Statistical Discrimination, Employer Learning, and Employment Differentials by Race, Gender, and Education

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Abstract

Previous papers on testing for statistical discrimination and employer learning require variables that employers do not observe directly, but are observed by researchers or data on employer-provided performance measures. This paper develops a test that does not rely on these specific variables. The proposed test can be performed with individual-level cross-section data on employment status, experience, and some variables on which discrimination is based, such as race, gender, and education. This paper shows that if employers statistically discriminate among unexperienced workers, but learn about their productivity over time, then the unemployment rates for discriminated groups will be higher than those for non-discriminated groups at the time of labor market entry and that the unemployment rates for discriminated groups will decline faster than those for non-discriminated groups with experience. Evidence from analysis using the March Current Population Survey for 1977-2010 supports statistical discrimination and employer learning.

Keywords: Employer Learning, Statistical Discrimination, Unemployment Rate

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1 Introduction

In hiring and wage-setting processes, employers make judgments about the value of workers using all information available at the time of making decisions. However, the productivity of workers is never perfectly observed, and employers must make predictions on the basis of limited information. For example, potential workers, at the time of labor market entry, do not have past labor market experience, and employers receive only noisy signals of worker productivity, such as curriculum vitae, recommendation letters, and interviews, as well as race, gender, and education. Moreover, employers' ability to screen the productivity of workers may depend on which race, gender, or education group the workers belong to. For example, two individuals of the same gender, education, and experience, but of different race may face unequal opportunity in the labor market even though there is no difference in their productivity. This type of discrimination may happen because employers are less able to evaluate the productivity of workers from one group than from another, which is also referred to as screening discrimination by Cornell and Welch (1996).

As young workers become experienced, past labor market performance records become available to employers allowing them to make better predictions. The theory of statistical discrimination, accompanied by the employer learning hypothesis, predicts that the degree of discrimination will decrease with the labor market experience of workers. Altonji and Pierret (2001) utilize this idea and propose an empirical test for statistical discrimination. Consider variables that are correlated with productivity. Some are directly observed by employers (e.g., education), while others are not observed by employers, but are observed by researchers (e.g., test scores). Using the National Longitudinal Study of Youth (NLSY79), they show that if employers statistically discriminate among young workers on the basis of easily observable characteristics, the coefficients on the easily observed variables in a wage equation should fall and the coefficients on hard-to-observe variables should rise over the worker's period of employment.

While the recent tests of statistical discrimination require some variables available to researchers but not observed by employers (Altonji and Pierret, 2001; Pinkston, 2006) or data on employer-provided performance measures (Neumark, 1999; Pinkston, 2003), such variables are difficult to find in practice. The key contribution of this paper is proposing a test that does not rely on those specific variables.[1] The data requirement for the proposed strategy is minimal. The theoretical model of this paper suggests that if employers statistically discriminate among young workers on the basis of easily observable characteristics such as race, gender, and education, but learn about their productivity over time, then the unemployment rates for discriminated groups will be higher than those for non-discriminated groups at the time of labor market entry and that the unemployment rates for discriminated groups will decline faster than those for non-discriminated groups with experience. Therefore, the test can be performed with individual-level repeated cross-section data on employment status, experience, and some variables on which discrimination is based, such as race, gender, and education.

This paper focuses on employment opportunities rather than wage levels because discrimination will influence the former more than the latter if the Equal Employment Opportunity Act prohibits wage differences among workers performing the same task. An obstacle to using this approach, however, is that employment is measured as a binary variable, whereas wages are measured continuously. Moreover, minimal data requirements limit the scope of the analysis. Therefore, to show that the predictions made by the theoretical model presented in this paper explain the empirical results, it must be that the results cannot be explained by other hypotheses, such as human capital theory, search and matching models, and the theory of taste-based discrimination. This paper concludes that the empirical findings are not consistent with these alternative hypotheses.

Section 2 of this paper develops the theory of statistical discrimination and employer learning to produce its implications on employment rates. Suppose that, without loss of generality, employers classify potential workers into two groups, A and B, where signals of group B work-

[1] A test proposed by Oettinger (1996) also does not require such variables, but requires job mobility and job tenure information. His model suggests that the gain from job change for African-American men should be smaller than that for white men. As a result, African-American men move less and the black-white difference in wages among men should increase with experience. Using the National Longitudinal Survery of Youth 1979, he finds support for his hypothesis.

ers are noisier than those of observationally equivalent group A workers. However, employers believe that group A and group B workers have the same productivity distributions. When employers receive applications from multiple potential workers, they evaluate the applicants based on their information set and hire subsets of applicants whose productivity signals satisfy their own pre-set criteria. If the information sets the employers have on a given worker are fairly different across the employers, this paper shows that more group A workers are expected to be employed than group B workers at any experience level conditioning on observable characteristics.

As young workers gain labor market experience, the employers' beliefs about their productivity will be updated. Since relatively less information is observed for the group B workers at the beginning of the employment process, the marginal gain of additional information is larger for group B workers as compared to that for group A workers of the same productivity. It also means that the distributions of employers' beliefs for the two groups will converge to the true productivity distributions which are assumed to be the same. As a result, any gap between group A and group B workers will narrow, and both groups of workers will have more equal labor market opportunities.

Section 3 applies the proposed strategy using the March Current Population Survey (CPS) for 1977-2010. The empirical findings are consistent with the theoretical predictions. First, the results are consistent with the predictions made by employer learning. More experienced individuals are more likely to be employed for any groups classified by race, gender, and education, and the growth rates in the employment rates are larger for the groups with initially lower employment rates. Second, the results suggest that employers statistically discriminate on the basis of race and education, but not on the basis of gender. Initially black workers are less likely to be employed than white workers when they are young, but the black-white gap in employment rates narrows with experience conditioning on gender and education. Similarly, education is positively correlated with the probability of getting employed, but the employment rates of low-educated workers grow faster than those of highly educated workers with experience conditioning on race and gender. However, there is no significant differences in employment rates for males and females conditioning on race, education, and experience.

2 Theoretical Framework

2.1 Statistical Discrimination at the Time of Labor Market Entry

Consider a labor market where employers announce job vacancies and potential workers apply for these positions. Applicants are allowed to apply for more than one position. When employers receive applications, they screen the applicants using all information available at the time of hiring. Each employer has his or her own pre-set productivity criteria, and applicants may receive job offers from the employer if their perceived productivity signals to the employer meet the criteria. When there are more qualified applicants than open positions, employers choose applicants based on their own hiring strategies. For example, employers may give initial offers to applicants with the highest evaluations or may choose randomly among the qualified applicants. Therefore, a sufficiently high signal is necessary for an offer, but does not guarantee an offer. There is no negotiation in hiring processes, but applicants with multiple job offers in hand are allowed to choose among the offered jobs. When turned down, employers may give offers to other qualified candidates, but it can be done only for a finite number of times due to time constraints. As a result, some positions may remain unfilled. Other positions may not be filled due to lack of qualified applicants. In general, the market does not clear, and some applicants will remain unemployed by the end of the period.

A potential worker i is characterized by the productivity, P_{ij}, when he or she is matched with an employer j. The productivity depends on two sets of measures, X_{ij} and η_i. Vector X_{ij} consists of variables that are directly observed by both employers and researchers, such as labor market experience and possibly job tenure. We assume that race, gender, and education are also observed by employers and researchers, but are not necessarily included in X_{ij}. Vector η_i consists of a finite number of skill measures, such as physical strength and IQ. Skill measures are unobservable to researchers, but may be partly observed by some employers. We assume that η_i has a multivariate normal distribution. Since different jobs require different skills, worker i's productivity at job j is specified through a linear combination of these factors,

$$P_{ij} = r' X_{ij} + r_j' \eta_i, \tag{1}$$

where r is a vector of parameters common to all employers and r_j is an employer-specific non-random weight.

When an employer j receives applications, he or she makes predictions about the productivity of the applicants. Let I_{ij} denote the set of information that employer j has about applicant i at the time when person i enter the labor market. The information set, I_{ij}, includes easily observable variables such as X_{ij} as well as race, gender, and education. In principle, however, I_{ij} is worker-employer-specific and may also include factors that are not observed by researchers and other employers. For example, if applicant i and employer j share a similar cultural background, but applicant i' and employer j' do not, I_{ij} will be richer than $I_{i'j}$ or $I_{ij'}$ if other things are equal.[2] A worker-employer-specific information set implies that different employers may rank the same applicant differently. More specifically, applicant i's true productivity (1) is perceived by employer j as

$$E\left[P_{ij}|I_{ij}\right] = r' X_{ij} + r_j' E\left[\eta_i|I_{ij}\right]. \tag{2}$$

While the information sets are worker-employer-specific, we additionally assume that employers categorize potential workers into groups on the basis of race, gender, and/or education and that their information sets for members of some groups are systematically richer than those of other groups. For example, suppose that employers classify individuals into two groups, group A and group B, but the fact that group A and group B workers share a common distri-

[2] Cultural background is broadly defined as in Cornell and Welch (1996) to include groups defined by language, ethnicity, school ties, neighborhood connections, or membership in social organizations, as well as race, gender, and education.

bution of productivity is common knowledge. Then, without loss of generality, assume that employers have richer information sets for group A workers than for group B workers,

$$I_{i \in A,j} \supset I_{i \in B,j} \text{ and } I_{i \in A,j} \neq I_{i \in B,j} \text{ for any } j. \tag{3}$$

Condition (3) is equivalent to assuming that the signals from group B workers are noisier than those from group A workers. Let S_{ij} denote the signal that employer j receives from applicant i's η_i. Then, a representation of (3) is assuming

$$S_{i \in A,j} = r_j' \eta_i + \xi_{i \in A,j} \text{ and } S_{i \in B,j} = r_j' \eta_i + \xi_{i \in B,j}, \tag{4}$$

where ξ is a normal random variable independent of η_i with $E\left[\xi_{i \in A,j}\right] = E\left[\xi_{i \in B,j}\right] = 0$ and $Var\left(\xi_{i \in A,j}\right) = \sigma_{A\xi}^2 < Var\left(\xi_{i \in B,j}\right) = \sigma_{B\xi}^2$. We use the common subscript i in (3) and (4) to emphasize the fact that the two workers are identical except for their group memberships.

The information gap given in (3) has an important implication for the variances of employers' expectations. It means that the ex ante variance of employer j's perceived productivity of group A members is strictly larger than the ex ante variance of employer j's perceived productivity of group B members,

$$Var\left(E\left[r_j' \eta_i | I_{i \in A,j}\right]\right) > Var\left(E\left[r_j' \eta_i | I_{i \in B,j}\right]\right) \qquad \text{for any } j. \tag{5}$$

To see this point, consider an extreme case where employer j does not have any screening ability for group B members. Then, the employer will evaluate the productivity of any group B workers as the unconditional expectation, $E\left[\eta_i | I_{i \in B,j}\right] = E\left[\eta_i\right]$, and we have $Var\left(E\left[r_j' \eta_i | I_{i \in B,j}\right]\right) = 0$. Another extreme example is the case where employer j has perfect knowledge about the productivity of group A members, $E\left[\eta_i | I_{i \in A,j}\right] = \eta_i$. In that case, the employer knows the productivity distribution of group A workers and $Var\left(E\left[r_j' \eta_i | I_{i \in A,j}\right]\right)$ will be equal to the variance of the productivity distribution, $Var\left(r_j' \eta_i\right)$.

Another way of deriving (5) is using the information structure given in (4). That is,

$$E\left[P_{ij}|I_{ij}\right] = E\left[P_{ij}|S_{ij}, X_{ij}\right] = r'X_{ij} + E\left[r_j'\eta_i|r_j'\eta_i + \xi_{ij}\right] = r'X_{ij} + \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_\xi^2}S_{ij}, \qquad (6)$$

where $\sigma_\eta^2 = Var\left(r_j'\eta_i\right)$. In the first example above, the signal is extremely noisy, $\sigma_{B\xi}^2 = \infty$, and all applicants from group B will be evaluated as $r'X_{ij}$. In the second example, the signal is perfect, $\sigma_{A\xi}^2 = 0$, and employers observe individual productivity perfectly, $r'X_{ij} + r_j'\eta_i$. Then we have

$$Var\left(E\left[r_j'\eta_i|I_{i\in A,j}\right]\right) = \frac{\sigma_\eta^4}{\sigma_\eta^2 + \sigma_{A\xi}^2} > \frac{\sigma_\eta^4}{\sigma_\eta^2 + \sigma_{B\xi}^2} = Var\left(E\left[r_j'\eta_i|I_{i\in B,j}\right]\right) \qquad \text{for any } j.$$

since $\sigma_{A\xi}^2 < \sigma_{B\xi}^2$. Therefore, (3) implies that group B members are more likely to be middle-ranked, while group A members will tend to be evaluated as top- or bottom-ranked workers. Since employers prefer more productive applicants, it is more likely for a group A worker to receive the initial offer than for a group B worker.

The fact that group A members are more likely to get initial offers does not necessarily imply a lower unemployment rate for group A than group B. Those who have multiple offers will decline some of their offers, and the employers may move to other qualified candidates. Consider an extreme case in which all employers have identical information sets. If these employers require the same skills, they will rank all the applicants the same, and this is equivalent to having only one employer in the entire labor market. For the market unemployment rate to be below 50%, which is the case in most economies, workers at the left tail of the rank distribution must be employed. Due to (5), a group A worker is more likely to be located at the top or at the bottom than a group B worker of the same productivity, and since the cutoff point for getting an offer is at the left tail of the distribution, the group A unemployment rate will be higher than the group B unemployment rate.

In a more the realistic case, however, information sets are likely to be heterogeneous among employers. Therefore, within any class of jobs that require the same skills, assume that the

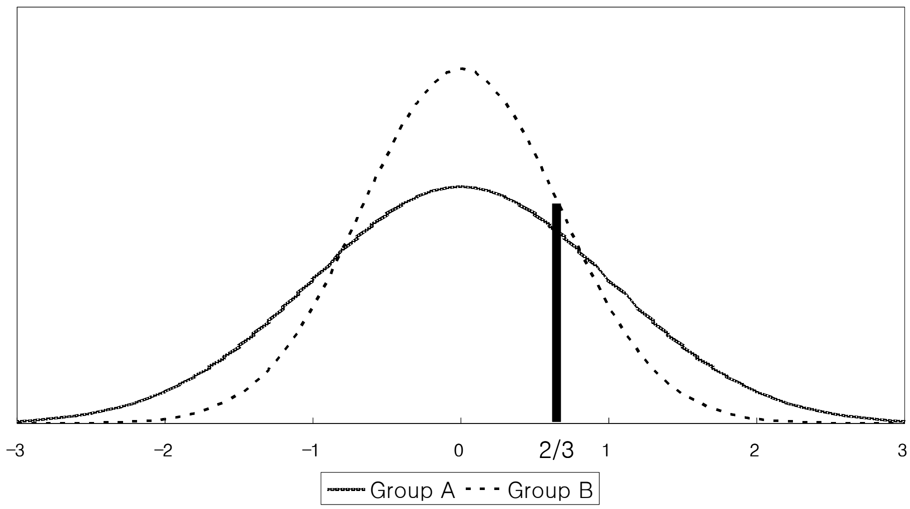

Figure 1: The Distribution of Workers' Productivity Perceived by an Employer

information sets are random across employers. Then, workers of the same skills will be ranked differently by different employers. If there are sufficiently many employers, it is possible to maintain the market unemployment rate below 50% even if each employer hires workers with signals in the right tail of the rank distribution only. An example is presented in Figure 1. Suppose that the expected productivity distributions for group A workers and group B workers are standard normal, $N(0,1)$, and normal with expectation zero and standard deviation 2/3, $N\left(0,(2/3)^2\right)$, respectively. Each employer gives offers to workers with signals exceeding 2/3. Then, the probability of getting an offer for a group A worker by an employer is about 0.25.[3] For a group B worker, the probability is about 0.16.[4] If there are ten employers in the market, since their information sets are independent of each other, the probability of not getting an offer from any of the employers is 0.056 for a group A worker and 0.175 for a group B worker.[5] Therefore, the group A unemployment rate is 5.6% and the group B unemployment rate is 17.5% in this market.

In sum, we expect that the unemployment rate for the group with more precise signals

[3] $\Pr\left(Z > \frac{2}{3}\right) = 1 - \Phi\left(\frac{2}{3}\right) = 0.25$, where Z is a standard normal random variable and $\Phi(\cdot)$ is its distribution function.

[4] Since the standard deviation is $\frac{2}{3}$, $\Pr\left(\frac{2}{3}Z > \frac{2}{3}\right) = 1 - \Phi(1) = 0.16$.

[5] Note that $0.056 = (1-0.25)^{10}$ and $0.175 = (1-0.16)^{10}$.

(i.e., group A) will be higher when I_{ij} is perfectly dependent across employers and that the unemployment rate for the group with noisier signals (i.e., group B) will be higher when I_{ij} is random across employers. In reality, the degree of dependency will lie somewhere in between the two extreme cases, but it is an interesting question to see which of the effects dominates the other. According to the statistical discrimination literature that focuses on wage discrimination, workers in the group with noisier signals (group B) earn lower wages than workers in the group with more precise signals (group A). Since in the data the group of individuals who earn on average lower wages also have higher unemployment rates, I_{ij} must be close to heterogeneous across employers rather than completely the same. The discussion in this section leads to proposition 1.

Proposition 1. When employers statistically discriminate against group B workers in comparison to group A workers, the group B unemployment rate will be larger than the group A unemployment rate at the time of labor market entry.

2.2 Experience, Employer Learning, and Statistical Discrimination

Suppose that worker i accepts an offer from employer j. Now, worker i produces an output, Q_{ijt}, at each experience level $t = 1, 2, ..., T$. Researchers, however, do not observe these outcomes. Then, the output, Q_{ijt}, net of the deterministic term, $r'X_{ij}$, is a proxy for $r_j'\eta_i$ of the worker:

$$\begin{aligned} q_{ijt} &= Q_{ijt} - r'X_{ij} \\ &= r_j'\eta_i + \varepsilon_{ijt}, \text{ for } t = 1, 2, ..., T, \end{aligned}$$

where ε_{ijt}'s are iid normal random variables with $E\left[\varepsilon_{i\in A,jt}\right] = E\left[\varepsilon_{i\in B,jt}\right] = 0$ and $Var\left(\varepsilon_{i\in A,jt}\right) = Var\left(\varepsilon_{i\in B,jt}\right) = \sigma_\varepsilon^2$ and are independent of ξ_{ij}. Employer j observes q_{ij1}, q_{ij2}, ..., q_{ijT}, in each period and subsequently updates his or her initial evaluation about η_i of worker i. The proof below is similar to that in Pinkston (2006).

$$E\left[P_{ij}|I_{ij},q_{ij1},...,q_{ijT}\right] = r'X_{ij}+E\left[r_j'\eta_i|r_j'\eta_i+\xi_{ij},r_j'\eta_i+\varepsilon_{ij1},...,r_j'\eta_i+\varepsilon_{ijT}\right]$$
$$= r'X_{ij}+\frac{\sigma_\eta^2}{\sigma_\eta^2+\frac{\sigma_\varepsilon^2\sigma_\xi^2}{T\sigma_\xi^2+\sigma_\varepsilon^2}}\left(\frac{\sigma_\varepsilon^2 S_{ij}+\sigma_\xi^2\sum_{t=1}^T q_{ijt}}{T\sigma_\xi^2+\sigma_\varepsilon^2}\right). \quad (7)$$

As workers become more experienced, employer j learns more about their productivity, and the distribution of evaluations approaches the true productivity distribution since

$$Var\left(E\left[P_{ij}|I_{ij},q_{ij1},...,q_{ijT}\right]\right)=\frac{\sigma_\eta^4}{\sigma_\eta^2+\frac{\sigma_\varepsilon^2\sigma_\xi^2}{T\sigma_\xi^2+\sigma_\varepsilon^2}}$$

approaches σ_η^2 as T gets larger. More importantly, the amount of learning is greater for group B workers than group A workers. To see this, it is sufficient to show that the weight for the cumulative outcomes is increasing in experience and initial noise,

$$\frac{d^2}{d\sigma_\xi^2 dT}\frac{\sigma_\eta^2}{\sigma_\eta^2+\frac{\sigma_\varepsilon^2\sigma_\xi^2}{T\sigma_\xi^2+\sigma_\varepsilon^2}}>0,$$

but this inequality holds because

$$\frac{d^2}{d\sigma_\xi^2 dT}\frac{\sigma_\varepsilon^2\sigma_\xi^2}{T\sigma_\xi^2+\sigma_\varepsilon^2}=-\frac{2\sigma_\varepsilon^4\sigma_\xi^2}{\left(T\sigma_\xi^2+\sigma_\varepsilon^2\right)^3}<0.$$

As a consequence, with the increase in experience, employers can better screen workers, and the group B unemployment rate will decrease at a faster rate than the group A unemployment rate.

Proposition 2. When employers statistically discriminate against group B workers in comparison to group A workers, and employers learn about the productivity of workers as they accumulate more experience, the group B unemployment rate will decrease at a faster rate than the group A unemployment rate.

3 Empirical Findings

3.1 Data

The sample is drawn from the Integrated Public Use Microdata Series (IPUMS) March Current Population Survey (CPS) for 1977-2010. It collects African-American and non-Hispanic white men and women between the ages of 15 and 64.

Table 1 reports employment rates by race, gender, education, and experience during the sample period. Overall, employment rates increase with experience for all groups, which is consistent with the employer learning hypothesis. Although this relationship may also be justified by human capital theory or search and matching models, these explanations will be ruled out by further analyses in later subsections. In the data, employment rates for blacks are initially lower than whites, but the employment rates of the former improve faster than the employment rates of the latter. This observation is consistent with statistical discrimination on the basis of race. Table 1 reveals a similar pattern among education groups, but not between gender groups.

Table 1. Employment Rates by Race, Gender, and Education at Different Experience Levels

Experience:	00-09	10-19	20-29	30-39	40-49	Total
White	0.908	0.950	0.960	0.961	0.957	0.944
Black	0.784	0.888	0.919	0.931	0.941	0.880
Male	0.882	0.941	0.953	0.954	0.950	0.932
Female	0.907	0.945	0.959	0.963	0.963	0.942
Less than High School	0.792	0.837	0.890	0.922	0.936	0.856
High School	0.877	0.926	0.947	0.956	0.960	0.929
Some College	0.934	0.953	0.962	0.962	0.964	0.952
University or Above	0.968	0.978	0.979	0.977	0.974	0.976

3.2 Empirical Specification and Results

This section tests for statistical discrimination and employer learning by evaluating whether propositions 1 and 2 hold empirically. We first test whether unemployment rates decline with experience. It does not prove the existence of employer learning, but is a necessary condition for employer learning. Human capital or search models make the same prediction. Then, we test whether African-Americans are less likely to be employed than non-Hispanic whites, whether females are less likely to be employed than males, and whether less educated individuals are less likely to be employed than more educated individuals at the time of labor market entry. It does not necessarily imply that there is statistical discrimination. These findings can be supported also by human capital theory or taste-based discrimination. Finally, we test whether the employment rates of the less-likely-to-be-employed group workers increase at a faster rate than those of the more-likely-to-be-employed group workers. Finding such patterns will serve as evidence of employer learning and statistical discrimination since such patterns are not consistent with human capital theory nor taste-based discrimination.

Variables used in this analysis are employment status, race, gender, education, experience, region, and calendar year. We specify a latent variable model

$$\begin{aligned} Y_{it}^{*} &= \beta' G_i + \gamma' G_i X_{it} + \mu_{region} + \mu_{year} + \varepsilon_{it} \\ E_{it} &= 1\left(Y_{it}^{*} > c\right), \end{aligned} \quad (8)$$

where E_{it} is an indicator for employment, G_i is a vector of easily observable variables, such as race, gender, and education, at the time of labor market entry including an intercept, $G_i X_{it}$ is the interaction between G_i and experience, X_{it}, μ_{region} and μ_{year} are region and calendar year dummy variables, and ε_{it} is an error term. ε_{it} is independent of the right hand side variables and has a standard normal distribution. Usually, the probit estimates are not interesting by themselves, but they are useful in this study because we are interested in their signs.

Column (1) presents an equation that includes an intercept and controls for black, experience, and black $\times$ experience. This corresponds to testing employer learning and statistical discrimination by examining whether experience is positively associated with the probability of employment, whether African-Americans are less likely to be employed than whites at the time of labor market entry, and whether their group employment rate rises faster than that of whites with experience. First, a positive experience coefficient estimate, 0.138*** (0.001), indicate the presence of employer learning. Second, a negative black coefficient estimate, -0.601*** (0.006), implies that there exists an initial black-white gap in employment rates. Finally, a positive coefficient estimate for black $\times$ experience, 0.101*** (0.003), is consistent with the prediction in proposition 2. In sum, the results suggest evidence of employer learning and statistical discrimination on the basis of race.

Column (2) tests employer learning and statistical discrimination on the basis of gender. Again, a positive experience coefficient estimate, 0.158*** (0.001), implies employer learning. However, the positive coefficient for the female dummy, 0.097*** (0.005), and the negative coefficient for female $\times$ experience, -0.005** (0.002), suggest that there is little evidence for statistical discrimination on the basis of gender. It is tempting to conclude that men would appear to be the discriminated group. These results, however, do not necessarily imply that there is no statistical discrimination on the basis of gender since there are selection involved in analyzing females' labor market participation. This point will be discussed later.

Table 2. Probit Estimates: Dep. Variable = 1 if employed, 0 if unemployed

	(1)	(2)	(3)	(4)
Constant	1.239***	1.161***	1.158***	1.150***
	(0.009)	(0.009)	(0.009)	(0.009)
Black	-0.601***			-0.547***
	(0.006)			(0.009)
Female		0.097***		0.111***
		(0.005)		(0.005)
Black × Female				-0.124***
				(0.013)
Education			0.744***	0.730***
			(0.005)	(0.007)
Black × Education				0.166***
				(0.021)
Female × Education				-0.055***
				(0.011)
Black × Female × Education				0.131***
				(0.029)
Experience/10	0.138***	0.158***	0.158***	0.142***
	(0.001)	(0.001)	(0.001)	(0.002)
Black × Experience/10	0.101***			0.095***
	(0.003)			(0.004)
Female × Experience/10		-0.005**		-0.003
		(0.002)		(0.002)
Black × Female × Experience/10				0.048***
				(0.006)
Education × Experience/10			-0.092***	-0.088***
			(0.002)	(0.003)
Black × Education × Experience/10				-0.055***
				(0.010)
Female × Education × Experience/10				-0.006
				(0.005)
Black × Female × Education × Experience/10				-0.003
				(0.014)
Observations	2247528	2247528	2247528	2247528

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Column (3) compares high school graduate workers with university graduate workers. The education variable takes on a value of zero for 12 years of education (high school graduates) and one for 16 years or more (BA degree or higher). It takes on a value of -0.5 for high school drop-outs and 0.5 for those who have 13-15 years of education. A positive education coefficient estimate, 0.744*** (0.005), implies that education is helpful for initial employment. The negative coefficient estimate for education $\times$ experience, -0.092*** (0.002), is consistent with employer learning and statistical discrimination on the basis of education. Overall, the results in columns (1) and (3) are consistent with propositions 1 and 2. African-American workers and low-educated workers have initially worse labor market opportunities in terms of employment probability, but their employment rates improve faster with employer learning.

Finally, column (4) includes the full set of variables. Consider eight groups of workers: all possible combinations of race (African-American and non-Hispanic white), gender (female and male), and education (high school graduates and university graduates). First, consider discrimination on the basis of race. A negative black coefficient estimate, -0.547*** (0.009), and a positive black $\times$ experience coefficient estimate, 0.095*** (0.004), suggest that high school graduate African-American male workers are statistically discriminated against in comparison to high school graduate white male workers. To test whether university graduate African-American male workers are statistically discriminated against university graduate white male workers, we examine the sum of the coefficients for black and black $\times$ education, -.381*** (0.023), and the sum of the coefficients for black $\times$ experience and black $\times$ education $\times$ experience, 0.040*** (0.011). The degree of racial discrimination is less for university graduates since the magnitude of the coefficients is smaller.

To evaluate evidence of racial discrimination among high school graduate female workers, we look at the sum of the coefficients for black and black $\times$ female, -0.670*** (0.009), and the sum of the coefficients for black $\times$ experience and black $\times$ female $\times$ experience, 0.143*** (0.005). These results suggest employer learning and statistical discrimination. For university graduate female workers, we examine the sum of the coefficients for black, black $\times$ female, black $\times$ education, and black $\times$ female $\times$ education, -0.373*** (0.021); and the coefficients for black $\times$ experience, black $\times$ female $\times$ experience, black $\times$ education $\times$ experience, and black $\times$ female $\times$ education $\times$ experience, 0.085*** (0.011). Again, these results suggest employer learning and statistical discrimination. In general, the results in column (4) are qualitatively the same as those in columns (1)-(3).

We now return to the discussion of statistical discrimination on the basis of gender. A major problem related to analyzing employment rates is that only females selected into working participate in the labor market, while most males do. To address the selection problem, Table 3 reports estimates based on a probit model where the dependent variable takes on a value of 1 if the individual is employed and 0 if the individual is unemployed or out of labor force. The results for gender in Table 3 are quite different from those in Table 2. In column (2) of Table 3, initially females work less, -0.181*** (0.003), and the proportion of working females does not change much over experience since the sum of the coefficients for experience and female $\times$ experience is close to zero, -0.004*** (.0001). In column (4), white high school graduate females works less than observationally equivalent males initially, -0.282*** (0.003), and the proportion of working white high school graduate females decreases with experience: the sum of the coefficients for experience and female $\times$ experience is -0.013*** (.0001). Similar patterns are found for females of other race and education groups. In sum, these results suggest that statistical discrimination on the basis of gender cannot be tested by Propositions 1 and 2 since they do not consider sample selection.

Table 3. Probit Estimates: Dep. Variable = 1 if employed, 0 if unemployed or out of labor force

	(1)	(2)	(3)	(4)
Constant	0.365***	0.431***	0.303***	0.494***
	(0.005)	(0.005)	(0.005)	(0.006)
Black	-0.455***			-0.445***
	(0.004)			(0.006)
Female		-0.181***		-0.282***
		(0.003)		(0.003)
Black × Female				0.132***
				(0.008)
Education			1.068***	1.244***
			(0.003)	(0.004)
Black × Education				0.161***
				(0.013)
Female × Education				-0.355***
				(0.006)
Black × Female × Education				0.286***
				(0.018)
Experience/10	0.031***	0.108***	0.037***	0.075***
	(0.001)	(0.001)	(0.001)	(0.001)
Black × Experience/10	0.081***			0.045***
	(0.002)			(0.003)
Female × Experience/10		-0.111***		-0.088***
		(0.001)		(0.001)
Black × Female × Experience/10				-0.034***
				(0.007)
Education × Experience/10			-0.154***	-0.218***
			(0.001)	(0.002)
Black × Education × Experience/10				-0.029***
				(0.006)
Female × Education × Experience/10				0.113***
				(0.002)
Black × Female × Education × Experience/10				0.064***
				(0.003)
Observations	3026269	3026269	3026269	3026269

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.3 Discussion and Alternative Explanations

This subsection discusses whether or not the predictions made by the theoretical model presented in this paper can also be explained by other hypotheses, such as human capital theory, search and matching models, and the theory of taste-based discrimination. The conclusion is that these alternative explanations are not consistent with the empirical results of this paper.

So far in the discussion, the rate of human capital attainment is set to be the same for the two groups of workers. However, a more realistic assumption is that group B workers have fewer opportunities for human capital investment than to group A workers. Employers may give fewer training or promotion opportunities to group B workers than group A workers. Then, the parameter vector r in (1) will be different for each of the two groups, and it will be more difficult for the prediction in proposition 2 to hold even if there is statistical discrimination in opportunities for human capital investment. However, this also implies that finding the pattern predicted by proposition 2 in the data will serve as strong evidence of statistical discrimination and employer learning. Therefore, the results in Table 2 support the hypotheses.

Search models predict that the probability of employment is an increasing function of experience. A basic model assumes that every worker receives a certain number of job offers drawn from a distribution each period. If an individual receives an offer above his or her reservation wage, the individual will work at the job. If all the offers are below the reservation wage, the individual will stay unemployed and will search again in the next period. Suppose that the number of offers that an individual receives is larger in more recent years than in earlier years. This is very likely because job announcements are much more accessible in more recent years. Then, if the search story can explain the findings of this paper, it has to be the case that the discriminated group workers should do better in terms of employment rates in more recent years as compared to earlier years. To confirm that this relationship holds, Table 3 shows the results presented in Table 1 separating over two periods, 1977-1993 and 1994-2010.

The employment rates for blacks with experience 0-9 are 73.4%, 10-19 are 86.1%, ..., and 40-49 are 93.3% during 1977-1993, but they are systematically higher during 1994-2010, especially when workers are young. This shows that African-Americans are doing much better in terms of employment rates than they were before. For whites, however, this improvement is smaller than two percentage points. These results are consistent with search models since the improvement in employment rates in recent years is more prominent for the discriminated group than for the non-discriminated group. However, when the population is split by gender or education groups, the improvement in employment rates does not vary across different gender/education groups and experience. Therefore, search models do not explain these findings.

Next, to see whether the findings for race are due to composition changes in education within race groups, Table 5 illustrates employment rates by race/education over experience. Among African-Americans, the improvement in employment rates over the two periods is small for all education groups and for all experience levels except for one case: those who are unexperienced and have some college education. Therefore, considering all these findings, we conclude that search models cannot explain the changes in employment rates by race, gender, and education over different experience levels.

Finally, consider the theory of taste-based discrimination. While this theory can explain why discriminated groups have lower employment rates at any experience level, it cannot explain why the gaps in employment rates between discriminated and non-discriminated groups narrow with experience. In these results, there is the possibility for taste-based discrimination since the narrowing does not imply full convergence at experience level 40-49, but it cannot be the whole story. However, even if the entire employment gap at the highest experience level is due to taste-based discrimination, it explains less than a two percentage point difference between discriminated and non-discriminated groups.

Table 4. Employment Rates by Race, Gender, and Education at Different Experience Levels over 1977-1993 and 1994-2010

	Experience:	00-09	10-19	20-29	30-39	40-49	Total
1977≤year≤1993	White	0.892	0.939	0.954	0.959	0.956	0.930
	Black	0.734	0.861	0.913	0.925	0.933	0.845
	Male	0.870	0.932	0.951	0.956	0.950	0.921
	Female	0.887	0.929	0.947	0.956	0.958	0.924
	Less than High School	0.778	0.842	0.901	0.925	0.938	0.863
	High School	0.871	0.919	0.951	0.962	0.962	0.922
	Some College	0.923	0.951	0.964	0.965	0.974	0.945
	University or Above	0.961	0.975	0.981	0.983	0.980	0.973
1994≤year≤2010	White	0.914	0.953	0.961	0.962	0.958	0.948
	Black	0.799	0.894	0.920	0.933	0.943	0.887
	Male	0.887	0.943	0.953	0.954	0.949	0.935
	Female	0.914	0.948	0.961	0.964	0.964	0.947
	Less than High School	0.798	0.835	0.885	0.919	0.934	0.852
	High School	0.880	0.928	0.947	0.954	0.960	0.931
	Some College	0.937	0.953	0.961	0.961	0.962	0.953
	University or Above	0.970	0.978	0.979	0.976	0.973	0.976

Table 5. Employment Rates by Race and Education at Different Experience Levels over 1977-1993 and 1994-2010

	Experience:	00-09	10-19	20-29	30-39	40-49	Total
White							
1977≤year≤1993	Less than High School	0.802	0.858	0.906	0.929	0.941	0.873
	High School	0.886	0.926	0.954	0.964	0.962	0.929
	Some College	0.933	0.956	0.966	0.967	0.975	0.951
	University or Above	0.964	0.976	0.982	0.983	0.979	0.974
1994≤year≤2010	Less than High School	0.823	0.857	0.897	0.925	0.937	0.867
	High School	0.898	0.936	0.952	0.957	0.960	0.939
	Some College	0.945	0.958	0.965	0.964	0.963	0.958
	University or Above	0.972	0.980	0.979	0.977	0.974	0.977
Black							
1977≤year≤1993	Less than High School	0.578	0.775	0.880	0.907	0.924	0.804
	High School	0.737	0.862	0.919	0.940	0.953	0.843
	Some College	0.819	0.904	0.949	0.938	0.961	0.878
	University or Above	0.919	0.948	0.965	0.987	1.000	0.945
1994≤year≤2010	Less than High School	0.595	0.736	0.835	0.899	0.924	0.775
	High School	0.775	0.875	0.908	0.929	0.953	0.876
	Some College	0.878	0.920	0.936	0.941	0.952	0.918
	University or Above	0.947	0.959	0.967	0.965	0.965	0.960

4 Concluding Remarks

This paper proposes a new test for statistical discrimination using basic individual characteristic variables. The test can be performed with individual-level cross-section data on employment status, experience, and some variables on which discrimination is based, such as race, gender, and education. The theoretical model produces testable implications for employment rates in the presence of statistical discrimination and employer learning. When employers statistically discriminate against some workers in comparison to other workers, the discriminated group's unemployment rate will be larger than the non-discriminated group's unemployment rate at the time of labor market entry. The theory of statistical discrimination, accompanied by the employer learning hypothesis, predicts that the discriminated group's unemployment rate will decrease at a faster rate than the non-discriminated group's unemployment rate as workers become more experienced. Empirical findings support statistical discrimination on the basis of race and education. The test, however, is not suitable for the case of gender discrimination because females' employment rates are affected by their selection into labor force.

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