employers at the time of hiring, and the variance of ϵ_H exceeds the variance of ϵ_L, then all of the implications of the above model hold true and H-sector employers may actually be less accurate in their predictions of new employees' future productivity than L-sector employers, even if only H-sector employers perfectly observe each new worker's general skill level θ. In other words, it is possible for greater uncertainty over occupation specific skills to swamp greater certainty over general skills.[9]

Finally, it is important to consider the consequences of relaxing the assumption that investing in the skill assessment is binary. Specifically, can the results coming from the model still arise if the investment in the skill assessment technology were a continuous decision, where an observed skill signal becomes more precise the greater the investment in the skill assessment technology?[10] For example, say the precision of the skill signal were an increasing convex function of the investment. Note, however, that this is essentially just a special case of the assumption employed in the model developed in the previous section, as optimal employer behavior under this new skill assessment technology will always be to either invest in the skill assessment technology until worker skill is perfectly revealed, or not invest at all. Hence, this skill assessment technology will necessarily lead to identical results as the situation as depicted in the model above.

Alternatively, rather than an increasing convex function, say the precision of the skill signal were an increasing concave function of the investment. In this case, employers in both sectors will invest in the skill assessment technology, but neither will generally invest enough to fully reveal each worker's general skill level. While H-sector employers will typically still invest more in the skill assessment technology than L-sector employers, the remaining imperfect information in the H-sector may be great enough such that, in an equilibrium under this technology, wages for an individual in the H-sector will be more affected by the average skill level of other workers of the same race, than wages in the L-sector. However, this result will not always be true. Specifically, it is still possible that even under this skill assessment technology, the differing incentives across sectors cause the relative investments in skill assessment to be such that the skill information

[9] Note that this modification to the model also means that, if the econometrician cannot observe the task specific skill, then the wage variation that remains after controlling for general skill does not necessarily have to be greater in the L-sector.

[10] Thank you to Gordon Dahl for raising this discussion.

in the H-sector is sufficiently more precise than in the L-sector to cause wages in the L-sector to depend more on the average skill level of other workers of the same race, than wages in the H-sector.

This discussion reveals that, even if the precision of the skill assessment signal were modelled as a continuous function of investment in the skill assessment technology, it is still quite plausible that cross sector differences in the importance of worker skill to productivity causes wages in the less skill-intensive job sector to depend more the average skill level of other workers of the same race, than wages in the more skill-intensive job sector. As shown in the previous section, such differing wage structures will have important implications with respect to the underlying causes of racial wage inequality across sectors. The next section examines these implications empirically, attempting to assess whether the model presented in the previous section is a reasonably accurate depiction of the labor market or should be rejected.

4 Empirically Analyzing the Black-White Wage Gap Across Labor Market Sectors

The model developed in Section 2 showed that technology differences across sectors will likely result in differences in skill assessment investment, and therefore skill assessment accuracy, across employment sectors. Under some technologies, this was shown to result in substantially different wage structures across employments sectors. Specifically, while wages in the more skill-intensive sector would depend primarily on individual worker skill, wages in the less skill-intensive sector would depend primarily on the average skill of all workers in of the same race in that sector.

Such differing wage structures across sectors were then shown to lead to four implications with respect to race and the labor market. First, since workers cannot be very accurately distinguished on the basis of skill in the less skill-intensive sector, and only the most skilled workers select themselves into the more skill-intensive sector, the mean and variance of wages should be greater in the more highly skill-intensive job sector, both overall and for each race individually. Second, if black workers enter the labor market with lower general skills than white workers on average, then the racial wage gap in the highly skill-intensive job sector should be primarily explained by the racial skill gap, but significant racial wage inequality may remain in the less skill-intensive sector even after controlling for racial skill differences. Intuitively, employers only engage in statistical discrimination when the productivity benefits of more accurately distinguishing workers on the basis of skill are outweighed by the costs of doing so. Third, the more racially equitable wage structure in the more skill-intensive sector causes black workers to have a greater incentive than equally skilled white workers to work in the more skill-intensive sector, implying that black workers should be more likely to work in the highly skill-intensive job sector than white workers with similarly measured general skill. Finally, because medium skilled black workers become more likely to choose to work in the more skill-intensive job sector than medium skilled white workers, black workers should be significantly under-represented among the most skilled workers in each job sector compared to the overall racial composition of that sector.

This section assesses whether these implications are consistent with real world data. Before doing so however, I first describe the data sets to be used, and examine the underlying forces assumed to be driving the results of the model. Namely, I assess whether there appears to exist two distinct sectors in the economy that can be distinguished by the relationship between a worker's general skill and a worker's productivity, and whether such technology differences across sectors cause employers in what is defined to be the more highly skill-intensive sector to invest more in skill assessment than employers in the less skill-intensive sector.

4.1 Data

I will use three separate data sets in the course of this empirical analysis. The primary data set 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 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 paper consists of male white and black workers, not in the low-income white or military oversamples, with valid ASVAB test scores, and a valid CPS wage and occupation for at least one year between 1989 and 1993.

The second data set to be used comes from The National Survey of Employers 1982 (NSE). This survey interviewed over 5,000 nationally representative American for-profit employers and was a 1982 follow-up to the Employers Opportunities Pilot Project (EOPP) of 1980. The primary goal of both surveys was to evaluate the effect of government training programs on hiring practices and outcomes of employers. In the course of this goal, 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. The sample used in this paper restricts the data to only firms with valid answers to a question regarding the number of hours spent "screening, interviewing, and testing" applicants during the course of hiring the most recently hired worker.

The third and final data set to be used comes from the employer portion of 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. The MCSUI consists of a household and employer survey. The household survey consists of a random sample of adults in Atlanta, Boston, Detroit, and Los Angeles. The data to be used in this analysis comes from the employer survey, 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.

4.2 Defining Sectors and Evaluating Skill Assessment Investment Across Sectors

Recalling the model presented in Section 2, the two labor market sectors were distinguished by the importance of each worker's general pre-market skills on his productivity. For the purposes of this analysis, the general pre-market skills alluded to in the model will refer to general academic skills such as the reading comprehension, vocabulary, writing, and arithmetic proficiency acquired prior to labor market entry. Given this definition of general skills, let us define the H-sector to be professional-technical-managerial-sales jobs, leaving the L-sector to be comprised of all other jobs. For these sectoral distinctions to be consistent with the model, the general pre-market academic skills described above must be significantly more important for productivity in the jobs designated to be in the H-sector than in jobs designated to be in the L-sector. While common wisdom suggests this to be true, data from the MCSUI is used to more formally evaluate this assertion.

The MCSUI collected data on the frequency different tasks were used in the most recently hired position. The tasks examined here consist of "reading instructions at least one paragraph in length" (Read), "Write paragraphs or memos" (Write), "Do arithmetic or other computations" (Math). Performing these tasks certainly requires the academic skills defined to be the general skills relevant for this analysis. Hence, the more often these tasks are performed, the more important general skills are likely to be for worker productivity.

Figures 1(a)-1(c) show that workers defined to be in H-sector jobs performed each task much more frequently than workers defined to be in the L-sector. In particular, workers in H-sector jobs are significantly more likely to perform each of these tasks daily and significantly less likely to never perform any these tasks, than workers in L-sector jobs. These findings give quantitative evidence to the common perception that general skills, as defined above, are far more important in the jobs defined to be in the H-sector than the jobs defined to be in the L-sector. Hence, the sectoral distinctions made above appear to be a justifiable division of the labor market in terms of the model presented in Section 2.

Next, we must examine whether this greater importance of general skills in the H-sector causes H-sector employers to invest more resources in evaluating and uncovering each individual worker's general skill level than do L-sector employers. While it is impossible to assess the degree to which each employer accurately observes each of its workers' general skill levels, it is possible to obtain some evidence describing the amount of resources each employer invests in assessing each worker's skills. In particular, it can be argued that the more time an employer spends recruiting, screening, testing, and interviewing candidates, the better the information it should have regarding the overall skills, including the general academic skills, of each candidate. Once again, the common perception is that employers hiring for the jobs defined to be in the H-sector spend far more time recruiting, screening, testing, and interviewing job candidates than employers hiring for L-sector jobs. This notion is confirmed using data from the NSE. As can be seen in Figure 2, employers hiring for H-sector jobs spend on average over 75 percent more time recruiting, screening, testing, and interviewing job candidates than employers hiring for L-sector jobs.

In order to ensure this result holds after controlling for employer and hired employee characteristics, Table 1 presents the results from an OLS regression of the log of hours spent recruiting, screening, testing, and interviewing job candidates on controls for whether or not the hired employee was hired for an H-sector position, the size of the employer, the number of applicants for the position, the gender of hired employee, the age of hired employee, and the employer's industry. As can be seen in the top row of Table 1, even after controlling for these other employer and employee characteristics, employers hiring for H-sector jobs spend almost 50 percent more time recruiting, screening, testing, and interviewing job candidates than employers hiring for L-sector jobs. While this finding does not conclusively prove that employers hiring for H-sector jobs have significantly more accurate information regarding the general academic skills of each of their hired workers than do L-sector employers, it does suggest that they at least have greater opportunity to observe these skills prior to hire.

4.3 Analyzing Implications Regarding Race and the Labor Market

The previous section showed that there appear to be significant differences in both the importance of general skills in productivity across employment sectors, as well as significant differences in skill assessment investment across employment sectors. This section uses the data sample from the NLSY79 to evaluate whether these cross sector differences manifest themselves in the labor market in the manner described by the model.

Mean and Variance of Wages Across Sectors

Table 2 describes how the mean and variance of wages differs across sectors and races. The unit of observation is a person-year, for the years 1989-1993. Therefore, if an individual has 3 years of valid wage and occupation data, he will provide 3 observations to the data set. However, since each individual's wage and occupation are likely not to be independent across years, the standard errors are adjusted to allow for correlation in wage across years for each individual.[11]

The results shown in Table 2 are consistent with Implication 1 from the model, as the mean and variance of wages are greater in the H-sector, both overall and for each race. Specifically, overall wages in the H-sector are almost fifty percent larger in the H-sector than the L-sector, with the wage premium for the H-sector being very similar across races. The overall variance of wages in wages is over twice as large in the H-sector than the L-sector, with the greater degree of variance in the H-sector being very similar for both black and white workers.

Racial Wage Inequality Across Sectors

The second implication of the model was that, after conditioning on general pre-market skill, the black-white wage gap should be effectively erased in the H-sector, but may remain significant in the L-sector. In order to examine this hypothesis, we first need to find a plausible measure of general skills, where general skills are defined to be the pre-market academic skills discussed in Section 3.2.

Although it is impossible to find a perfect measure of such skills, Neal and Johnson [1996] (as well as others) have argued that scores from AFQT tests can be taken to be a noisy, but accurate measure of these general pre-market academic skills. The AFQT test consists of the vocabulary, reading comprehension, arithmetic, and numeric portions of the ASVAB test. The ASVAB test is a test used by the United States Military to assess skills of new recruits in order to determine which jobs to assign the recruits to. Both the AFQT and the ASVAB tests are 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 tests are simply used to assess the general skills acquired by a recruit prior to taking the test, in order to place the new recruit at jobs most appropriate to his or her skill level. These scores are clearly affected by many influences including teachers, parents, peers, and social effects. However, it seems quite justifiable to say that an individual's AFQT score provides at least a noisy but accurate measure of his or her general academic skill.[12]

[11]Specifically, standard errors are clustered by individual. The interpretation of each coefficient is that, were the data collection repeated using identical sampling and we were to re-estimate the model, we would expect to obtain coefficient estimates within the 95% confidence interval of each coefficient 95% of the time (Stata User Guide (1997)).

[12]The test has been evaluated numerous times to determine whether it is racially biased in its results

The military administered ASVAB tests to most of the NLSY79 respondents in order to re-norm the test.

Table 3 describes the black-white wage gap over the labor market as a whole. The coefficients in Table 3 come from OLS regressions of log wages on dummy variables for whether the respondent is black, as well as controls for the year of the wage observation, birth year, and other characteristics determined prior to labor market entry. As before, the unit of observation for this analysis is a person-year, for the years 1989, 1990, 1991, 1992, and 1993, and standard errors are adjusted to allow for non-independence for an individual's wage and occupations across years.[13] While this analysis could be done using wage data for only one particular year, thereby limiting each individual to appear only once, such estimates would sacrifice valuable information since individuals switch jobs and receive raises over the course of years.[14]

The first column of Table 3 estimates the unconditional racial wage gap using the data set created for this analysis. The coefficient on the black dummy variable of -0.26 implies that, in the early 90s, black workers in their late twenties and early thirties made roughly 26 percent less than white workers of similar age. The coefficient on the black dummy variable in column 2 of Table 3 shows how this overall racial wage gap changes after controlling for general pre-market skills as measured by AFQT scores. Column 3 further controls for other plausible variables that may capture, or at least be correlated with, different dimensions of general skills, including education, potential experience,[15] family characteristics,[16] as well as region of residence.

We can see that after conditioning on the measures of general skill, the racial wage gap falls to roughly 6 percent. This finding corresponds to Neal and Johnson [1996],

or predictive power. There have been no studies as of yet showing strong evidence for any such bias. See Neal and Johnson [1996] for more in depth discussion.

[13]Given that respondents were born between 1957 and 1964, wages are observed when the respondents were in their late twenties and early thirties.

[14]All regression specifications were also run for each year separately. Although coefficient estimates differed across years, they did differ meaningfully from any of the general findings of this analysis. Results available from author upon request.

[15]Potential experience equals age - education - 6

[16]Family characteristics include the educational attainment of parents, whether the individual's mother and/or father was employed as a professional when the individual was 14, whether the individual lived in a two parent family at the age of 14

who show that conditioning on AFQT scores and education lowers the overall black-white wage gap by over two-thirds. As discussed by Neal and Johnson, the implication of this finding is that much of the overall black-white wage gap appears to be due to the significant racial gap in the general academic skills acquired prior to labor market entry. This is not surprising given that the large and significant coefficient on AFQT score implies that the skills measured by this score are rewarded substantially in the labor market, and the fact that the average AFQT score for black workers is over one standard deviation lower than the average score for white workers.[17]

The more novel results of this paper, however, start in Table 4. In these specifications, I divide the sample up into the the H-sector (professional-technical-managerial-sales jobs) and the L-sector (all other jobs) and run the log wage regressions on each sector separately. As can be seen from the coefficients on the black dummy variable in columns 1 and 4, the unconditional racial wage gap is large and significant in both sectors, at 13 percent in the H-sector and 23 percent in the L-sector. However, Column 2 shows that, after controlling for AFQT scores, the coefficient on the black dummy variable actually becomes positive and insignificantly different from zero in the H-sector. This means black and white workers with similar AFQT scores are paid similarly in what is defined to be the H-sector. Furthermore, column 3 shows that this result remains after further controlling for the schooling, potential experience, parental, and regional characteristics. By comparison, columns 5 and 6 show that the coefficient on the black dummy variable in the L-sector regressions remains at -0.10 or below after controlling for AFQT scores and other control variables. In other words, black workers appear to be paid roughly 10 percent less than white workers with similar AFQT scores in the L-sector. These results mean that all of the previously observed conditional black-white wage inequality over the labor market as a whole results from the conditional inequality in the L-sector only. These findings are consistent with the implications of the model presented in Section 2.

Two further findings from Table 4 are also worth noting. First, the coefficient on AFQT score in the H-sector is up to twice as large as it is in the L-sector. Second,

[17] AFQT scores have been age adjusted and normalized to have a population mean of zero and a standard deviation of one. The average AFQT score for white workers in this sample is 0.41, while the average AFQT score for black workers in this sample is -0.71

the squared AFQT term is significantly negative in the L-sector, but actually positive (although not significantly so) in the H-sector. Similarly, the coefficients on the educational dummies, especially those for at least a four years of college, are much greater in the H-sector than the L-sector. These findings are consistent both with the assumption that general academic skills are more highly valued in the H-sector than the L-sector, as well as with the assumption that H-sector employers can more directly tie compensation to each worker's general academic skill level. However, the fact that the coefficient on AFQT score remains significantly positive in the L-sector regressions suggests that pre-market academic skills are still important for productivity in the L-sector, and that L-sector employers can at least partially observe each worker's general skill level.

Likelihood of Working in the H-sector

The third implication of the model from Section 3 was that, due to the more racially unbiased nature of the wage schedules in the H-sector, black workers should be more likely to work for an H-sector employer than white workers of similarly measured general skill. To examine this hypothesis, Table 5 presents the results of a probit analysis, where the dependant variable in each specification equals one if the worker works in the H-sector and zero otherwise.[18]

As can be seen in the first column of Table 5, without conditioning on AFQT scores, black workers are roughly 17 percentage points less likely to work in the H-sector than white workers. However, the latter two columns show that after conditioning on AFQT scores, black workers actually become 5 percentage points more likely to work in the H-sector than white workers with similar AFQT scores.[19] This means that blacks are roughly 25 percent more likely than whites to work in the H-sector after controlling for AFQT scores.[20] This finding provides evidence consistent with the notion that black

[18]Once again, each observation is a person-year, with standard errors clustered by each person.

[19]Dummy variables for 2 or more years of college and 4 or more years of college were not included in this probit analysis because they are clearly endogenous to the decision of which sector to work in. Specifically, if an individual decides he wants to attempt to work in the H-sector, he most often will have to attend college to do so. Hence, the decision to attend college is a rough proxy for the decision to work in the H-sector.

[20]This greater likelihood is calculated at by using the probit results from specification 3 to predict the likelihood of working in the H-sector for black and white workers with all other variables held constant at the overall sample means.

workers responded to the differing wage structure across sectors.

Racial Make-up of Most Skilled Workers in Each Sector

The final implication from the model presented above was that black workers should be under-represented among the most skilled workers in the each sector as long as more than half of each race chooses to work in the L-sector. Since only 15 percent of black workers and 33 percent of white workers work in the H-sector, this implication should also hold true if the model is a correct depiction of the labor market. For it to be true, it must be the case that if S_j^p represents the skill cutoff such that p percent of the workers in the j-sector have a skill level greater than S_j^p, then black workers make up a smaller proportion of the group of j-sector workers with skill level greater than S_j^p than they do of the group of j-sector workers with a skill level less than S_j^p. This appears to also hold true in the data used here.

Table 6 uses two definitions for the "most skilled" (and "least skilled") members of a sector. Definition (i) defines the most (least) skilled members of a sector as individuals who have AFQT scores in the top 10 (bottom 90) percent of that sector. Similarly, definition (ii) defines the most (least) skilled members of a sector as individuals who have AFQT scores in the top 20 (bottom 80) percent of that sector.[21]

The top section of Table 6 shows that, using either definition for most (least) skilled, black workers make up a significantly smaller proportion of the most skilled workers in the L-sector than they do of the least skilled workers in the L-sector, for each year from 1989 to 1993. Similarly, the bottom section of Table 6 shows the analogous results for the H-sector. Like in the L-sector, black workers are under-represented among the most skilled workers in the H-sector (under either definition of most skilled). In both cases and under either definition, the degree of under-representation of black workers among the most skilled is quite large, especially the L-sector. This is consistent with the model presented in Section 2, but as stated before, can also be consistent with a model of perfect information.

[21] Technically, according to the model, the skill cutoff S_L^p should be such that more than half of white workers have a skill level lower than this cutoff. The AFQT score cutoff to be in both the top 10 percent and top 20 percent of the L-sector AFQT distribution is high enough such that more than half of white workers have an AFQT score lower than either cutoff.

4.4 Alternative Hypotheses

The results described in the previous section are consistent with the model presented in Section 2, where statistical discrimination occurs only in the less skill-intensive labor sector due to the high incentive for employers in the more skill-intensive sector to make the investments necessary to accurately observe each worker's general academic skill level. This section examines what other theories may also be consistent with these results.

Preference Based Discrimination in Less Skill-Intensive Sector Only

One possible conjecture is that the results presented in the previous section are not due to market forces causing H-sector employers to overcome the informational constraints that can lead to statistical discrimination, but rather due to market forces causing H-sector employers to overcome preference based discrimination. Because general academic skills are much more important for productivity in the H-sector, bigotry is much more costly for H-sector employers than L-sector employers. For example, if an L-sector employer chooses to offer white workers higher wages than similarly skilled black workers, it will end up with less skilled workers on average than L-sector employers who offer similarly skilled black and white workers equal wages. However, since general skills contribute only marginally to productivity in these L-sector jobs, this discriminatory L-sector employer may still have overall productivity relatively close to the non-discriminatory employer. Hence, a firm acting in this way may be able to remain in business for quite awhile. On the other hand, an H-sector employer who engages in such bigoted behavior will likely have much lower overall productivity than non-discriminatory H-sector employers. This substantially lower productivity will cause this employer to be unable to compete effectively, driving it out of business quite quickly.

The difficulty with this argument remains the same as more general preference based discrimination models—as long as general skills are at all important for productivity in the L-sector, the bigoted L-sector employers should eventually be forced out of business by competition. However, if employers face significant constraints to accessing this L-sector labor pool, bigoted employers could persist indefinitely. Such constraints can be argued to have contributed to the racial inequality that persisted throughout the United States in the pre-civil rights south, but the widespread existence of such constraints is harder to justify for the national labor market in the early 1990s examined here.

Government Anti-Discrimination Legislation

A second possible argument consistent with the above empirical findings is that government legislation, legal actions, and affirmative action laws have been more effective at combating discrimination in the H-sector than the L-sector. While this may be true, it is not necessarily contradictory to the model described in Section 2. Greater legal pressure against discriminatory wages would give employers strong incentives to use other characteristics besides race to assess the skills of workers and applicants. Therefore, one effect of anti-discrimination laws and affirmative action may be to force employers to invest more in skill assessment technologies. Therefore, greater anti-discrimination legal pressures in the H-sector would simply reinforce the already greater incentive H-sector employers have to more accurately assess individual worker skill. However, it is impossible to tell from this analysis whether the primary reason H-sector employers invest more in skill assessment technology and pay more racially unbiased wages is the greater importance of skill in productivity in the H-sector, or greater anti-discrimination legal pressures in the H-sector. This topic is left for future work.

Unobserved Variable Bias

Finally, and maybe most notably, the findings shown in the previous section may be attributable to an unobserved variable bias and not to the discriminatory reasons modelled in Section 2.[22] Specifically, say there is some skill (or set of skills) s that cannot be observed by the econometrician, but can be observed by employers and is known to workers. Furthermore, say this skill s is not perfectly correlated with the general academic skills captured by AFQT scores, and white workers generally have greater levels of this skill s than black workers of similar AFQT scores. If a skill such as s exists <u>and</u> this skill only contributes significantly to productivity in L-sector jobs, then the empirical results documented in the previous section may be due to this unobserved variable bias and not the story laid out in Section 2. Specifically, employers may compensate workers for for both their observed general skill and their unobserved (to the econometrician) skill s. This would make black workers earn less on average than their white counterparts with

[22] Thank you to Maria Cancian for raising this possibility.

similarly measured general skill. Moreover, since black workers have lower levels of this other skill s on average than white workers with similarly measured general skill, black workers will be more likely than their white counterparts of similarly measured general skill to choose to work in the H-sector where this unobserved skill is not important. Such differential selection across races would also lead to blacks being under-represented among the most skilled in each sector, as measured by observed general skill.

This unobserved variable story is certainly a valid concern. However, it is not obvious what skill or skills the unobserved variable s would refer to. One possibility is cultural familiarity with the dominant group. For example, many jobs require contact and communication with clients, customers, or other employees. If black workers have different patterns of dress, different mannerisms, or different communication styles than the majority white workers, such differences may make black workers less "productive" to employers than white workers of similar general academic skills. In order for this to explain the results from the previous section however, style of dress, mannerisms, and/or communication styles must only matter in the L-sector jobs, or racial differences in style of dress, mannerisms, and/or communication styles only exist among workers who choose to work in the L-sector. While both are possible, it is hard to think of why this would be the case and, to my knowledge, there is no direct evidence that either of these assertions are true.[23]

It may also be the case that there is preference based discrimination in both sectors, but there is an unobserved skill in the H-sector, where black H-sector workers generally have higher levels of this skill than white H-sector workers. For example, employers may feel that, on average, black workers face greater constraints to attaining high levels of academic achievement than white workers. Therefore, employers see black workers in the H-sector as having more motivation and initiative than white workers of similar academic achievement. While this story is once again plausible, it also raises the question of how preference based discrimination can exist in a seemingly competitive H-sector labor market. In particular, why doesn't a slightly less racist H-sector employer hire only highly skilled black workers by offering them a slightly higher wage than whites

[23]Moreover, if these racial differences do not appear among H-sector workers, the question becomes "Why not?". After all, if H-sector black workers are able to shed these "unproductive" traits, why can't L-sector workers also?

of similar measured academic skill? By doing so, this employer could attain greater productivity at a lower price than its more racist competitors and eventually run them out of business.

While this story and the other alternative hypotheses are not without questions of their own, they do suggest further important lines for future research.

5 Summary and Conclusion

The model developed in the first part of this paper shows how differing technologies across employers may cause employers hiring in the more skill-intensive job sector to invest more resources in assessing each worker's general skill level than employers hiring in the less skill-intensive job sector. Such differing investment levels across sectors will lead to differing information concerning worker skill across sectors, theoretically making it it possible for wages in the more highly skill-intensive sector to be based primarily on each worker's general skill level, while wages in the less skill-intensive sector to primarily depend on the average skill level of the other members of a worker's racial group.

Such differing wage structures across sectors leads to four primary implications with respect to race and the labor market. First, because employers in the less skill-intensive sector cannot differentiate between workers of the same race on the basis of skill, and only the more skilled workers choose to work in the more highly skill-intensive sector, the mean and variance of wages should be greater in the more highly skill-intensive job sector, both overall and for each race. Second, the wage structures imply that, if black workers enter the labor market with a lower average skill level than white workers, then any racial wage gap in the highly skill-intensive sector should primarily be explained by racial differences in general skill, while substantial racial wage inequality may remain in the less-skill intensive sector even after controlling for racial differences in skill in that sector. Third, the more racially unbiased wage structure in the more highly skill-intensive job sector should cause black workers to be more likely to work in the highly skill-intensive sector than white workers with similarly measured skill level. Finally, because of the differential sorting across races, black workers should be under-represented among the most skilled workers in each sector compared to the overall racial composition of each sector.

Analyzing these implications using data from The National Longitudinal Survey of Youth 1979 (NLSY79), as well as the Multi-City Study of Urban Inequality and the The National Survey of Employers 1982, showed that there do appear to be substantial differences across employers in the degree to which a worker's academic skills affect productivity, and that employers hiring for jobs that are highly academically skill-intensive spend roughly 45 percent more time assessing the skills of potential workers. Moreover, data from the NLSY79 confirms that the mean and variance of wages are both significantly higher in the more highly skill-intensive sector (both overall and for each race separately), and that entire racial wage gap is explained by racial differences in pre-market academic skills (as measured by AFQT scores) in the highly skill-intensive sector, while an 11 percent racial wage gap remains in the less skill-intensive sector after controlling for pre-market academic skills. Furthermore, while black workers are less likely overall to work in the highly skill-intensive sector than whites, they are roughly 25 percent more likely than whites with similar pre-market skills to work in the highly skill-intensive sector. Finally, black workers are indeed found to be significantly underrepresented among the most skilled (as measured by AFQT scores) workers in each sector.

These results provide evidence consistent with the model put forth in Section 2 of this paper. This suggests that it may be important not to treat the labor market as one homogeneous entity when analyzing racial wage differences in the economy, as the labor market for lower skilled workers may be fundamentally different than the labor market for higher skilled workers. While a substantial source of racial wage inequality in both sectors appears to lie in racial differences in general academic skills acquired before entering the labor market, there may be substantially differential treatment of similarly skilled black and white workers in the less skill-intensive job market due to informational constraints. Therefore, policies that provide incentives for employers in the less skill-intensive sector to invest greater resources in assessing the general skills of workers and applicants may be an effective labor market intervention for decreasing racial wage inequality. Moreover, other potential benefits of such policies include more efficient sorting of workers across sectors and a greater representation of black workers among supervisory positions in the less skill-intensive sector (if supervisory positions are usually given to the most skilled workers in the sector).

As discussed in Section 4, a possible benefit of affirmative action programs is to prompt employers to spend more resources on assessing the skills of workers and applicants. While affirmative action programs have historically been more prominent for jobs and careers in the more highly skill-intensive job sector (e.g. law firms, university faculties), the results from this paper suggest that such programs may now have more substantial effects in the less skill-intensive job sector.

At this point, these conclusions remain somewhat tentative however, as Section 4 discussed a variety of other explanations that may also account for the empirical findings described in Section 3 of this paper. These alternative explanations included preference based discrimination in the less skill-intensive sector only, greater effects of affirmative action and other anti-discrimination programs in the more skill-intensive sector, and unobserved variable bias. While these theories all offer plausible alternatives to the primary argument presented in this paper, each required particular assumptions for which there currently exists little evidence. Therefore, while more research is certainly necessary to definitively pin down what explanation, or combination of explanations, most accurately describe the empirical findings of this paper, the model laid out at the outset of this paper arguably provides the most plausible story at this time.

Appendix

Proof of existence and uniqueness of θ^*

From the definition of θ^e we know that $\alpha_H + \beta_H\theta' - c < \alpha_L + \beta_L\theta' - c$ for all $\theta' < \theta^e$. Since we also know that $\theta' - E[\theta|\theta < \theta']$ approaches zero as θ goes to negative infinity, we know there must exist some $\underline{\theta}$ such that $\alpha_L + \beta_L\underline{\theta} - c < \alpha_L + \beta_L E[\theta|\theta < \underline{\theta}]$. Therefore, if we choose a $\underline{\theta} < \theta^e$, we know that

$$\alpha_H + \beta_H\underline{\theta} - c < \alpha_L + \beta_L E[\theta|\theta < \underline{\theta}].$$

Furthermore, since $E[\theta|\theta < \theta']$ will converge to $E[\theta]$ (a finite number) as θ' goes to infinity, we know there exists a $\overline{\theta}$ such that

$$\alpha_H + \beta_H\overline{\theta} - c > \alpha_L + \beta_L E[\theta|\theta < \overline{\theta}].$$

Because $\theta' - E[\theta|\theta < \theta']$ was assumed to be continuous and strictly increasing in θ', then the above inequalities and the Intermediate Value Theorem imply that there exists a unique θ^* such that $\alpha_H + \beta_H\theta^* - c = \alpha_L + \beta_L E[\theta|\theta < \theta^*]$.

Proof of Implication 4

To show that Implication 4 is true, first we will examine the L-sector. Note that if the proportion of group b workers in the population is denoted λ, then the proportion of the L-sector made up of group b workers is equal to

$$\frac{1}{1 + \frac{1-\lambda}{\lambda}\frac{F_w(\theta_w^*)}{F_b(\theta_b^*)}}. \tag{6}$$

Defining the "most skilled" workers in the L-sector as the group of workers with a skill level greater than some skill level $S_L < \theta_b^*$ (i.e this cutoff is relevant for workers in the L-sector from both groups), then the proportion of this group that is made up from group b workers is equal to

$$\frac{1}{1 + \frac{1-\lambda}{\lambda}\frac{F_w(\theta_w^*) - F_w(S_L)}{F_b(\theta_b^*) - F_b(S_L)}}. \tag{7}$$

Equations (6) and (7) reveal that a smaller fraction of group b workers among the most skilled members of the L-sector than in the L-sector as a whole as long as

$$\frac{F_w(\theta_w^*)}{F_b(\theta_b^*)} < \frac{F_w(\theta_w^*) - F_w(S_L)}{F_b(\theta_b^*) - F_b(S_L)},$$

which can be re-arranged to get

$$\frac{F_b(\theta_b^*)}{F_w(\theta_w^*)} < \frac{F_b(S_L)}{F_w(S_L)}. \tag{8}$$

Now, recalling that $\theta_b^* < \theta_w^*$, we also know equation (8) will hold as long as

$$\frac{F_b(\theta_b^*)}{F_w(\theta_b^*)} < \frac{F_b(S_L)}{F_w(S_L)}. \tag{9}$$

Finally, given our assumption that F_w and F_b are both normal distributions with similar variance and $\mu_b < \mu_w$, it will be true that $\frac{F_b(\theta)}{F_w(\theta)}$ will be decreasing in θ as long as θ is high enough such that $F_w(\theta) \geq 1/2$. Therefore, as long as S_L is high enough such that $F_w(S_L) \geq 1/2$ but $S_L < \theta_b^*$, it is necessarily true that equation (9) holds, implying equation (8) also holds, confirming the first part of Implication 4.

Turning to the H-sector, note that the proportion of the H-sector made up of group b workers is equal to

$$\frac{1}{1 + \frac{1-\lambda}{\lambda}\frac{1-F_w(\theta_w^*)}{1-F_b(\theta_b^*)}}. \tag{10}$$

If we define the "most skilled" workers in the H-sector as the group of workers with a skill level greater than some skill level $S_H > \theta_w^*$, then the proportion of this group that is made up from group b workers is equal to

$$\frac{1}{1 + \frac{1-\lambda}{\lambda}\frac{1-F_w(S_H)}{1-F_b(S_H)}}. \tag{11}$$

Equations (10) and (11) reveal that a smaller fraction of group b workers among the most skilled members of the L-sector than in the L-sector as a whole as long as

$$\frac{1-F_w(\theta_w^*)}{1-F_b(\theta_b^*)} < \frac{1-F_w(S_H)}{1-F_b(S_H)}.$$

which can be re-arranged to get

$$\frac{1-F_b(S_H)}{1-F_w(S_H)} < \frac{1-F_b(\theta_b^*)}{1-F_w(\theta_w^*)}. \tag{12}$$

Now, recalling that $\theta_b^* < \theta_w^*$, we also know equation (12) will hold as long as

$$\frac{1-F_b(S_H)}{1-F_w(S_H)} < \frac{1-F_b(\theta_b^*)}{1-F_w(\theta_b^*)}. \tag{13}$$

Once again, given our assumption that F_w and F_b are both normal distributions with similar variance and $\mu_b < \mu_w$, it will be true that $\frac{1-F_b(\theta)}{1-F_w(\theta)}$ will be decreasing in θ as long as θ is high enough such that $F_b(\theta) \geq 1/2$. Therefore, as long as θ_b^* is high enough such that $F_b(\theta_b^*) \geq 1/2$ and $S_H > \theta_b^*$, it is necessarily true that equation (13) holds, implying equation (12) also holds, confirming the second part of Implication 4.

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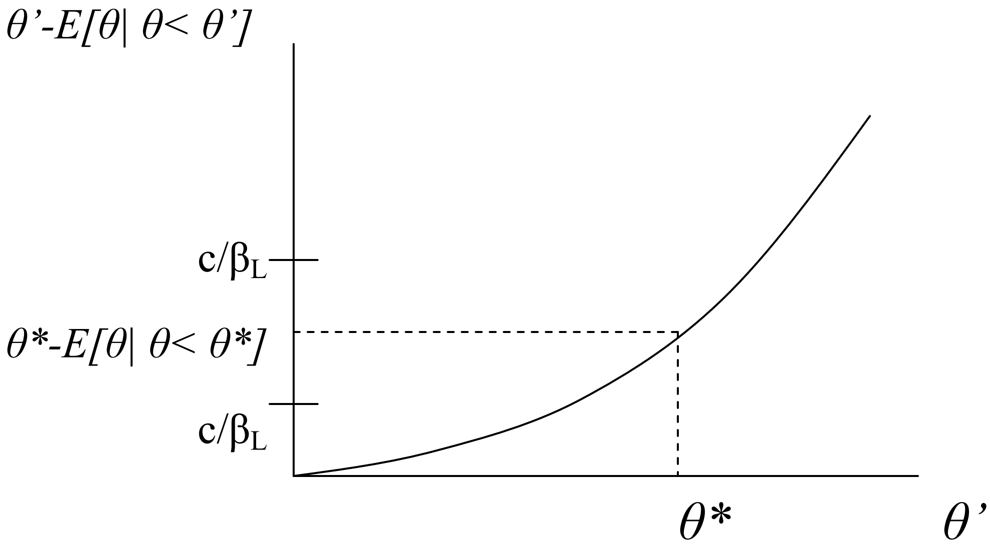

Figure 1 – Graphical depiction of Assumption (A1). Shape of *θ'-E[θ| θ< θ']* derived for normally distributed *θ*.

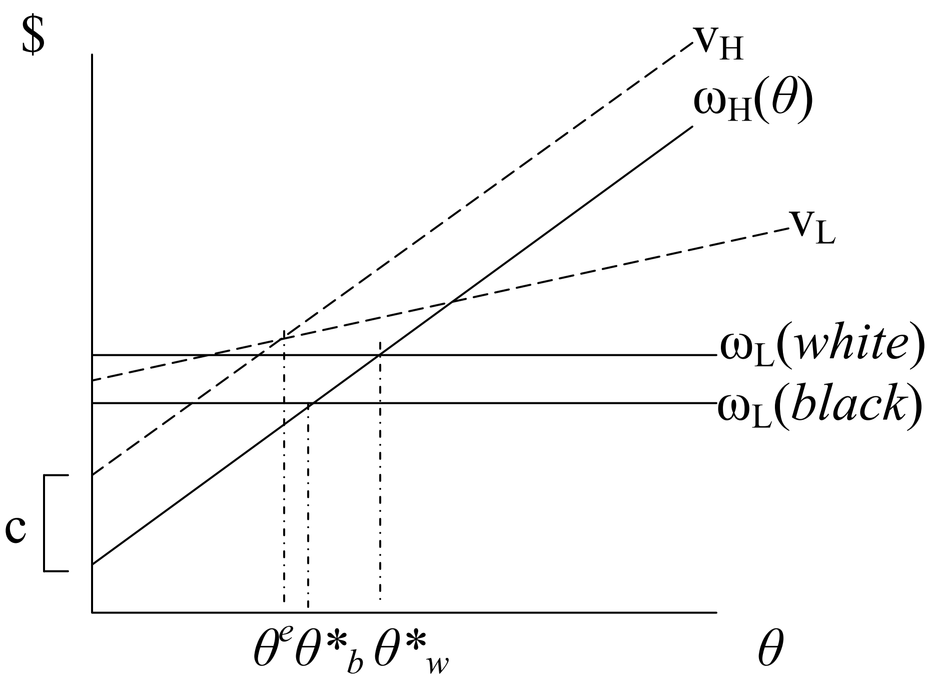

Figure 2 - Dashed lines depict the productivity functions in both sectors, Solid lines depict equilibrium wage schedules in both sectors for both races.

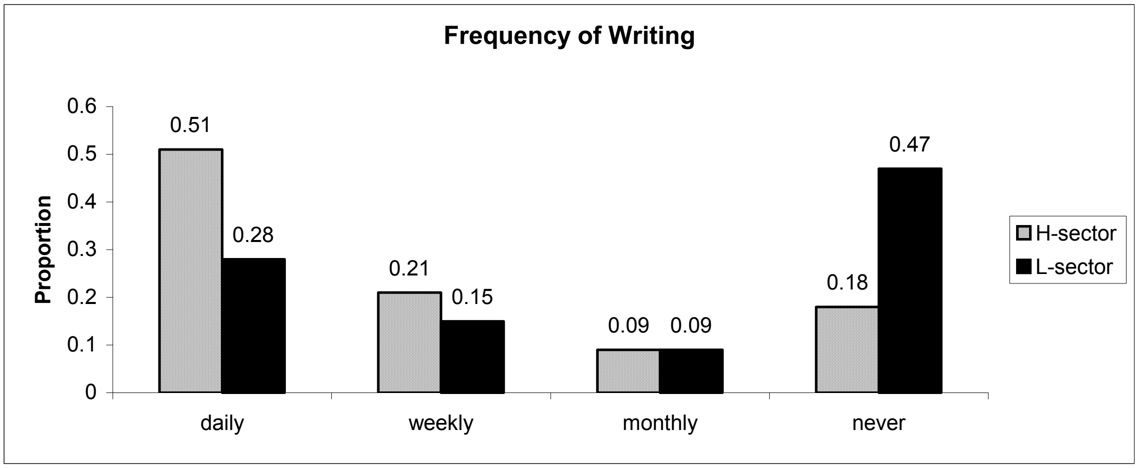

Figure 1(a)

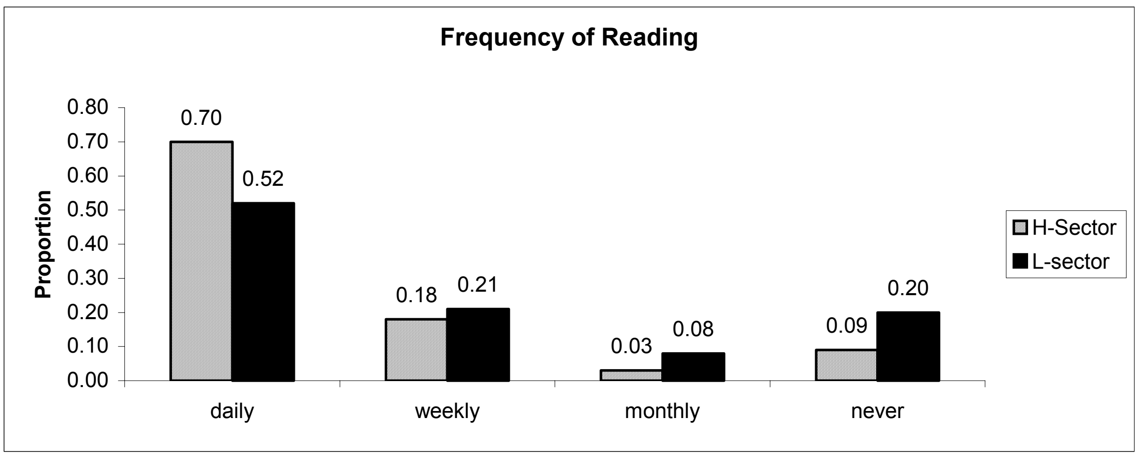

Figure 1(b)

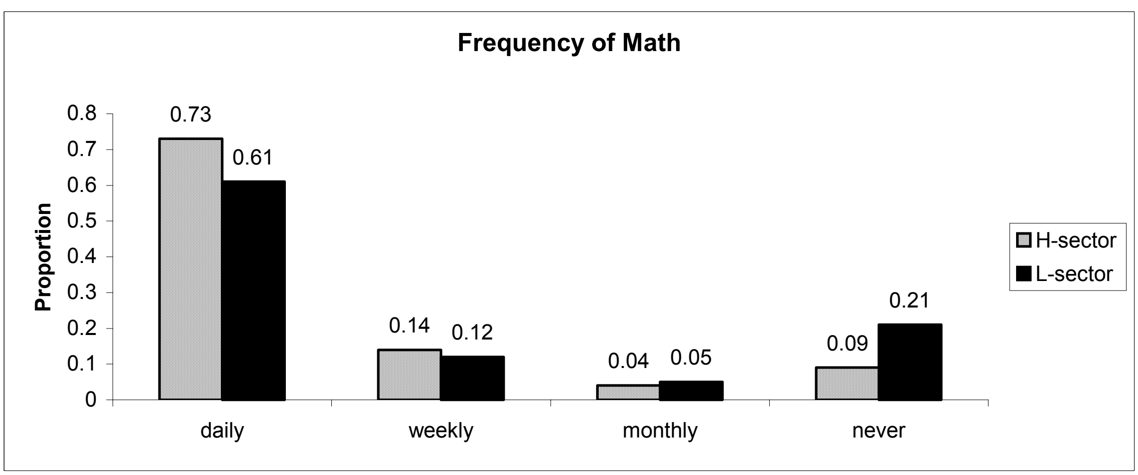

Figure 1(c)

Note: Data used for Figures 1(a)-(c) come from the Multi-City Study of Urban Inequality. H-sector consists of professional-technical-managerial-sales jobs, L-sector consists of all other jobs. Cross sector differences in daily and never categories significant at the 1 percent level.

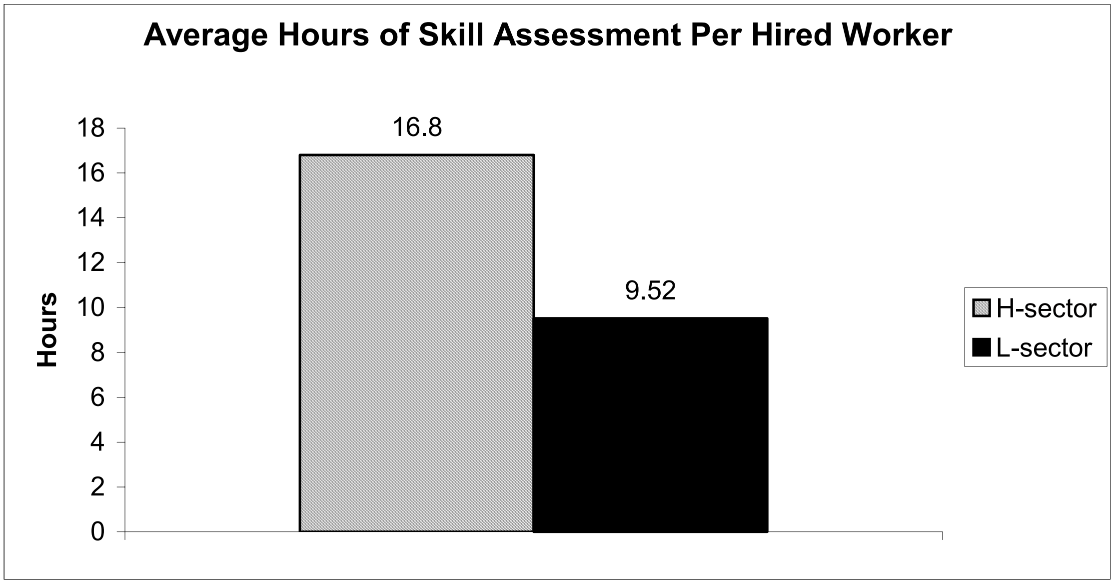

Figure 2

Note: Data for Figure 2 come from National Survey of Employers. Hours of skill assessment come from employer response to question asking number of hours spent recruiting, screening, and interviewing all applicants for most recent position hired divided by number of individuals hired for most recent position. H-sector consists of professional-technical-managerial-sales jobs, L-sector all other jobs. Cross sector difference significant at the 1 percent level.

Table 1: OLS Results of Log Hours of Skill Assessment per Hired Worker

Variable	(1)	(2)
H-sector	0.44**	0.45**
	(0.062)	(0.063)
Number of Employees	0.0003**	0.0003**
	(0.0001)	(0.0001)
Number of Applicants	0.0003	0.0003
	(0.0002)	(0.0002)
female	-	0.13*
		(0.052)
Age > 50	-	-0.18
		(0.115)
Age 30 - 50	-	0.07
		(0.057)
Agriculture	-	-0.34
		(0.582)
Mining	-	-0.22
		(0.211)
Construction	-	-0.17
		(0.109)
Manufacturing	-	0.001
		(0.087)
Transportation	-	0.006
		(0.125)
Wholesale Trade	-	0.11
		(0.091)
Retail Trade	-	-0.34**
		(0.065)
Financial	-	0.06
		(0.099)
Constant	1.61**	1.64**
	(0.029)	(0.060)
Adjusted R-squared	0.062	0.085
Sample size	2,166	2,166

Note: Data comes from NSE. Dependant variable is total man hours spent recruiting, screening, and interviewing all applicants when hiring for most recent position hired divided by number of individuals hired for the most recent position. Dummy variables for missing observations for each variable are also included. H-sector is professional-technical-managerial-sales jobs. Two asterisks indicate significance at one percent level. Standard errors in parentheses.

Table 2 - Mean and Variance of Wages

Group	Mean		Variance	
	H-sector	L-sector	H-sector	L-sector
Whole Population	14.43	9.72	66.96	28.32
std. error	(0.215)	(0.088)	(5.721)	(2.093)
no. of observations	3,425	9,596	3,425	9,596
no. of individuals	1,182	2,043	1,182	2,043
White	14.81	10.61	68.69	30.00
std. error	(0.249)	(0.119)	(6.474)	(2.867)
no. of observations	2,705	5,574	2,705	5,574
no. of individuals	933	1,583	933	1,583
Black	12.99	8.49	57.79	23.38
std. error	(0.413)	(0.119)	(12.016)	(2.962)
no. of observations	720	4,022	720	4,022
no. of individuals	303	1,086	303	1,086

Note: Data comes from NLSY. Sample contains all non-hispanic males not in the low-income white or military oversamples, with valid wage and occupation data for at least one year between 1989 and 1993, and valid AFQT scores. "Whole Population" estimates may not be representative of United States Population, as NLSY79 oversampled black individuals. However, race specific estimates come from samples designed to be representative of each race in United States population. Standard errors in parentheses, and were adjusted to account for clustering by individual.

Table 3: Log Wage Regressions (whole labor market)

Conditioning Variable	(1)	(2)	(3)
black	-0.26**	-0.06**	-0.06**
	(0.016)	(0.019)	(0.020)
AFQT score	-	0.18**	0.10**
		(0.010)	(0.012)
AFQT score squared	-	0.02*	-0.01
		(0.008)	(0.008)
black*AFQT	-	0.02	0.01
		(0.019)	(0.019)
12 years or more of educ.	-	-	0.07**
			(0.021)
14 years or more of educ.	-	-	0.11**
			(0.020)
16 years or more of educ.	-	-	0.24**
			(0.027)
potential experience	-	-	0.05**
			(0.010)
potential experience squared	-	-	-0.001**
			(0.000)
lived with both parents at 14	-	-	0.02
			(0.019)
mother high school grad	-	-	0.033*
			(0.018)
mother college grad	-	-	0.038
			(0.030)
mother professional	-	-	-0.033
			(0.024)
father high school grad	-	-	0.033*
			(0.019)
father college grad	-	-	-0.010
			(0.025)
father professional	-	-	0.045*
			(0.021)
age	0.13**	0.07*	-
	(0.042)	(0.040)	
age squared	-0.002*	-0.001	-
	(0.001)	(0.001)	
controls for year of observation	yes	yes	yes
controls for region of country	no	no	yes
constant	0.048	0.93	1.86**
	(0.637)	(0.596)	(0.068)
R-squared	0.07	0.18	0.23
number of observations	13,021		
number of individuals	3,225		

Note: Data comes from NLSY. Sample contains all non-hispanic males not in the low-income white or military oversamples, with valid wage and occupation data for at least one year between 1989 and 1993, and valid AFQT scores. AFQT scores adjusted for age and normalized to have a population mean of zero and a standard deviation of one. Dummy variable for missing observations for each variable also included. Two asterisks mean significant at the 1 percent level. Standard errors in parentheses, and were adjusted to account for clustering by individual.

Table 4: Log Wage Regressions By Sector

Conditioning Variable	H-Sector (1)	(2)	(3)	L-Sector (4)	(5)	(6)
black	-0.13**	0.05	0.05	-0.23**	-0.11**	-0.10**
	(0.032)	(0.037)	(0.038)	(0.016)	(0.022)	(0.024)
AFQT score	-	0.21**	0.12**	-	0.12**	0.07**
		(0.026)	(0.029)		(0.012)	(0.013)
AFQT score squared	-	0.02	0.01	-	-0.03**	-0.03**
		(0.016)	(0.016)		(0.010)	(0.010)
black*AFQT	-	-0.00	0.02	-	-0.03	-0.03
		(0.038)	(0.036)		(0.022)	(0.022)
12 years or more of educ.	-	-	0.003	-	-	0.08*
			(0.082)			(0.022)
14 years or more of educ.	-	-	0.08*	-	-	0.010*
			(0.049)			(0.023)
16 years or more of educ.	-	-	0.18**	-	-	0.08*
			(0.046)			(0.036)
potential experience	-	-	0.07**	-	-	0.03**
			(0.016)			(0.011)
potential experience squared	-	-	-0.002**	-	-	0.000
			(0.001)			0.000
lived with both parents at 14	-	-	0.06	-	-	0.011
			(0.040)			(0.020)
mother high school grad	-	-	0.04	-	-	0.03
			(0.038)			(0.019)
mother college grad	-	-	0.06	-	-	-0.01
			(0.037)			(0.041)
mother professional	-	-	-0.06	-	-	-0.03
			(0.036)			(0.029)
father high school grad	-	-	-0.02	-	-	0.04*
			(0.040)			(0.020)
father college grad	-	-	0.02	-	-	-0.04
			(0.033)			(0.033)
father professional	-	-	0.04	-	-	0.04*
			(0.032)			(0.025)
age	0.08	0.03	-	0.16**	0.11**	-
	(0.083)	(0.078)		(0.045)	(0.044)	
age squared	-0.001	-0.000	-	-0.002**	-0.002*	-
	(0.001)	(0.001)		(0.001)	(0.001)	
controls for year of observation	yes	yes	yes	yes	yes	yes
controls for region of country	no	no	yes	no	no	yes
constant	0.88	1.48	1.74*	-0.44	0.33	1.98**
	(1.25)	(1.17)	(0.122)	(0.676)	(0.655)	(0.082)
adjusted R-squared	0.03	0.12	0.18	0.06	0.12	0.15
number of observations	3,425			9,596		
number of individuals	1,236			2,669		

Note: Data comes from NLSY. Sample contains all non-hispanic males not in the low-income white or military oversamples, with valid wage and occupation data for at least one year between 1989 and 1993, and valid AFQT scores. AFQT scores adjusted for age and normalized to have a population mean of zero and a standard deviation of one. H-sector is professional-technical-managerial-sales jobs, L-sector is all other jobs. Dummy variable for missing observations for each variable also included. Two asterisks mean significant at the 1 percent level. Standard errors in parentheses, and were adjusted to account for clustering by individual.

Table 5: Probit Analysis of Probability of Working in H-sector

Conditioning Variable	Dependent variable equals 1 if worker works in H-sector (1)	(2)	(3)
black	-0.17**	0.05**	0.05**
	(0.013)	(0.017)	(0.019)
AFQT score	-	0.22**	0.17**
		(0.008)	(0.008)
AFQT score squared	-	0.04**	0.04**
		(0.006)	(0.006)
12 years or more of educ.	-	-	0.10**
			(0.020)
lived with both parents at 14	-	-	0.01
			(0.107)
mother high school grad	-	-	0.04
			(0.029)
mother college grad	-	-	0.06*
			(0.028)
mother professional	-	-	0.04*
			(0.022)
father high school grad	-	-	0.05**
			(0.017)
father college grad	-	-	0.07**
			(0.024)
father professional	-	-	0.08**
			(0.020)
age	-0.003	-0.07*	-0.06
	(0.037)	(0.037)	(0.036)
age squared	0.000	0.0012*	0.001
	(0.000)	(0.0006)	(0.001)
controls for year of observation	yes	yes	yes
controls for region of country	no	no	yes
observed probability	0.26	0.26	0.26
log likelihood	-7,241.0	-5,931	-5,635

Note: Data comes from NLSY. Sample contains all non-hispanic males not in the low-income white or military oversamples, with valid wage and occupation data for at least one year between 1989 and 1993, and valid AFQT scores. AFQT scores adjusted for age and normalized to have a population mean of zero and a standard deviation of one. H-sector is professional-technical-managerial-sales jobs, L-sector is all other jobs. Dummy variable for missing observations for each variable also included. Two (one) asterisks mean significant at the 1 (10) percent level. Coefficients have been normalized to represent marginal change at the mean. Standard errors in parentheses, and were adjusted to account for clustering by individual.

Table 6 - Racial Compostion of Workforce by Sector and Skill Level

	Proportion Black			Proportion Black		
	"Most Skilled (i)" (AFQT score in highest 10% of sector) (1)	"Least Skilled (i)" (AFQT score in lowest 90% of sector) (2)	Difference (3)	"Most Skilled (ii)" (AFQT score in highest 20% of sector) (4)	"Least Skilled (ii)" (AFQT score in lowest 80% of sector) (5)	Difference (6)
L-sector						
1989	0.08	0.46	-0.39**	0.09	0.51	-0.42**
	(0.018)	(0.011)	(0.022)	(0.014)	(0.012)	(0.019)
1990	0.09	0.46	-0.37**	0.1	0.5	-0.40**
	(0.020)	(0.012)	(0.024)	(0.015)	(0.012)	(0.019)
1991	0.08	0.45	-0.37**	0.1	0.5	-0.40**
	(0.020)	(0.012)	(0.023)	(0.015)	(0.013)	(0.020)
1992	0.09	0.45	-0.36**	0.09	0.5	-0.40**
	(0.021)	(0.012)	(0.024)	(0.015)	(0.013)	(0.019)
1993	0.09	0.46	-0.37**	0.09	0.5	-0.41**
	(0.020)	(0.012)	(0.024)	(0.015)	(0.013)	(0.020)
H-sector						
1989	0.07	0.21	-0.14**	0.06	0.23	-0.17**
	(0.032)	(0.016)	(0.036)	(0.021)	(0.018)	(0.027)
1990	0.07	0.23	-0.15**	0.05	0.25	-0.20**
	(0.032)	(0.016)	(0.036)	(0.019)	(0.018)	(0.026)
1991	0.06	0.23	-0.17**	0.07	0.25	-0.18**
	(0.031)	(0.016)	(0.035)	(0.022)	(0.018)	(0.029)
1992	0.06	0.24	-0.18**	0.06	0.26	-0.20
	(0.029)	(0.016)	(0.033)	(0.020)	(0.018)	(0.027)
1993	0.06	0.21	-0.16	0.05	0.23	-0.19
	(0.027)	(0.015)	(0.031)	(0.018)	(0.017)	(0.025)

Note: Data comes from NLSY. Sample contains all non-hispanic males not in the low-income white or military oversamples, with valid wage and occupation data for the year of observation, and valid AFQT scores. H-sector is professional-technical-managerial-sales jobs, L-sector is all other jobs. Two asterisks mean significant at the 1 percent level. Standard errors in parentheses.