

Biased Screening and Discrimination in the Labor Market

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The traditional economic analysis of discrimination is based on Gary Becker's study of taste discrimination by employers, employees, and consumers. More recent work by Kenneth Arrow (1972, 1973) has attempted to interpret intergroup wage differences in an alternative framework as a rational reaction to uncertainty in labor markets. His model of "statistical discrimination" demonstrates that when the screening process used to determine a worker's qualifications is costly, and prior expectations of productivity differ across race or sex groups, then wage differentials may arise between workers of identical productivity.

By implicitly assuming a perfect screening process, Arrow ignores a potentially important source of wage differentials, namely the fact that the screening process might be a more reliable predictor of productivity for one group than for another.¹ Our paper generalizes the Arrow model in two ways. First, in contrast to Arrow, we assume that all groups have *identical* distributions of productivity. Secondly, the screening process used by the firm to determine an applicant's productivity is "biased" in the sense that: a) members of various groups may "pass" the test in different proportions

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¹In a rather different framework, Edmund Phelps has allowed for the reliability of the screening process to differ across groups. However, as Dennis Aigner and Glen Cain have shown, Phelps' assumption that *all* applicants are hired by the firm leads to the conclusion that expected wages are identical across groups, as long as the groups under consideration have the same expected productivity. Thus they argue that Phelps' model is inadequate as an explanation of discrimination in the labor market.

despite their identical productivity distributions; and b) the predictive power of the test might vary across groups. Our objective is to analyze the effects of these types of biases in the screening process on the wage differentials between different population groups.

I. The Model

Consider a perfectly competitive industry consisting of homogeneous firms. To help any particular firm determine the productivity of any given applicant, a screening process costing C dollars is undertaken.² As a result of the screening each worker is assigned a score: passing (\hat{Q}) or failing (\hat{U}). The firm is assumed to hire all those (and only those) individuals who pass the test, i.e., the \hat{Q} applicants. Moreover, the population can be partitioned into two mutually exclusive productivity groups in terms of the qualifications necessary to perform the job in question: qualified individuals (Q) and unqualified individuals (U). Finally, the firm is assumed to know the distribution of productivity in each group. That is, the firm knows the probability, $P_i(Q)$, that an individual from group i is qualified for the job. For expositional simplicity we consider two race groups, whites ($i = w$) and blacks ($i = b$).

Within this framework, Arrow's model is obtained by making two specific assumptions. First, the test is a *perfect* predictor of productivity, hence $P_i(\hat{Q}) = P_i(Q)$.³ Sec-

²Note that due to our assumptions of homogeneous firms the testing procedure must be identical across firms. See A. Michael Spence and Joseph Stiglitz for a more extensive discussion of the role of screening in the labor market.

³The assumption that the applicant's productivity is known with certainty upon testing is similar to the

only, the proportion of qualified whites is higher than the proportion of qualified blacks, $P_w(Q) > P_b(Q)$.⁴ Given these assumptions, the following conditions must hold in equilibrium for a risk-neutral firm:

$$(1) P_i(Q)[MP_i - w_i] = C \quad (i = w, b)$$

where w_i is the competitive wage for group i , and MP_i is the value of marginal product of qualified group i workers. These conditions have a straightforward economic interpretation. Applicants who score \bar{U} are not hired, and hence do not contribute to the gains of the firm. If, on the other hand, an applicant is predicted (correctly) to be qualified, the gain to the firm is given by the difference between the marginal product of a qualified worker and the wage. Weighting this difference by the probability of being qualified yields the expected return from screening one more applicant and, in equilibrium, this return must equal the marginal cost of screening. Assuming that *qualified* white workers and *qualified* black workers are perfect substitutes in production, $MP_w = MP_b$, the equilibrium wage differential is given by

$$(2) w_w - w_b = \frac{C}{P_w(Q)P_b(Q)}[P_w(Q) - P_b(Q)]$$

If the proportion of qualified workers is larger in the white population than in the black population, qualified whites will receive higher wages than their equally qualified black counterparts. That is, the existence of uncertainty about productivity coupled with the costs incurred in de-

termining that productivity will lead to firm behavior, which in effect makes qualified blacks “pay” for their group’s smaller expected productivity.

Note that the wage differential vanishes when the two groups under consideration have the same productivity distribution. Our model (to be presented below) differs in that even abstracting from group productivity differences and setting $P_w(Q) = P_b(Q)$, we are able to generate wage differentials. This is accomplished by allowing for imperfect testing. In particular, we assume that screening processes are biased against blacks so that blacks having the same productivity as whites tend to perform worse on the test and/or the test is of a lower predictive power for blacks than for whites. This hypothesis has received extensive study in the psychological literature with respect to differences in IQ scores between whites and blacks. Two explanations have been advanced to explain this phenomenon. The first states that the score differential can be attributed to real differences in ability which might be due to genetic and/or environmental differences across races. The second argument states that the score differential is due to a “cultural bias” in the test: since intelligence tests are prepared by members of the “ruling” white middle class, it is inevitable that the test questions will be loaded in favor of experiences familiar to this group.⁵ Because of our assumption of identical productivity distributions across races, it is this latter type of effect which we are considering.

The introduction of imperfect testing affects the equilibrium conditions described earlier since the firm must take account of the possibility that some individuals who pass the test will in fact be unqualified. Let MP_q (MP_u) denote the marginal product of a qualified (unqualified) worker. Due to our assumption that qualified (or unqualified) whites and blacks are perfect substitutes in production, both MP_q and MP_u are invariant to race. From the point of view of

common assumption in job search models that all job characteristics are known to the applicant upon searching the firm. See the authors for a relaxation of this assumption in job search models.

⁴Arrow introduced this model in terms of employer *beliefs* concerning the joint distribution of productivity and test scores in each racial group. Note, however, that it is inconsistent to have both perfect testing and beliefs which are erroneous; that is, beliefs that will not be confirmed by a perfect screening process. In order to be internally consistent, it must be assumed that employer beliefs concerning the productivity distribution in each race group are indeed justified.

⁵For a more extended discussion of these hypotheses, see Anne Anastasi and Arthur Jensen.

the firm, therefore, the expected marginal product of an employee from race group i is $\overline{MP}_i = P_i(Q | \hat{Q})MP_q + P_i(U | \hat{Q})MP_u$. This expected marginal product is a weighted average of the marginal products of qualified and unqualified workers. The weights sum to unity and consist of the probabilities that a worker is qualified (unqualified) given that he has passed the test. Thus the equilibrium conditions must be modified to

$$(3) \quad P_i(\hat{Q})[P_i(Q | \hat{Q})MP_q + P_i(U | \hat{Q})MP_u - w_i] = C \quad (i = w, b)$$

From equation (3) we obtain the market wage differential:

$$(4) \quad w_w - w_b = [P_w(Q | \hat{Q}) - P_b(Q | \hat{Q})] \cdot (MP_q - MP_u) + \frac{C}{P_w(\hat{Q})P_b(\hat{Q})} \cdot [P_w(\hat{Q}) - P_b(\hat{Q})]$$

If the bias is such that a black applicant has a smaller probability of passing the test, despite the absence of group productivity differences, then the second term in (4) will be positive. This term represents the “cost effect” of biased testing, and it will favor whites. It is important to note the similarity between the cost term here and the wage differential in the Arrow model as given by equation (2). Either imperfect testing or true differences in the productivity distributions will generate a term of this form, and thus the two models yield identical predictions with respect to the cost effect of discrimination.

Only imperfect testing, however, creates the additional “productivity effect” given by the first term in equation (4). The sign of this term will depend upon how $P_i(Q | \hat{Q})$ differs across races and, of course, these conditional probabilities are related to the joint distribution of productivity and test scores. To examine how the screening bias affects this joint distribution, a change of variables is useful. In particular, define a random variable Y_i which is set equal to unity if the individual is truly qualified and zero otherwise. Similarly, let Z_i equal unity if the individual passes the test and zero

otherwise. Given these definitions, we can then measure the predictive power of the test by computing the correlation coefficient between the random variables Y_i and Z_i , yielding:⁶

$$(5) \quad r_i = \frac{(P_i(\hat{Q}))^{1/2} (P_i(Q | \hat{Q}) - P(Q))}{(P_i(\hat{U}))^{1/2} (P(Q)P(U))^{1/2}} \quad (i = w, b)$$

Given equation (5) we can solve for $P_i(Q | \hat{Q})$ and substitute into the wage differential in (4) yielding:

$$(6) \quad w_w - w_b = (P(Q)P(U))^{1/2} \cdot \left\{ r_w \frac{(P_w(\hat{U}))^{1/2}}{(P_w(\hat{Q}))^{1/2}} - r_b \frac{(P_b(\hat{U}))^{1/2}}{(P_b(\hat{Q}))^{1/2}} \right\} \cdot (MP_q - MP_u) + \frac{C}{P_w(\hat{Q})P_b(\hat{Q})} \cdot [P_w(\hat{Q}) - P_b(\hat{Q})]$$

Therefore the productivity effect of biased screening is seen to depend upon the racial differences in r_i and $P_i(\hat{Q})$. To isolate the separate effects of these two variables it is illuminating to first consider two special cases.

CASE 1: Suppose that the screening process has the property that $r_w > r_b$ and $P_w(\hat{Q}) = P_b(\hat{Q})$. Thus while whites and blacks pass the screening process with equal probability, the test performs its task of “matching” qualified applicants [$Y_i = 1$] with passing scores [$Z_i = 1$] more reliably for whites than for blacks.

A simple example will illustrate this point. Consider a firm which screens four applicants from each race group, and suppose that the distributions of Y_i (productivity) and Z_i (test scores) are as given in Table 1. It is clear that although $P_w(\hat{Q}) = P_b(\hat{Q}) = .5$, the test does a much better job

⁶It can easily be shown that Y_i and Z_i are characterized by the following properties: $E(Y_i) = P(Q)$, $E(Z_i) = P_i(\hat{Q})$, $var(Y_i) = P(Q)P(U)$, $var(Z_i) = P_i(\hat{Q})P_i(\hat{U})$, $cov(Y_i, Z_i) = P_i(Q \cap \hat{Q}) - P(Q) \cdot P_i(\hat{Q})$. Note that we omit the subscript i from the probabilities $P(Q)$ and $P(U)$ since the productivity distribution is invariant to race.

TABLE 1

Whites		Blacks	
Y_w	Z_w	Y_b	Z_b
1	1	1	1
1	1	1	0
0	0	0	1
0	0	0	0

of predicting the productivity of white applicants. In fact, the test predicts perfectly for whites [$r_w = 1$], yet the predictions for blacks are totally random [$r_b = 0$]. If the screening process has these properties, it can be seen from (6) that the productivity effect is positive and the cost effect vanishes. Since the white applicants hired are likely to be of better quality, white workers in the firm will have a higher expected marginal product, $\overline{MP}_w > \overline{MP}_b$, and hence a higher wage.

CASE 2: Suppose the screening process is such that $P_w(\hat{Q}) > P_b(\hat{Q})$ and $r_w = r_b$. Thus although a greater proportion of white applicants receive passing scores, the ability of the test to predict qualifications is equal for both groups.

The plausibility of this case is illustrated by the example in Table 2. We find that although $P_w(\hat{Q}) > P_b(\hat{Q})$, the correlation coefficients are equal, $r_w = r_b = .58$. Since two of the four applicants from each race are truly qualified [$Y_i = 1$], a perfect testing procedure would grant passing scores to precisely these individuals. Due to the bias, however, one of the two qualified blacks is erroneously assigned a failing score, while one of the two unqualified whites is assigned a passing score. Thus the test is too selec-

TABLE 2

Whites		Blacks	
Y_w	Z_w	Y_b	Z_b
1	1	1	1
1	1	1	0
0	1	0	0
0	0	0	0

tive for blacks, dilutes the quality of the white labor force, and these errors (although opposite in nature) have identical effects on the correlation coefficients.

Given these properties, we see from equation (6) that the first term is negative, thus this type of biased testing produces a productivity effect which favors blacks. The reason is that by being more selective for black applicants, those blacks who do pass the test are more likely to be qualified than their white counterparts in the firm, hence $\overline{MP}_b > \overline{MP}_w$. Therefore, abstracting from the cost effect, we find that a testing bias in which firms are much more selective in screening blacks actually improves the relative position of black workers hired.⁷

CASE 3: In general, a biased test will, of course, create a cost effect favoring whites, as well as a productivity effect ambiguous in sign. In fact, the productivity effect will be positive, zero, or negative depending on

$$(7) \quad \frac{r_w^2}{r_b^2} \begin{matrix} \geq \\ \leq \end{matrix} \frac{P_w(\hat{Q})P_b(\hat{U})}{P_b(\hat{Q})P_w(\hat{U})}$$

We have seen that there are two opposing influences on the relative productivity of black workers. First, by being more selective in the hiring of blacks, those blacks who are hired are likely to be of better average quality. However, this effect is counterbalanced by the fact that the scores of black applicants may be less informative than those of whites, so that being selective and hiring only the highest ranked blacks need not necessarily improve the expected productivity of black workers.

⁷It can be shown that the productivity effect will exist only if $0 < r < 1$, where r is the common level of the correlation coefficient. If the screening process provides no useful information on the applicant's productivity, then the random variables Q and \hat{Q} are statistically independent and $P_w(Q|\hat{Q}) = P_b(Q|\hat{Q}) = P(Q)$. No productivity effect exists since all workers hired, whether white or black, are randomly chosen by the firm. Hence biased screening must worsen the relative position of blacks through the cost effect. Similarly, if the test were of perfect quality all those individuals who passed, white or black, would be qualified with certainty. Again, the productivity effect would vanish.

It is important to emphasize that the screening biases discussed in this paper change the expected productivity of workers from each race group *within* the firm despite the fact that the population distributions of productivity are identical. These differences in productivity will in turn affect the interpretations of observed wage differences between black and white workers. In particular, suppose that the net effect of biased screening is that $\overline{MP}_b > \overline{MP}_w$ (as in Case 2 above). An important empirical implication of this result is that the observed market wage differential *underestimates* the true extent of discrimination. That is, since biased screening leads to the hiring of superior blacks, in order to compute the true magnitude of discrimination we must take the observed wage differential and add onto it the difference in expected productivity between races. Alternatively, if $\overline{MP}_b < \overline{MP}_w$, the market wage differential would *overestimate* the true extent of discrimination.

II. Summary

Statistical discrimination models have provided an explanation of why information on race is rationally taken into account by profit-maximizing employers. We have expanded the analysis by considering the case in which the firm uses a screening process which does not provide perfect information on an applicant's productivity and which is biased against members of a particular race group. We considered the two consequences of this bias on the screening process: First, the bias might result in one race group (for concreteness, blacks) obtaining lower scores despite the fact that the productivity distribution is invariant to race. Secondly, the bias might also affect

the quality of the test in the sense that black scores would be less reliable measures of productivity. It was shown that by introducing the realistic concept of screening bias, wage differentials between black and white workers could be explained without recourse to assumptions of differential ability distributions across groups.

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