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A Test of Screening Discrimination with Employer Learning

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Abstract

This paper tests for the presence of screening discrimination, a type of statistical discrimination that occurs when employers are less able to evaluate the ability of workers from one group than from another. Using data from the 2000 release of the NLSY79, the author examines wage equations in a framework of employer learning to test the hypothesis that the market receives less reliable productivity signals at labor market entry from black men than from white men. The estimation results support this hypothesis. Variables that are difficult for employers to observe, such as the AFQT score, had less influence on the wages of black men (and easily observed variables had more influence) than on the wages of white men. The influence of hard-to-observe variables on wages, however, increased faster with experience for black men.

KEYWORDS: screening discrimination with employer learning, statistical discrimination

A TEST OF SCREENING DISCRIMINATION WITH EMPLOYER LEARNING

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This paper tests for the presence of screening discrimination, a type of statistical discrimination that occurs when employers are less able to evaluate the ability of workers from one group than from another. Using data from the 2000 release of the NLSY79, the author examines wage equations in a framework of employer learning to test the hypothesis that the market receives less reliable productivity signals at labor market entry from black men than from white men. The estimation results support this hypothesis. Variables that are difficult for employers to observe, such as the AFQT score, had less influence on the wages of black men (and easily observed variables had more influence) than on the wages of white men. The influence of hard-to-observe variables on wages, however, increased faster with experience for black men.

This paper tests for the presence in the U.S. labor market of a type of statistical discrimination, referred to as “screening discrimination,” that is characterized by employers’ being less able to evaluate the ability of workers from one group than they are workers from another. In a typical screening discrimination model, the signal of worker productivity that employers receive at either the time of hiring or the time of labor market entry is less reliable for one group than for another. In contrast, in the other type of statistical discrimination, “rational stereotyping,” employers believe that

average productivity differs between groups, and they use group membership as a signal.

There have been two main explanations for how a difference in the quality of initial productivity signals could arise between groups. The most commonly cited is that of Lang (1986), who argued that communication differences reduce the ability of employers or supervisors to evaluate workers from groups other than their own. More recently, Lundberg and Startz (2004) proposed that this difference could arise from agents’ learning the relationship between signals and productivity through repeated

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transactions with randomly selected partners if members of one group are encountered more frequently than members of another.

The literature on screening discrimination is largely theoretical, with little empirical evidence backing it up. Only one previous paper, Pinkston (2003), has found statistically significant evidence that the hypothesized information difference exists. Using a survey of employers, in that earlier study I found evidence suggesting that the signals employers receive at the time of hiring are less reliable for women than for men, but employers appear to learn more about women than men as the employees' tenure at the firm increases. The current paper contributes to this literature by examining differences between black and white men in the signals of worker productivity that the entire labor market receives at the time of a worker's entry. I also consider how this difference affects the influence of employer learning on wages as the worker accumulates labor market experience instead of focusing on what one employer learns during the worker's tenure.

The starting point of this paper is the employer learning model of Altonji and Pierret (1997, 2000). Altonji and Pierret showed that if wages are regressed on variables that are easily observed by employers and variables that are hard for employers to observe but still correlated with productivity, employer learning implies that the coefficients on the hard-to-observe variables will rise with experience while those on easily observed variables will fall. They pointed out that if the market is less able to evaluate workers from one group than workers from another at the time of labor market entry, employer learning will have a greater impact on the wages of the less well evaluated group. I show that employers' inability to evaluate one group of workers as well as another will also result in less weight initially being placed on hard-to-observe variables than on easily observed variables. This paper tests both of these predictions for black and white men using a large panel from the NLSY.

1. Previous Literature

1.1. The Screening Discrimination Literature¹

The fundamental assumption of all screening discrimination models is that employers are not able to evaluate workers from one group as accurately as they are workers from another at the time of either labor market entry or hiring. Aigner and Cain (1977) showed that this does not necessarily lead to discriminatory outcomes on average. What it does imply is that the wages of the disadvantaged group will be based less on their individual signals and more on the population mean than will the wages of the other group. In the most basic setting, this does not lead to differences in average wages across groups unless average productivity differs across groups.

Lundberg and Startz (1983) expanded the basic setting described by Aigner and Cain (1977) to allow screening discrimination to affect investment in unobservable human capital. Members of the disadvantaged group invest less in hard-to-observe human capital because their wages are based less on signals of their individual ability. The result is that average productivity, and therefore average wages, can differ across groups even if innate ability is the same across groups on average.

Several other papers have provided explanations of how screening discrimination could lead to economic discrimination. For example, if the productivity of workers depends on how well they are matched to a task they are suited to, as in Lundberg (1991), members of the group that is less accurately evaluated will be matched to an appropriate task less frequently and will be less productive on average (and thus paid less). Oettinger (1996) presented a model of asymmetric informa-

¹See Altonji and Blank (1999) for a survey of this literature and other work addressing issues of race and gender in the labor market. See Balsa, McGuire, and Meredith (2005) for tests of statistical and screening discrimination in health care.

tion in which gains to mobility are lower for the group with the noisier initial signal. Asymmetric information also plays a role in Milgrom and Oster (1987) by allowing firms to “hide” disadvantaged workers in lower-level jobs.

Both Cornell and Welch (1996), who first used the term “screening discrimination,” and Lundberg and Startz (2004) developed models in which agents choose transaction partners whose expected ability meets a standard based on opportunity costs. In Cornell and Welch’s model, workers are chosen for promotion or hiring when their expected productivity given a signal is the highest of those under consideration. In the search model of Lundberg and Startz, agents trade with a potential partner if the expected value of doing so is higher than the value of continued search. In both cases, having a more informative signal causes the variance of a group’s conditional expectation to be higher, resulting in members of that group being more likely to be hired (or promoted, or otherwise selected).

Despite this theoretical interest, only two other papers have looked for empirical evidence of the underlying information problem hypothesized by screening discrimination. Although primarily concerned with rational stereotyping, Neumark (1999) performed a test of screening discrimination based on a measurement error story. He regressed starting wages on an employer-provided performance evaluation and compared the coefficient on this performance evaluation under OLS and IV specifications, with age and education instrumenting for the performance evaluation. His instruments are valid under the assumption that the performance evaluation contains all information possessed by the employer at the time of hiring. His estimates suggested some difference in the quality of initial information between men and women, but the difference is not statistically significant.

In a recent study (Pinkston 2003), I found statistically significant evidence of differences between men and women in the quality of productivity signals. Specifically, I

found that worker productivity signals observed at the time of hiring have a large impact on the starting wages of men, but essentially no impact on the starting wages of women. I also found that employer learning over workers’ tenure is more important for women than for men, which is consistent with women providing less reliable initial signals than men do.

The current paper differs from Pinkston (2003) in the choice of groups compared and also in the data used to test for screening discrimination. I test for differences between black and white men in the quality of productivity signals that the market receives at the time of labor market entry, not the quality of signals that employers observe at the time of hiring. Both that new focus and my attention to what employers learn based on workers’ total experience (as opposed to employer learning over workers’ tenure) reflect an important difference between the data the two studies used. The employer-provided performance evaluation used in Pinkston (2003) could easily reflect some degree of match-specific productivity; in contrast, the AFQT scores used in this paper reflect only general ability. While in my earlier study I examined learning over tenure and could allow ambiguity about whether my performance measure represented general or match-specific productivity, this paper, by using a measure of general ability and assuming that all employer learning is public, is restricted to examining employer learning based on workers’ experience in the labor market.² One potential advantage of considering experience in the labor market instead of tenure is that tenure itself, and especially employer learning over a worker’s tenure, is more likely to be influenced by the discriminatory practices of individual employers than is experience.

²Evidence of learning with tenure in addition to experience using AFQT score could indicate private (asymmetric) employer learning, but exploring that issue would require a more sophisticated model and is well outside the scope of this paper.

1.2. Previous Learning Papers

Altonji and Pierret (1997) (hereafter, AP)³ suggested using differences in the influence of employer learning on wages to identify differences between groups in the quality of initial signals; however, they never examined employer learning separately for different groups. The current paper performs this test, examining employer learning separately for black and white men.

AP's main purpose was to use the wage effects of employer learning as a measure of the degree to which employers use easily observed variables, such as education and race, to statistically discriminate between, or "rationally stereotype," workers. A worker's wage will become more dependent on actual productivity and less dependent on easily observed variables as firms learn more about the worker. If the econometrician has data on variables that are difficult for employers to observe but correlated with worker productivity, the coefficients on those hard-to-observe variables in wage regressions will increase with experience.

Using data from the NLSY, AP found that employers do use the information contained in education variables, with the importance of those variables decreasing in experience as the importance of AFQT score and father's education increases. On the other hand, they did not find evidence that employers fully use the information contained in race, possibly due to other racial differences simply dominating the effects of statistical discrimination.

Farber and Gibbons (1996) (hereafter, FG) also used data from the NLSY to examine employer learning. They regressed hard-to-observe variables, such as AFQT score, on all other variables in the wage equation and then used the residuals in their analysis. The effect of education on wages did not vary due to employer learn-

ing, as it did in AP, because these residuals are not correlated with education as AFQT score itself is. The estimation results in FG also suggest the existence of employer learning.

2. The Public Learning Model

2.1. The Basic Model

First, assume that as each worker i in group j enters the labor market, all firms observe a signal of productivity, S_{0i} . Let μ_i denote the log of the worker's actual productivity and assume that productivity has the same distribution across groups: $\mu \sim N(m, \sigma_\mu^2)$.⁴

Following earlier work on screening discrimination, assume that the signal of initial productivity that is observed by the market takes the form

$$S_{0i} = \mu_i + \varepsilon_{0i}$$

where $\varepsilon_{0i} \sim N(0, \sigma_{sj}^2)$ and is independent of μ_i for each group j . Groups are distinguished by the variance of this initial signal, σ_{sj}^2 . Considering two groups, the group with the higher signal variance is referred to as the disadvantaged group, and the group with the lower variance is referred to as the comparison group. The empirical work that follows will investigate the possibility that black men are the disadvantaged group, in this sense, vis-à-vis white men.

Assume that the log of the worker's wage equals the expected log of productivity. The log of the initial wage is

$$\begin{aligned} (1) \quad w_{0i} &= E(\mu | S_{0i}) = \frac{\sigma_{sj}^2}{\sigma_{sj}^2 + \sigma_\mu^2} \cdot m \\ &+ \frac{\sigma_\mu^2}{\sigma_{sj}^2 + \sigma_\mu^2} S_{0i} \\ &= \alpha_{m0} \cdot m + \alpha_{s0} \cdot S_{0i} \end{aligned}$$

³This was later published as Altonji and Pierret (2000), but the published version does not discuss this test.

⁴The assumption that average productivity does not vary by group is made for simplicity. None of the predictions tested in this paper are affected by this assumption.

(See DeGroot 1970.) It is easy to see that higher values of σ_{sj}^2 will lead to higher values of α_{m0} and lower values of α_{sj} . Thus, as in previous work on screening discrimination, members of the disadvantaged group will be paid wages that depend more on the population mean and less on their individual signals because their signals are less reliable.

Assume now that in all later periods of experience, $t = 1, 2, \dots$, the market observes an additional signal of productivity for each worker,

$$s_{it} = \mu_i + \psi_{it},$$

where $\psi_{it} \sim N(0, \sigma_{\psi}^2)$ and ψ_{it} are independent of μ , ε , and each other. Note that the variance of the error term ψ_{it} is assumed not to vary with experience or group. In other words, the market collects information at the same rate for all workers after labor market entry. One can think of these later signals as coming from observations of worker output, making them less subjective than an initial signal based on interviews, for example. The assumption that these later signals do not vary in noise across groups is crucial to some of the results of this section. Because it is also potentially controversial, it will be discussed in greater depth in Section 3.2.

Combining the initial signal, s_{0j} , and all of the later signals, s_t , the market forms an updated signal in each period of the form

$$\begin{aligned} S_{ij} &= \frac{\sigma_{\psi}^2}{t\sigma_{sj}^2 + \sigma_{\psi}^2} \cdot s_{0j} \\ &+ \sum_{\tau=1}^t \frac{\sigma_{sj}^2}{t\sigma_{sj}^2 + \sigma_{\psi}^2} s_{\tau} \\ &= \mu + \eta_{ij} \end{aligned}$$

for each level t of experience (dropping the i subscripts for convenience), where $\eta_{ij} \sim N(0, \sigma_{ij}^2)$ and

$$\sigma_{ij}^2 = \frac{\sigma_{sj}^2 \sigma_{\psi}^2}{t\sigma_{sj}^2 + \sigma_{\psi}^2}.$$

The market's expectation conditional on S_{ij} will take the familiar form

$$\begin{aligned} (2) \quad E(\mu|S_{ij}) &= \frac{\sigma_{ij}^2}{\sigma_{ij}^2 + \sigma_{\mu}^2} \cdot m + \\ &\frac{\sigma_{\mu}^2}{\sigma_{ij}^2 + \sigma_{\mu}^2} \cdot S_{ij} \\ &= \alpha_{mj} m + \alpha_{sj} S_{ij}. \end{aligned}$$

It is a matter of simple algebra to show that $E(\mu|S_{ij}) = E(\mu|s_{0j}, s_1, s_2, \dots, s_t)$, but the updated market signal, S_{ij} , is used in this paper to simplify presentation and improve intuitive appeal.

The important predictions that come from equation (2) are driven by the variance of the updated signal, σ_{ij}^2 . The role of σ_{ij}^2 in equation (2) is analogous to that of σ_{sj}^2 in equation (1): α_{mj} is increasing in σ_{ij}^2 and α_{sj} is decreasing in σ_{ij}^2 . In equation (2) α_{mj} will be larger and α_{sj} smaller for the disadvantaged group because the variance of the updated signal, σ_{ij}^2 , is increasing in the variance of the initial signal, σ_{sj}^2 .⁵ The coefficient α_{sj} will increase with experience, while α_{mj} will decrease, because the updated signal becomes more reliable with experience.⁶

More important, the precision of the updated signal increases more rapidly for the disadvantaged group, implying that the effect of employer learning on expected productivity and wages (that is, the increase in α_{sj} and decrease in α_{mj}) will be larger for the disadvantaged group.⁷ This prediction, of course, depends on the assumption that the reliability of later market signals (σ_{ψ})

⁵Formally,

$$\frac{\partial \sigma_{ij}^2}{\partial \sigma_{sj}^2} = \frac{(\sigma_{\psi}^2)^2}{(t\sigma_{sj}^2 + \sigma_{\psi}^2)^2} > 0.$$

⁶The variance of the updated signal decreases in experience:

$$\frac{\partial \sigma_{ij}^2}{\partial t} = - \frac{\sigma_{sj}^2}{(t\sigma_{sj}^2 + \sigma_{\psi}^2)^2} \cdot \sigma_{\psi}^2 < 0.$$

⁷This follows because the second derivative of σ_{ij}^2 on t and σ_{sj}^2 is negative:

$$\left(\frac{\partial(\sigma_{ij}^2)^2}{\partial t \partial \sigma_{sj}^2} = \frac{-2(\sigma_{\psi}^2)^2 \sigma_{sj}^2}{(t\sigma_{sj}^2 + \sigma_{\psi}^2)^3} < 0 \right)$$

does not vary between groups. The predicted difference in learning would be dampened, or possibly reversed, if the later market signals were also less reliable for the disadvantaged group (see Section 3.2).

2.2. The Learning Model with Additional Signals

In the previous subsection, it was assumed that all of the market’s information about a worker consisted of an initial signal, s_{0t} , and later signals of productivity, s_{it} . In reality, the market is likely to observe other variables, such as education, that signal the worker’s productivity. Furthermore, the estimation I present later in this paper will consider the implications of employer learning for the weight put on these easily observed variables in wage regressions. In this subsection, therefore, I extend the basic model of employer learning to include easily observed variables like education and show how the influence of these variables on wages changes with experience.

Let there be some signal, Z_t , that is easily observed by the market and the econometrician. Assume there is a function, $f(\cdot)$, such that

$$f(Z) = \mu + \zeta,$$

where $\zeta \sim N(0, \sigma_Z^2)$; ζ is independent of μ , ε , and all ψ_t ; and neither $f(Z)$ nor σ_Z^2 varies by race or labor market experience. For simplicity, I will assume that $f(Z) = Z\delta$ in what follows.

If the market observes Z and knows δ , it is trivially easy to show that

$$(3) \quad E(\mu | S_{jt}, Z) = \alpha_{mj}m + \alpha_{zj}Z\delta + \alpha_{sj}S_{jt}.$$

As in equation (2), α_{mj} is larger for the disadvantaged group, decreasing in t and decreasing faster for the disadvantaged group. The coefficient on the market’s updated signal, α_{sj} , is smaller for the disadvantaged group, increasing in t and increasing faster for the disadvantaged group.

The coefficient on the easily observed signal behaves similarly to the coefficient on the population mean. The initial weight put on $f(Z)$, $\alpha_{zj|t=0}$, is larger for the disad-

vantaged group because the market’s other information for that group, s_{0t} , is less precise than it is for the comparison group. The weight put on $f(Z)$ will also decrease with experience, and will decrease faster with experience for the disadvantaged group.⁸ The last two results are also derived in AP. The result for the initial weight put on education or other easily observed variables extends the screening discrimination framework of Aigner and Cain (1977) and others.

As an aside, note that wage regressions could also fit the predictions of equation (3) if screening discrimination combined with asymmetric information allowed employers to set wages below expected productivity, as in Milgrom and Oster (1987). In that model, the wages of white men at labor market entry would be more correlated with productivity than would those of black men because white men are more “visible” to the market; however, as more black men are promoted over time, or the market receives other signals of their ability, their wages would become increasingly correlated with individual ability. As long as (a) wages are set in a manner that incorporates public information about workers, (b) the market has less information about the average black man at labor market entry than about the average white man, and (c) the market accumulates more information about workers over time through some mechanism, wages will follow the basic predictions from equation (3).

3. Estimation

As discussed above, the difference in the quality of the market’s initial information

⁸Formally,

$$\alpha_{zj} = \frac{\sigma_{\mu}^2 \sigma_Z^2}{\sigma_{\mu}^2 \sigma_Z^2 + \sigma_{\psi}^2 \sigma_{\mu}^2 + \sigma_{\mu}^2 \sigma_Z^2}$$

The relevant derivatives are

$$\frac{\partial \alpha_{zj}}{\partial t} = \frac{\partial \alpha_t^2}{\partial t} \cdot \frac{(\sigma_{\mu}^2)^2 \sigma_Z^2}{\Delta^2} < 0, \text{ and}$$

$$\frac{\partial^2 \alpha_{zj}}{\partial t \partial \sigma_{sj}^2} = \frac{\partial^2 \alpha_t^2}{\partial t \partial \sigma_{sj}^2} \cdot \frac{(\sigma_{\mu}^2)^3 (\sigma_Z^2)^2}{\Delta^3} < 0.$$

that is proposed by screening discrimination models generates two main predictions in the public learning framework. First, less weight will be put on the initial signal and more weight put on the population mean and the other observed signals in the log wage equations of the disadvantaged group than in those of the comparison group. Second, the influence of the market's learning on wages will be greater for the disadvantaged group than for the comparison group under the maintained assumptions.

3.1. Implications for the Estimated Equations

Recalling that wages equal expected productivity in this case and the conditional expectation in equation (3), the wages of a worker from group j with t years of experience can be expressed as

$$w = \alpha_{mj}m + \alpha_{Ztj}f(Z) + \alpha_{stj}S_{tj}$$

$$= \alpha_{mj}m + \gamma_{Ztj}Z + \alpha_{stj}S_{tj}$$

where S_{tj} is the market's updated signal, m is the mean of μ , and Z is education or another easily observed variable.

The wage equation must now be adapted to use variables that are hard for employers to observe but correlated with productivity because no more direct measure of S_{tj} exists in the data. Consider a variable, V , that is correlated with productivity and observed by the econometrician, but is not observed by the market. In all of my regressions this is an AFQT score.⁹ Assume that the vari-

ance of V , σ_V^2 , and the covariance of V and productivity, $\sigma_{V\mu}^2$, do not vary with experience, and that $\sigma_{V\mu}^2 / \sigma_V^2$ is the same for both groups.¹⁰ Replacing S_{tj} in the log wage equation with V yields

$$(4) \quad w = \alpha_{mj}m + \gamma_{Ztj}Z + \alpha_{stj}V + \alpha_{stj}(S_{tj} - V).$$

Assuming that η_{tj} , the error in the updated signal, is uncorrelated with V , it is easily shown that the OLS estimate of α_{stj} , $\hat{\alpha}_{stj}$, from this regression will be biased, but will be biased by the same proportion for both groups. Specifically,

$$E(\hat{\alpha}_{stj}) = \alpha_{stj} \frac{\sigma_{V\mu}^2}{\sigma_V^2}.$$

The assumptions that neither σ_V^2 nor $\sigma_{V\mu}^2$ varies with experience and $\sigma_{V\mu}^2 / \sigma_V^2$ does not vary across groups imply that the basic results for S_{tj} will hold when S_{tj} is replaced by a hard-to-observe variable such as V . Specifically, the weight put on V in wage equations will be smaller for the disadvantaged group, will be increasing in experience, and will be increasing in experience faster for the disadvantaged group than for the comparison group. The possibility that $\sigma_{V\mu}^2 / \sigma_V^2$ is smaller for black men (that is, AFQT scores are less meaningful) will be addressed in the next subsection.

Assuming that $(S_{tj} - V)$ is uncorrelated with Z (a condition that will obtain if, for example, Z , S_{tj} , and V are related to each

⁹Although the results of AP, FG, and this paper all suggest that employers would benefit from giving employees tests that resemble the AFQT, the use of employee testing by firms in no way suggests that AFQT score is not itself difficult to observe. Even if employers give their own tests, they will still not actually observe the AFQT score. The employer-administered test will simply be another signal of worker productivity, and could even be considered part of S_{tj} . In any case, the results I present later in the paper, as well as those of AP and FG, suggest that employer-provided testing does not reveal something equivalent to AFQT scores to the market. If it did, we

would not find the evidence of learning that we do when we use AFQT score.

AP also used father's education as a hard-to-observe variable. In earlier estimation, father's education acted as an easily observed variable for black men. Sibling's education had little or no effect. I experimented with the use of school quality measures (the percentage of disadvantaged students and the percentage of teachers with a master's degree), but they rarely had any statistically significant effect, and they acted as easily observed variables for black men when they were significant.

¹⁰Note that this allows for differences between groups in average AFQT scores and productivity even though I have implicitly assumed that there are no such differences. It also allows the variance of AFQT score to differ across groups as long as $\sigma_{V\mu}^2$ also varies such that $\sigma_{V\mu}^2 / \sigma_V^2$ is the same for both groups.

other only through their relationship to μ), α_{Zt} is also unaffected by replacing S_{jt} with V . As a result, the coefficient on easily observable variables, such as years of schooling completed, should be larger at labor market entry but should decrease with experience.

In estimation results presented later in the paper, equation (4) will usually be approximated with linear interaction terms in experience (or potential experience). Since the constant and the coefficient on experience may include effects that are not due to learning, such as discrimination, α_{mj} cannot be reliably identified. The basic log wage equation will take the form

$$(5) \quad w = X\beta_t + Z\gamma_0 + Z \cdot t\gamma_t + V\alpha_0 + V \cdot t\alpha_t + \phi,$$

where X includes a constant and experience, and the error term ϕ is analogous to $\alpha_{sj}(S_{jt} - V)$ in equation (4). I also estimate a specification that interacts Z and V with quartic potential experience terms for comparison.

Again following AP, I will also estimate specifications that restrict α_t to equal 0 in equation (5) for comparison. Without the interaction of V and experience included to pick up the increasing correlation of wages with productivity, employer learning does not predict changes in the coefficients on Z with experience. If effects other than employer learning caused the coefficient on Z to rise with experience, adding AFQT score interacted with experience should cause the coefficient on $Z \cdot t$ to become less positive than it had been.

Summarizing the implications of screening discrimination and public learning for the coefficients in equation (5),

- Screening discrimination implies that the initial weight put on Z , γ_0 , should be larger for black men than for white men, while the initial weight put on V , α_0 , should be smaller for black men.
- The public learning model implies that the coefficient on V interacted with experience (α_t) will be positive, while the coefficient on Z interacted with experience (γ_t) will become more negative (or less positive) when

the interaction of V and experience is added to the equations.

- Screening discrimination implies that the coefficients on the interactions of both easily observed and hard-to-observe variables (α_t and γ_t) should be larger in magnitude for black men than for white men.

3.2. Three Deviations from Maintained Assumptions

A few of the assumptions made above require additional comment. First, consider the assumption from Section 2 that signals accumulated by the market with experience, s_t , are equally reliable for both groups. This assumption can be justified by arguing that later signals are less subjective because they come from direct observation of output, which varies randomly around true ability. Such an argument is clearly more convincing for some jobs than for others.¹¹ It is certainly possible that the market evaluates black men less accurately than white men after each period of experience, as well as at the time of labor market entry. If that were the case, the prediction that learning would have a greater impact on the wages of black men would not necessarily hold. The effect of the initial signals being less reliable would be counteracted, or at least dampened, by the effect of the later signals also being less reliable.

Even if the later signals of productivity (in addition to the initial signals) were less reliable for black men, my estimation could still provide evidence of screening discrimination. First, the prediction that the initial weight put on AFQT scores relative to easily observed variables will be lower for black men than for white men is unaffected by differences in the reliability of later signals. Second, results that suggest employer learning is more important for black men than

¹¹In an attempt to examine learning in such jobs, I tried to repeat some of my estimation using a sample of workers in jobs that had some form of pay for performance. Unfortunately, the survey includes this information too infrequently for this to produce any statistically significant results.

for white men would still provide evidence of screening discrimination, because such a result would require the effect on learning of less reliable initial signals to be strong enough to overpower the effect of less reliable later signals.

Second, I assumed in Section 3.1 that the ratio of the AFQT score's covariance with productivity to the variance of the AFQT score ($\sigma_{\nu\mu}^2 / \sigma_{\nu}^2$) was the same for both groups. It is possible, however, that AFQT scores are less reliable indicators of productivity for black men than for white men. If this were the case, my estimation could produce a "false positive" in which less weight is put on AFQT scores in the wages of black men than in the wages of white men due to the test's reliability instead of the reliability of signals the market observes. Of course, if AFQT score were a more reliable signal of productivity for black men than for white men, more weight would be put on AFQT score in the wage equations of black men.¹²

Fortunately, even if AFQT scores are less reliable for black men, a comparison of employer learning could still provide evidence of screening discrimination. It can be shown that if AFQT scores are less reliable for black men, evidence of employer learning in their wage regressions will be reduced. As a result, evidence of screening discrimination based on differences in employer learning would require the effect of differences in initial signal reliability to dominate the effect of differences in the reliability of AFQT scores.

Finally, it is possible that the function, $f(\cdot)$, that relates education, Z , to productivity varies by race. If δ varied by race, it would affect γ_{Zj} , but it would have no effect on α_{Sij} . On the other hand, if the reliability of $f(Z)$ varied by race, both γ_{Zj} and α_{Sij} would be affected. The group with the

larger value of σ_Z^2 would have a larger α_{Sij} and a smaller α_{Zij} for any t .¹³ Furthermore, a larger σ_Z^2 would exaggerate any evidence of learning from the interaction of AFQT score and experience, but have an ambiguous effect on analogous evidence from education. If education were a more reliable signal for black men, it could cause my estimates to suggest the presence of screening discrimination even when none existed; however, it would also dampen (and possibly reverse) evidence of screening discrimination based on employer learning.

Table 1 provides a quick summary of how these deviations from my maintained assumptions would affect the interpretation of my results. A smaller coefficient on AFQT scores for black men could be caused by either less reliable initial productivity signals, AFQT scores themselves being less reliable signals of productivity, or education being a more reliable signal of productivity. Evidence of screening discrimination based on employer learning, on the other hand, could not be caused by either later signals or AFQT scores being less reliable for black men. It could be caused by education being less reliable for black men, but that would counteract evidence of screening discrimination from initial effects. None of these biases, therefore, could replicate both of the predictions of employer learning that I test for.

4. Data and Regression Specifications

The estimates presented in this paper use data from the 2000 release of the NLSY79. The NLSY data are well suited to the analysis in this paper. First, they include AFQT scores, which appear correlated with general productivity but would

¹²Skipping ahead to the data section, the standard deviation of AFQT score is smaller for black men; however, it is impossible to know what this implies about $\sigma_{\nu\mu}^2 / \sigma_{\nu}^2$ or any resulting bias without also knowing how (or if) $\sigma_{\nu\mu}^2$ differs by race.

¹³The relevant derivatives are

$$\frac{\partial \alpha_{Sij}}{\partial \sigma_Z^2} = \frac{(\sigma_{\mu}^2)^2 \sigma_{ij}^2}{\Delta^2} > 0,$$

$$\frac{\partial \alpha_{Zij}}{\partial \sigma_Z^2} = - \frac{\sigma_{\mu}^2 \sigma_{ij}^2 (\sigma_{\mu}^2 + \sigma_{ij}^2)}{\Delta^2} < 0.$$

Table 1. Effects of Deviations from Key Assumptions on the Tested Predictions.

Tested Prediction	Deviation I	Deviation II	Deviation II
	Later signals of productivity are also less reliable for black men.	AFQT scores are less correlated with productivity for black men.	Education is a more reliable signal for black men.
The initial weight put on AFQT scores relative to easily observed variables is lower for black men.	No effect.	Could cause a "false positive." The initial signals of black men would appear less reliable than they should.	Could cause a "false positive." The initial signals of black men would appear less reliable than they should.
The effect of employer learning on wages is greater for black men.	The predicted effect would be dampened or counteracted.	The predicted effect would be dampened or counteracted.	Evidence of this effect from AFQT scores would be dampened or counteracted.

be hard for employers to observe. Second, the data provide a large panel that follows workers over several years of their career. Because they are structured as a panel, the data contain detailed information on employment histories, including actual work experience.

I calculate actual experience by summing weeks worked since the last interview in every year after the respondent left school for the final time and dividing by 52.¹⁴ Potential experience is defined as age minus the highest grade completed minus 6. All wages are converted to 1987 dollars, and the AFQT measure is the percentile score adjusted for age at the time of testing.¹⁵

The data used in the estimation are limited to observations for black and white men who have left school for the final time

when they start the job in question, are not in the military, and have completed at least 8 years of schooling.¹⁶ In each survey year I consider only the current or most recent job (the CPS job), as long as real hourly wages are between \$2 and \$300. The restriction on wages drops 667 observations, leaving 49,505. Restricting attention to jobs with at least 35 hours per week but not more than 100 drops another 4,002 observations. Because I am interested in employer learning, which takes place to a greater degree earlier in careers, I drop 1,693 observations in which potential experience is greater than 20 years. (This is also the maximum of potential experience in AP, which uses 1992 NLSY data.) Finally, I impose two restrictions intended to improve the reliability of my experience measures. I drop 592 observations from just over 70 individuals who had more than 4 years of potential experience in 1979, and I drop 2,258 observations in which calcu-

¹⁴This includes weeks worked in 1975–77 if the worker was not in school in 1979 and potential experience suggests that he would have left school before that year. Estimation using different definitions of labor market entry produced qualitatively similar results.

¹⁵This adjustment is the same as that used by AP. The adjusted score is the person's percentile score, minus the average score of people the same age in 1979, divided by the standard deviation of scores for people that age.

¹⁶In previous versions of this paper, I looked only at men with at least 12 years of schooling. I compared the results again under both schooling restrictions and found (to my surprise) that evidence of learning was not stronger in the more educated sample. Furthermore, standard errors were often higher in the more educated and more restricted sample due to the smaller sample size.

lated actual experience exceeds potential experience by more than one year. The resulting sample has 29,503 observations for white men and 11,457 observations for black men, covering the early careers of 3,488 white men and 1,312 black men.

Table 2 contains the means and standard deviations of key variables for white and black men. As expected, average wages are higher for white men (9.75) than for black men (7.66). The average of adjusted AFQT scores for black men is only -0.735 , compared to 0.169 for white men, and the average years of education are 12.75 for white men and 12.4 for black men. The means of potential experience and actual experience are 9.32 and 6.89 for white men, respectively, versus 10.02 and 6.62 for black men.

In all of the analysis that follows, years of schooling is the main easily observed (Z) variable, and adjusted AFQT score is the hard-to-observe (V) variable. Missing value dummy variables for AFQT score and its interactions are included, when appropriate. Except for wage growth specifications, all regressions include a quartic time trend and interactions of that time trend with schooling, AFQT score, and a dummy for missing values of AFQT score to allow the return to education and ability to vary between years.¹⁷ Regressions also include a quartic polynomial of potential or actual experience, as well as the occupation of the worker on his first job after entering the job market and an indicator of urban residence.¹⁸ The experience measure is divided by 10 in all regressions.

The next section concludes with a set of wage growth regressions that use first differences to condition for individual fixed effects.¹⁹ The variables of interest are grade

Table 2. Means and Standard Deviations of Key Variables.

<i>Independent Variable</i>	<i>White Men</i>	<i>Black Men</i>
Real Hourly Wage	9.7461 (7.1418)	7.6649 (5.4347)
Log of Real Hourly Wage	2.1325 (0.5099)	1.9151 (0.4614)
Potential Experience	9.3178 (4.9248)	10.0187 (4.9277)
Actual Experience	6.8916 (4.6537)	6.6179 (4.4833)
Highest Grade Completed	12.7535 (2.2902)	12.4109 (1.8534)
Adjusted AFQT Score ^a	0.1689 (0.9414)	-0.7346 (0.6792)
AFQT Score Missing	0.0471 (0.2120)	0.0335 (0.1800)
Training ^b	0.4147 (0.4665)	0.3382 (0.4488)
Observations	29,503	11,457

Notes: Standard deviations are in parentheses. All means are unweighted.

^aMeans and standard deviations if not missing.

^bTraining is predicted prior to 1988. See Section 4 for more detail.

Source: Year-2000 release of the NLSY79.

and AFQT score interacted with the change in the experience measure divided by 10. Because the NLSY began surveying people every two years after 1994, the change in potential experience is two years from 1996 on. The regressions control for changes in urban residence and include dummy variables for year, which capture both the time trend and changes in potential experience.²⁰

The wage growth equations are also used to examine the possible effects of human capital accumulation through on-the-job training. (I address the reasoning behind

¹⁷My main results were unchanged in specifications that did not allow the returns to ability to vary with time or controlled for it differently. AP and FG used similar controls.

¹⁸As in AP, occupation on the first job is intended to control for different career paths without itself being affected by employer learning, as current occupations might.

¹⁹In these regressions I drop 66 observations that involve a change in hourly wages of greater than \$50.

²⁰The disadvantage of using first differences is that it is not possible to separate changes in potential experience from changes in time. Results that are consistent with employer learning are also consistent with changes in the return to ability over time.

Table 3. Evidence of Employer Learning and Screening Discrimination for White and Black Men. (Log Wage Regressions with Potential Experience)

<i>Independent Variable</i>	<i>White Men</i>			<i>Black Men</i>		
	<i>1</i>	<i>2</i>	<i>3</i>	<i>1</i>	<i>2</i>	<i>3</i>
Grade	0.090 (0.009)	0.066 (0.009)	0.060 (0.011)	0.123 (0.015)	0.107 (0.015)	0.131 (0.018)
Grade × Pot. Exp./10	-0.001 (0.009)	-0.003 (0.009)	0.002 (0.011)	-0.040 (0.015)	-0.041 (0.015)	-0.065 (0.018)
AFQT Score	—	0.123 (0.010)	0.148 (0.028)	—	0.139 (0.021)	0.018 (0.058)
AFQT Score × Pot. Exp./10	—	—	-0.026 (0.028)	—	—	0.126 (0.057)
Observations	29,503	29,503	29,503	11,457	11,457	11,457

Notes: Standard errors (in parentheses) are Huber/White, accounting for multiple observations per person. All regressions include a quartic time trend and interactions of that time trend with grade, AFQT score, and a dummy variable for missing values of AFQT score, as well as dummy variables for first occupation after labor market entry and urban residence. A missing value dummy for AFQT score and its interaction with experience are included when appropriate.

adding training variables to my regression in the next section.) The main problem with examining training in the NLSY is that before 1988 the survey did not ask about training that went on for a month or less. I follow AP in attempting to deal with this problem by using the training variables after 1988 to predict training in earlier years.²¹ In a log wage regression, total training the worker has accumulated should enter positively according to the standard human capital story, while the coefficient on current training should reflect the cost of training. In practice, this accumulated training measure sums predicted values up to 1988. Using first differences only requires that I have current and lagged training, keeping any problems caused by my use of predicted training to a minimum and eliminating any fixed effects that might be correlated with training.

²¹I use a probit MLE to estimate training as a flexible function of grade, AFQT score, and experience, while also controlling for urban residence and the first occupation after leaving school. I then predict training for the sample prior to 1988.

5. Results

The regression results presented in Table 3 are consistent with black men being less accurately evaluated by the market at the time they enter the work force than white men are. The coefficient on AFQT score in column (2), where AFQT score × potential experience is not included, is 0.139 (0.021) for black men and 0.123 (0.010) for white men. Once AFQT score × potential experience is added to the log wage regressions, the coefficient on AFQT score captures only the initial effect of AFQT score. The coefficient on AFQT score in column (3) falls to 0.018 (0.058) for black men, while it barely changes for white men (0.148 [0.028]).²² AFQT score may have at least as

²²Note that Neal and Johnson (1996) presented results that are similar to those in column (2) of Table 3 and concluded that the returns to ability are roughly similar for black and white men. The results in column (3) clearly show that the returns to ability are much smaller for black men than for white men at labor market entry. This suggests that the racial difference they observed in ability could indeed have been caused by black men having less incentive to invest in accumulating skills prior to labor market entry, as suggested by Lundberg and Startz (1983).

Table 4. Evidence of Employer Learning and Screening Discrimination for White and Black Men. (Log Wage Regressions with Actual Experience)

<i>Independent Variable</i>	IV Estimates: Experience Endogenous					
	<i>White Men</i>			<i>Black Men</i>		
	<i>1</i>	<i>2</i>	<i>3</i>	<i>1</i>	<i>2</i>	<i>3</i>
Grade	0.092 (0.010)	0.071 (0.010)	0.070 (0.011)	0.129 (0.015)	0.112 (0.016)	0.139 (0.018)
Grade × Pot. Exp./10	-0.006 (0.014)	-0.010 (0.014)	-0.009 (0.016)	-0.077 (0.025)	-0.082 (0.025)	-0.124 (0.030)
AFQT Score	—	0.109 (0.011)	0.116 (0.028)	—	0.151 (0.021)	0.018 (0.054)
AFQT Score × Pot. Exp./10	—	—	-0.009 (0.038)	—	—	0.205 (0.078)
Observations	29,503	29,503	29,503	11,457	11,457	11,457

Notes: Standard errors (in parentheses) are Huber/White, accounting for multiple observations per person. All regressions include a quartic time trend and interactions of that time trend with grade, AFQT score, and a dummy variable for missing values of AFQT score, as well as dummy variables for first occupation after labor market entry and urban residence. A missing value dummy for AFQT score and its interaction with experience are included when appropriate. Potential experience and its interactions instrument for actual experience and its interactions.

large an overall effect on the wages of the average black man as on the wages of the average white man, but almost none of that effect exists at labor market entry for black men.²³

The coefficients on AFQT score × potential experience provide stronger evidence of screening discrimination. The coefficient for black men (0.126 [0.057]) is significantly larger than that for white men (-0.026 [0.028]), suggesting that employer learning plays a much larger role in determining the wages of black men than the

wages of white men. To make these differences more concrete, a one standard deviation increase in the adjusted AFQT score raises log wages at labor market entry by 0.143 (0.027) for white men but by only 0.018 (0.056) for black men. After five years of potential experience, the effect of a one standard deviation increase is 0.131 (0.015) for white men but rises to 0.079 (0.032) for black men. After 10 years of potential experience the effect for black men actually exceeds the effect for white men (0.139 for black men versus only 0.118 for white men).²⁴

The results in Table 3 for grade completed are also consistent with screening discrimination but provide little evidence of employer learning. Consistent with the

²³As discussed above, AFQT score itself could be a more reliable signal of productivity for white men than for black men. To examine this possibility empirically, I repeat the estimation of Table 3 with both the score on the word knowledge section used in place of AFQT score and the score on the math section in place of AFQT score. The motivation for doing this is that the language sections of the test seem likely to be more affected than the math sections by racial differences in test reliability. The resulting estimation produced results that resembled those in Table 3, regardless of which test I used.

²⁴This appears to be due to the use of linear interaction terms. Estimates from a specification with quadratic interaction terms did not reveal the same pattern. These estimates were very noisy, however, and I will only present the rate of change in the effect of AFQT score at different levels of potential experience (see Table 5).

prediction that the wages of black men will initially depend more on easily observed variables than do those of white men, the coefficient on grade completed in column (3) is significantly larger for black men (0.123 [0.017]) than for white men (0.058 [0.011]). The coefficients on grade interacted with potential experience fall as AFQT score and its interaction are added for black men but not for white men; however, none of these changes are statistically significant.

If learning takes place over actual experience in the labor market, estimates of learning using potential experience will be biased. Table 4 repeats the analysis of Table 3 with IV estimates that use potential experience and its interactions as instruments for actual experience and its interactions. I use this instrumental variables approach when using actual experience because actual experience itself might contain information about worker productivity. As AP pointed out, estimates from wage regressions that test for employer learning will be biased if the regressions condition on information that evolves with time in the labor market.

The evidence of learning and screening discrimination, especially from AFQT score and its interactions, is even stronger in Table 4 than in Table 3. The coefficient on AFQT score for black men falls significantly from 0.151 (0.021) to 0.018 (0.054) when $(\text{AFQT score} \times \text{Experience}) / 10$ is added to the regression, while the coefficient on AFQT score is almost unchanged for white men and highly significant (moving from 0.109 [0.011] to 0.116 [0.028]). In contrast, the coefficient on years of schooling is significantly higher in column (3) for black men than for white men (0.139 [0.018] versus 0.070 [0.011]). More important, employer learning has a larger effect on the wages of black men than on those of white men. The coefficient on $(\text{AFQT score} \times \text{Experience}) / 10$ is 0.205 (0.078) for black men, significantly higher than it is for white men (-0.009 [0.038]).²⁵

²⁵OLS regressions that used actual experience (not shown) produced qualitatively similar results.

The linear interactions used so far assume that the rate of learning is constant with experience. To make sure that this assumption is not driving my results, I estimate regressions with quartic interaction terms.²⁶ Table 5 presents the second derivatives of log wage on the variable listed at the top of each column and experience (evaluated at 0, 1, 3, 5, 10, and 15 years). The top panel presents OLS estimates using potential experience and the bottom panel presents IV estimates using actual experience. These derivatives reflect the rate of learning at each experience level and are equivalent to the coefficients on the interactions with experience in the linear case.

The results presented in Table 5 back up the main finding reported in the previous tables: employer learning is more important for black men than for white men. Although most of the results from these nonlinear specifications suffer from high standard errors, the second derivative with respect to AFQT score and experience is positive and statistically significant for black men at 5 and 10 years of potential experience (0.0158 [0.073] and 0.174 [0.070], respectively), and at 3 and 5 years of actual experience (0.412 [0.147] and 0.316 [0.150]). This second derivative is typically smaller for white men and is never statistically significantly different from zero; however, only at 10 years of potential experience is the difference between races statistically significant. Finally, the derivatives of log wages with respect to grade and experience are typically smaller (less positive or more negative) when the AFQT score interactions are included (Regression II) than when only AFQT score is included (Regression I), but the differences between equations are never statistically significant.

Table 6 presents results from wage growth regressions that use first differences to con-

²⁶I also estimated the linear specifications for observations with potential experience ≤ 2 , ≤ 5 , ≤ 10 . The results did not differ qualitatively from those presented above.

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Table 5. Evidence of Employer Learning and Screening Discrimination Using Quartic Interactions of the Experience Measure. (2nd Derivative on Variable Listed and Experience)

<i>Experience</i>	<i>White Men</i>			<i>Black Men</i>		
	<i>Regression I</i>	<i>Regression II</i>		<i>Regression I</i>	<i>Regression II</i>	
	<i>Grade</i>	<i>Grade</i>	<i>AFQT Score</i>	<i>Grade</i>	<i>Grade</i>	<i>AFQT Score</i>
OLS with Potential Experience						
Exp. = 0	0.000 (0.047)	-0.013 (0.058)	0.054 (0.130)	0.100 (0.092)	0.114 (0.111)	-0.080 (0.308)
Exp. = 1	0.000 (0.031)	-0.009 (0.039)	0.036 (0.090)	0.055 (0.061)	0.060 (0.078)	-0.009 (0.215)
Exp. = 3	0.000 (0.015)	-0.003 (0.020)	0.007 (0.045)	0.000 (0.029)	-0.018 (0.034)	0.096 (0.101)
Exp. = 5	0.000 (0.012)	0.002 (0.015)	-0.014 (0.037)	-0.034 (0.020)	-0.064 (0.023)	0.158 (0.073)
Exp. = 10	-0.002 (0.011)	0.006 (0.014)	-0.036 (0.034)	-0.050 (0.019)	-0.082 (0.022)	0.174 (0.070)
Exp. = 15	-0.012 (0.014)	-0.002 (0.018)	-0.040 (0.042)	-0.040 (0.023)	-0.055 (0.027)	0.079 (0.080)
IV with Actual Experience						
Exp. = 0	-0.125 (0.110)	-0.134 (0.135)	0.046 (0.267)	-0.096 (0.245)	-0.268 (0.286)	0.623 (0.742)
Exp. = 1	-0.092 (0.065)	-0.109 (0.081)	0.059 (0.175)	-0.092 (0.137)	-0.226 (0.159)	0.542 (0.462)
Exp. = 3	-0.046 (0.025)	-0.065 (0.033)	0.059 (0.074)	-0.089 (0.049)	-0.176 (0.054)	0.412 (0.147)
Exp. = 5	-0.014 (0.023)	-0.027 (0.028)	0.036 (0.063)	-0.087 (0.050)	-0.145 (0.060)	0.316 (0.150)
Exp. = 10	0.010 (0.023)	0.025 (0.025)	-0.055 (0.052)	-0.087 (0.044)	-0.118 (0.053)	0.151 (0.117)
Exp. = 15	-0.019 (0.029)	-0.003 (0.032)	-0.062 (0.066)	-0.086 (0.067)	-0.074 (0.084)	-0.050 (0.182)

Notes: Standard errors (in parentheses) are Huber/White, accounting for multiple observations per person. All regressions include AFQT score and its missing value dummy, a quartic time trend and interactions of that time trend with grade, AFQT score and a dummy variable for missing values of AFQT score, as well as dummy variables for first occupation after labor market entry and urban residence. Interactions of the missing value dummy with experience terms are included in Regression II.

dition for individual fixed effects. In the top panel, the variables of interest are grade and AFQT score interacted with the change in potential experience divided by 10.²⁷ The bottom panel presents IV estimates

using the change in potential experience as an instrument for the change in actual experience.

The results in both panels are consistent with the results in previous tables, although the coefficient on AFQT score \times $\Delta(\text{Experience})$ is no longer significantly larger for black men than it is for white men. In addition to a smaller sample size, however, these results suffer from the fact

²⁷The change in potential experience is 1 from 1980 to 1994 and 2 from 1996 through 2000 due to the NLSY going to 2-year interview intervals after 1994.

Table 6. A Comparison of Employer Learning for White and Black Men.
(Evidence from Wage Growth Equations)

Variable	White Men				Black Men			
	1	2	3	4	1	2	3	4
OLS with Potential Experience								
Grade \times Change in Exp./10	0.051 (0.009)	0.028 (0.010)	0.043 (0.009)	0.022 (0.011)	0.033 (0.017)	0.017 (0.019)	0.019 (0.017)	0.007 (0.019)
AFQT Score \times Change in Exp./10	—	0.113 (0.022)	—	0.106 (0.022)	—	0.135 (0.051)	—	0.112 (0.053)
Training	—	—	0.002 (0.007)	0.001 (0.007)	—	—	0.022 (0.013)	0.020 (0.013)
Lagged Training	—	—	0.027 (0.007)	0.026 (0.007)	—	—	0.016 (0.012)	0.017 (0.012)
Observations	23,556	23,556	23,556	23,556	8,844	8,844	8,844	8,844
IV with Actual Experience								
Grade \times Change in Exp./10	0.048 (0.008)	0.027 (0.010)	0.040 (0.009)	0.021 (0.011)	0.029 (0.015)	0.016 (0.017)	0.018 (0.016)	0.007 (0.017)
AFQT Score \times Change in Exp./10	—	0.112 (0.025)	—	0.106 (0.025)	—	0.145 (0.057)	—	0.122 (0.059)
Training	—	—	0.003 (0.007)	0.001 (0.007)	—	—	0.023 (0.013)	0.020 (0.013)
Lagged Training	—	—	0.025 (0.008)	0.025 (0.008)	—	—	0.015 (0.012)	0.016 (0.012)
Observations	23,556	23,556	23,556	23,556	8,844	8,844	8,844	8,844

Notes: Standard errors (in parentheses) are Huber/White, accounting for multiple observations per person. All regressions also include the change in urban residence and dummy variables for year. Columns (2) and (4) include an interaction of the AFQT score missing value dummy and change in experience divided by 10. Training is predicted for all years prior to 1988. The predictions are based on separate probit MLEs for each race that specify training from 1988 on as a flexible function of potential experience, grade, and AFQT score.

that changes over calendar time in the return to ability cannot be separated from the effect of an extra year of experience.²⁸ The coefficient on AFQT score \times Δ (Experience) is 0.135 (0.051) for black men and 0.113 (0.022) for white men when potential experience is used. When I use actual experience, the analogous coefficients are 0.145 (0.057) for black men and 0.112 (0.025) for white men.

²⁸An examination of changes between years in the effects of AFQT score interacted with the quartic time trend from the regressions used to create Tables 3 and 4 shows that the return to AFQT score increased significantly over the years for white men, but was flat (and may actually have decreased) for black men.

As discussed in Section 4, first differences alleviate (but do not eliminate) the problems involved in using predicted training variables to examine the effects of training on my results. As AP discussed in detail, the effects of human capital accumulation through training cannot be separated from the effects of learning if higher AFQT scores are correlated with greater returns to training. This is not likely driving my results unless one believes that AFQT score is correlated with returns to training only for black men and not for white men. Columns (3) and (4) of Table 6 add current and lagged training to the wage growth regressions to check for this possibility.

The results presented in columns (3) and (4) of Table 6 are consistent with training having some effect on wages, while also

supporting the existence of employer learning. The results do not, however, suggest that workers share the costs of training through lower wages. In fact, the coefficient on current training is positive and statistically significant for black men (0.023 [0.013]) in column (3).²⁹ Furthermore, although adding training does reduce evidence of employer learning, this effect is not statistically significant. The coefficients on AFQT score \times Δ (Experience) are still statistically significant and positive, and slightly larger for black men (0.112 [0.053] in OLS and 0.122 [0.059] in IV) than for white men (0.106 [0.022] in OLS and 0.106 [0.025] in IV).

6. Conclusions

The evidence presented in this paper suggests that the signals of worker productivity that employers observe when workers first enter the labor market are less reliable for black men than for white men, as proposed by models of screening discrimination. This evidence consists of two main findings.

First, wages at the time of labor market entry are based less on hard-to-observe variables and more on easily observed variables for black men than for white men. The coefficient on AFQT score in log wage equations is statistically significant and positive for white men but essentially zero for black men when the interaction of AFQT score and experience is included in the regression. Furthermore, the effect of highest grade completed on early wages is significantly larger for black men than for white men.

The second main finding is that employer learning has a larger impact on the wages of black men than on the wages of white men, which is consistent with firms'

putting more weight on later signals of productivity for black men because their initial signals are less reliable. The effect of AFQT score on log wages increases significantly with either potential or actual experience for black men but does not change for white men. Regardless of whether actual or potential experience is used, the difference between races in the coefficients on AFQT score interacted with experience is statistically significant. Although differences in the coefficients on grade interacted with experience are not statistically significant, they do at least move in the predicted direction for black men when interactions of AFQT score and experience are added.

Although the evidence presented in this paper is an important contribution to the literature on screening discrimination, it also leaves room for future empirical research. First of all, the results suggest that the difference in information hypothesized by screening discrimination models exists, but they provide no evidence suggesting that this difference leads to economic discrimination. Future research will have to investigate specific models of screening discrimination if it is to provide evidence of an empirical link between screening discrimination and economic discrimination.

The cause of employers' greater difficulty evaluating black than white men would also be an interesting topic for future research. For example, if one believed that employers learn to evaluate members of a group through experience with that group, as proposed by Lundberg and Startz (2004), or invest more in evaluating members of a group that they encounter more frequently, one would expect to find less evidence of screening discrimination in areas (or occupations, or cohorts) where employers were likely to have a higher ratio of black men in their work force. Of course, this would probably also require information on the race (and possibly gender) of the worker's employer or supervisor in order to distinguish employers' learning to evaluate workers from different groups from workers' being more likely to be paired with supervisors from their own group.

²⁹This is more consistent with a story in which training acts as a proxy for promotions and promotions are associated with one-time increases in wages. A model such as Milgrom and Oster (1987) could then explain why this pattern is seen for black men but not white men.

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