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. Evidence from analysis using the March Current Population Survey for 1977-2010 supports statistical discrimination and employer learning. The empirical findings are not explained by alternative hypotheses, such as human capital theory, search and matching models, and the theory of taste-based discrimination.

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 gain more experience, past labor market performance records become available to employers allowing them to make better predictions about their future performance. 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 1979 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 status and wage rates provide different degrees of information: employment is measured as a binary variable, whereas wages are measured continuously. Moreover, minimal data requirements limit the scope of the analysis.[2] 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 the

[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 should move less and the black-white difference in wages among men should increase with experience. Also not using those variables, Moro (2003) structurally estimates an equilibrium labor market model with statistical discrimination. His model, however, does not prove statistical discrimination as the results can also be generated by taste-based discrimination.

[2] Ritter and Taylor (2011) use the NLSY79 to examine whether the black-white employment gap can be explained by the associated disparity in AFQT scores, a variable available to researchers but not observed by employers. They find a large unexplained unemployment differential and explain it using a model that utilizes statistical discrimination.

predictions of these alternative hypotheses.

Section 2 of this paper discusses the theory of statistical discrimination and employer learning to produce its implications on employment opportunities. Suppose that, without loss of generality, employers classify potential workers into two groups, A and B, where signals of group B workers are noisier than those of observationally equivalent group A workers. However, employers believe that group A workers and group B workers have the same productivity distributions. A worker's productivity is defined by a finite set of skill measures. When employers receive applications from multiple potential workers, the employers evaluate the applicants based on their information set and hire the subsets of applicants whose productivity signals satisfy their own pre-set criteria. If across employers the information sets on a given worker are fairly different and these employers require different skills, 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 workers 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. 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 becoming 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, the proposed test, similar to other research, does not provide clean results in detecting statistical discrimination on the basis of gender as females participating in the labor force are self-selected. To verify that these empirical findings are not driven by a specific sample, this paper also applies the test using the NLSY79 for 1979-2010 and confirms that the empirical findings are robust.

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.[3] A good match occurs if a worker meets an employer who values the worker's skills. In other words, the quality of a match is proportional to $r'_j \eta_i$, the inner product of employer j's vector of skill weights and worker i's vector of skill measures.

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.[4] A worker-employer-specific information set implies that differ-

[3] This setup of production is an extension of Lundberg and Startz (1983) with job-specific weights for a vector of different abilities.

[4] Cultural background is broadly defined as in Cornell and Welch (1996) to include groups defined by

ent 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 workers and group B workers share a common distribution 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 $Var\left(\xi_{i\in A,j}\right) = \sigma^2_{A\xi} < Var\left(\xi_{i\in B,j}\right) = \sigma^2_{B\xi}$. 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 in (2). 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

language, ethnicity, school ties, neighborhood connections, or membership in social organizations, as well as race, gender, and education.

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, (2) can be rewritten by

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

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, conditional on X_{ij}, 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 conditional on X_{ij} does

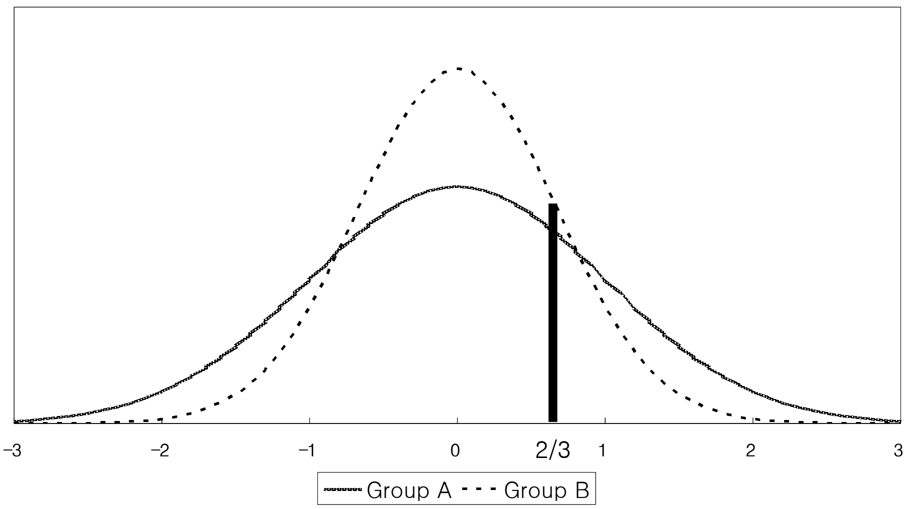

Figure 1: The Distribution of Workers' Productivity Perceived by an Employer

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 heterogeneous among employers. Therefore, within any class of jobs that require the same skills, assume that the 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 has his or her pre-set productivity threshold given as a function of his or her information set, and suppose that each employer gives offers to all applicants with signals exceeding 2/3. Then, the probability of getting an offer for a group A worker by an employer is about 0.25.[5] For a group B worker, the probability is about 0.16.[6] 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.[7] Therefore, the group A unemployment rate is 5.6% and the group B unemployment rate is 17.5% in this market.

In the labor market, we expect that the unemployment rate for the group with more precise signals (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. This paper does not provide a direct estimate of the dependency, but we can rely on other papers to address this point. 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). In this literature, the groups of workers with lower wages include African-Americans, women, and the low-educated. These individuals who earn lower wages on average than individuals in other groups, as we present later in Table 1, also have higher unemployment rates in the data. This suggests that I_{ij} in the real world must be more heterogeneous across employers rather than completely identical. 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.

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

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

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

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. The output, Q_{ijt}, net of the deterministic term, $r'X_{ij}$, is a proxy for $r_j'\eta_i$ of the worker:

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

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}. We assume that the distributions of the ε_{ijt}'s and r_j are common knowledge and that learning on Q_{ijt} and X_{ij} takes place publicly, so that the entire market learns about q_{ijt}. As before, each employer has his or her own pre-set productivity threshold for already employed workers determined by the perceived signal of the worker's quality and observable characteristics.

After observing q_{ij1}, q_{ij2}, ..., q_{ijT}, in each period, employer j subsequently updates his or her initial evaluation about η_i of worker i. The proof below is similar to that in Pinkston (2006).

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

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

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

While employed, workers are allowed to search for alternative jobs, quit their current jobs, and move to new jobs. New offers arrive with different employer-specific skill weights. A worker is more likely to quit and move if the match quality of the new offer is better than the quality of the current employer. In this case, workers are continuously employed and employer learning continues. The proposed test of this paper is not affected by job-to-job movements.

Learning does not take place if worker i is unemployed. There are two reasons for unemployment in a period. First, worker i may have never been employed. He or she still has a chance to find a job in the next period as different employers may weight his or her vector of skills differently and a new signal will be drawn from (4). Second, worker i may have been laid off by employer j and did not find a new job in that period. This is likely to happen if worker i's skill and employer j's job-specific weight are not a good match or worker i was unlucky in production. In the case of a bad match, worker i can improve the match quality in the following period by meeting new employers, possibly those that have favorable weights to his or her skills. In both cases, once employed, employers learn according to (7).

As workers continue to become employed from unemployment and move to new jobs from current jobs, workers are more likely to be continuously employed, and the market learns more precisely about the productivity of these workers. Due to (7), employers learn more about group B workers than group A workers. Consequently, 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. We include in the sample African-American and non-Hispanic white men and women between the ages of 15 and 64, but exclude individuals in the non-civilian labor force and those living in group quarters. Potential experience is obtained by simply subtracting the number of the years of schooling and five from age. As a result of this derivation, about 0.3% of the sample have negative potential experience, and these observations are excluded from the analyses.

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.[8] Moreover, faster improvement in employment rates when workers are less experienced suggests that employers learn quickly as reported in Lange (2007). 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.

[8] This pattern is also true for a given birth cohort, but those results are not reported in this paper.

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

Potential Experience:	00-09	10-19	20-29	30-39	40-49	Total	Observations
White	0.909	0.950	0.960	0.961	0.956	0.944	2,650,033
Black	0.784	0.888	0.919	0.931	0.940	0.880	365,153
Male	0.883	0.941	0.953	0.954	0.948	0.932	1,447,469
Female	0.908	0.945	0.959	0.963	0.962	0.942	1,567,717
Less than High School	0.792	0.834	0.889	0.921	0.933	0.854	585,190
High School	0.877	0.926	0.947	0.956	0.960	0.929	1,053,906
Some College	0.933	0.952	0.961	0.962	0.963	0.951	718,600
University or Above	0.968	0.978	0.979	0.976	0.973	0.976	657,490

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 birth year.[9] We specify a latent variable model

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

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, X_{it} is potential experience, μ_{region} and $\mu_{birthyear}$ are region and birth year dummy variables, and ε_{it} is an error term. The error term, ε_{it}, is treated as 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, 0.125*** (0.002), indicate the presence of employer learning. Second, a negative black coefficient estimate, -0.589*** (0.006), implies that there exists an initial black-white gap in employment rates. Finally, a positive coefficient estimate for black $\times$ experience, 0.097*** (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, 0.134*** (0.002), implies employer learning. However, the positive coefficient for the female dummy, 0.107*** (0.005), and the negative

[9] The birth year dummy variables enter the model to account for differences in employment rates between cohorts of workers. For example, a 40-year-old African-American high school graduate in 1977 likely faced very different opportunities at labor market entry than a 40-year-old worker of the same group in 2010. These dummy variables, however, are not the additive cohort-specific fixed effects as the model is non-linear.

coefficient for female × experience, -0.008*** (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.

Column (3) compares high school graduate workers with university graduate workers. The education variable is obtained by subtracting 12 from the number of the years of schooling and then dividing it by four. In effect, this variable takes on a value of zero for 12 years of schooling (high school graduates) and one for 16 years (BA degrees or equivalent). A positive education coefficient estimate, 0.701*** (0.005), implies that education is helpful for initial employment. The negative coefficient estimate for education × experience, -0.104*** (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, -0.545*** (0.009), and a positive black × experience coefficient estimate, 0.093*** (0.005), 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 × education, -.398*** (0.022), and the sum of the coefficients for black × experience and black × education × experience, 0.041*** (0.009). The degree of racial discrimination is less for university graduates since the magnitude of the coefficients is smaller.

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

	(1)	(2)	(3)	(4)
Constant	1.137***	1.099***	1.036***	1.000***
	(0.129)	(0.129)	(0.129)	(0.129)
Black	-0.589***			-0.545***
	(0.006)			(0.009)
Female		0.107***		0.112***
		(0.005)		(0.005)
Black × Female				-0.115***
				(0.013)
Education			0.701***	0.681***
			(0.005)	(0.007)
Black × Education				0.147***
				(0.019)
Female × Education				-0.040***
				(0.010)
Black × Female × Education				0.156***
				(0.027)
Experience/10	0.125***	0.134***	0.143***	0.136***
	(0.002)	(0.002)	(0.002)	(0.002)
Black × Experience/10	0.097***			0.093***
	(0.003)			(0.005)
Female × Experience/10		-0.008***		-0.007***
		(0.002)		(0.002)
Black × Female × Experience/10				0.047***
				(0.006)
Education × Experience/10			-0.104***	-0.098***
			(0.002)	(0.003)
Black × Education × Experience/10				-0.053***
				(0.007)
Female × Education × Experience/10				-0.002
				(0.004)
Black × Female × Education × Experience/10				-0.018
				(0.011)
Observations	2,245,735	2,245,735	2,245,735	2,245,735

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

To evaluate evidence of racial discrimination among high school graduate female workers, we look at the sum of the coefficients for black and black × female, -0.660*** (0.009), and the sum of the coefficients for black × experience and black × female × experience, 0.140*** (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 × female, black × education, and black × female × education, -0.357*** (0.021); and the coefficients for black × experience, black × female × experience, black × education × experience, and black × female × education × experience, 0.070*** (0.010). 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 self-selected females participate in the labor market, while most males do.[10] To address the problem of selection into the labor force, 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.[11] It is worth noting that while using the employment-to-population ratio resolves the sample selection problem, this measure does not completely fit to the requirements of the test implied by Propositions 1 and 2 because the sample includes individuals who do not have an intent to work.

[10] More precisely, labor force participation, over the studied timeframe, has declined for younger cohort men and has risen dramatically for younger cohort women. These cohort-specific effects are partly controlled for by birth year dummy variables.

[11] This approach has been used by Neal (1994) in the context of black-white wage gap among women.

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

	(1)	(2)	(3)	(4)
Constant	-0.371***	-0.256***	-0.465***	-0.288***
	(0.049)	(0.050)	(0.049)	(0.050)
Black	-0.408***			-0.412***
	(0.004)			(0.006)
Female		-0.216***		-0.312***
		(0.003)		(0.003)
Black × Female				0.137***
				(0.008)
Education			0.942***	1.081***
			(0.003)	(0.004)
Black × Education				0.206***
				(0.012)
Female × Education				-0.305***
				(0.005)
Black × Female × Education				0.307***
				(0.017)
Experience/10	0.045***	0.106***	0.057***	0.097***
	(0.001)	(0.001)	(0.001)	(0.001)
Black × Experience/10	0.055***			0.016***
	(0.002)			(0.003)
Female × Experience/10		-0.104***		-0.082***
		(0.001)		(0.001)
Black × Female × Experience/10				0.068***
				(0.004)
Education × Experience/10			-0.169***	-0.214***
			(0.001)	(0.002)
Black × Education × Experience/10				-0.062***
				(0.004)
Female × Education × Experience/10				0.093***
				(0.002)
Black × Female × Education × Experience/10				-0.042***
				(0.006)
Observations	3,015,186	3,015,186	3,015,186	3,015,186

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

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, -0.216*** (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, 0.002* (0.001). In column (4), white high school graduate females works less than observationally equivalent males initially, -0.312*** (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 0.015*** (0.001). 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.

3.3 Evidence from the NLSY79

In this subsection, we apply the proposed test to a sample drawn from the NLSY79 for 1979-2010. This exercise is useful in several aspects. First of all, we can verify whether the empirical findings are robust to other data sets and compare our findings with those of previous papers on wage discrimination. Second, the NLSY79 individuals are born over a narrow period of 1957-1964, and this alleviates concerns about cohort effects.

From the NLSY79, we include in our sample the cross-sectional sample of whites and blacks and the oversample of blacks. In this approach, an individual in a given year is classified as unemployed if he or she was in the labor force for at least 26 weeks of the year and was unemployed for at least half of the period while in the labor force. This measure is constructed using three variables: the numbers of weeks employed, unemployed, and out of labor force. Observations with any of the three variables missing are dropped. In addition, among the non-missing observations, for about 3% of the sample the three variables do not add up to 52 and are excluded from the analyses. The overall unemployment rate of the sample is 6.36%, and the unemployment rate estimate is quite stable under different classifications.

Table 4. Probit Estimates from the NLSY79: Dependent Variable = 1 if employed, 0 if unemployed

	(1)	(2)	(3)	(4)
Constant	1.804***	1.549***	1.301***	1.487***
	(0.105)	(0.103)	(0.111)	(0.113)
Black	-0.730***			-0.601***
	(0.022)			(0.031)
Female		0.080***		0.119***
		(0.021)		(0.032)
Black × Female				-0.295***
				(0.046)
Education			0.733***	0.607***
			(0.023)	(0.042)
Black × Education				0.059
				(0.064)
Female × Education				0.018
				(0.066)
Black × Female × Education				0.378***
				(0.099)
Experience/10	0.106***	0.132***	0.160***	0.171***
	(0.010)	(0.010)	(0.007)	(0.015)
Black × Experience/10	0.077***			0.008
	(0.014)			(0.020)
Female × Experience/10		-0.011		-0.075***
		(0.014)		(0.021)
Black × Female × Experience/10				0.167***
				(0.030)
Education × Experience/10			-0.111***	-0.044
			(0.015)	(0.028)
Black × Education × Experience/10				-0.034
				(0.042)
Female × Education × Experience/10				-0.045
				(0.042)
Black × Female × Education × Experience/10				-0.118*
				(0.062)
Observations	119,980	119,980	119,980	119,980

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

Table 4 presents the probit estimates, where the dependent variable is one minus the unemployment rate. Overall, the NLSY79 estimates are qualitatively the same as the CPS estimates in Table 2.[12] In column (1), employer learning and statistical discrimination on the basis of race are supported by a negative black coefficient estimate, -0.730*** (0.022) and a positive coefficient estimate for black $\times$ experience, 0.077*** (0.014). In column (4), where the full set of variables are included, the corresponding estimates are -0.601*** (0.031) and 0.008 (0.020). The evidence of learning is weaker, but the estimates have the expected signs. Column (2) presents employer learning and statistical discrimination on the basis of gender, and similar to the CPS results the evidence is not very clear. In column (3), the positive coefficient estimate for education, 0.607*** (0.042), and the negative coefficient estimate for education $\times$ experience, -0.111*** (0.015), are consistent with employer learning and statistical discrimination on the basis of education. This evidence is weaker in column (4), but the signs of the estimates are consistent with Propositions 1 and 2.

3.4 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 as alternative hypotheses. We find that these alternative explanations, at least as currently developed, are not adequate in explaining the estimates of this paper.

With regard to human capital theory, 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.[13] Employers may give fewer training or promotion opportunities to

[12] A table that corresponds to Table 3 for the NLSY79 is not reported in this paper, but the results are again very similar to those in Table 3. In this case, not working is defined by being unemployed or out of labor force for at least 26 weeks of the year.

[13] It is possible that disadvantaged workers get more on-the-job training once hired. Holzer and Neumark (2000) find that African-American male workers spend more time with supervisors or coworkers in the presence of affirmative action. However, there is no clear evidence that this informal training leads to a higher rate of

group B workers than group A workers. Moreover, if African-Americans get more education than whites of similar cognitive ability, as Lang and Manove (2011) find, African-Americans would have fewer chances for training conditional on education. 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.

Next, we consider the theory of taste-based discrimination. In a static model, this theory can explain why discriminated groups have lower employment rates at any experience level, but it cannot explain why the gaps in employment rates between discriminated and non-discriminated groups narrow with experience. In our results, there is the possibility for taste-based discrimination since the two employment rates do not fully converge at experience level 40-49. 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.

Finally, we discuss whether taste-based discrimination accompanied by search models can produce results that are consistent with the empirical results of this paper. This discussion relies heavily on Lang and Lehmann (2011). We begin by presenting Table 5, where the men's black-white employment gap is much larger among low-educated than among high-educated workers.[14] Lang and Lehmann state that this pattern is not explained by any search model, even though there has been an increase in research in this field of search models with taste-based discrimination. Moreover, they point out that while taste-based discrimination models can generate wage and unemployment duration differentials between group A workers and group B workers when combined with search, no existing model for taste-based discrimination can explain the unemployment differential.

human capital investment. They find, however, that women get signficantly more formal on-the-job training when affirmative action is present.

[14]Further conditioning on birth year does not change the pattern qualitatively.

Table 5. Male's Employment Rates by Race and Education
at Different Experience Levels

Potential Experience:	00-09	10-19	20-29	30-39	40-49	Total
White						
Less than High School	0.801	0.850	0.896	0.923	0.929	0.862
High School	0.883	0.929	0.948	0.953	0.955	0.930
Some College	0.933	0.955	0.962	0.961	0.959	0.952
University or Above	0.967	0.981	0.979	0.976	0.972	0.977
Black						
Less than High School	0.581	0.769	0.851	0.894	0.908	0.776
High School	0.764	0.872	0.897	0.915	0.947	0.862
Some College	0.855	0.911	0.929	0.929	0.941	0.905
University or Above	0.933	0.952	0.965	0.954	0.970	0.952

4 Concluding Remarks

This paper proposes a new testing procedure for statistical discrimination and employer learning 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 based on the CPS support employer learning and statistical discrimination on the basis of race and education. Replicating the test using the NLSY79, the data set which others have extensively used in this literature, supports the validity of the proposed test. This paper provides a theory for one of the well-known empirical regularities that the black-white employment gap is larger among low-skilled than among high-skilled workers. Alternative hypotheses do not produce results that are consistent with the empirical findings of this paper, but this does not imply that the proposed test completely rules out the possibility of alternative explanations. It would be useful to explore other approaches to find evidence for discrimination and learning, and these are left for future research.

5 References

Altonji, Joseph G. 2005. "Employer Learning, Statistical Discrimination and Occupational Attainment." *American Economic Review (Papers and Proceedings)*, 95(2), 112-117.

Altonji, Joseph G., and Charles R. Pierret. 2001. "Employer Learning and Statistical Discrimination." *Quarterly Journal of Economics*, 116 (1, February), 313-350.

Cornell, Bradford and Ivo Welch. 1996. "Culture, Information, and Screening Discrimination." *Journal of Political Economy*, 104(3, June), 542–571.

Holzer, Harry J. and David Neumark. 2000. "What Does Affirmative Action Do?" *Industrial and Labor Relations Review*, 53(2, Jan), 240-271.

Lang, Kevin and Michael Manove. 2011. "Education and Labor Market Discrimination." *American Economic Review*, 101(3, June). 1467–1496.

Lang, Kevin and Jee-Yeon K. Lehmann. 2011. "Racial Discrimination in the Labor Market: Theory and Empirics." NBER Working Paper, forthcoming in *Journal of Economic Literature.*

Lange, Fabian. 2007. "The Speed of Employer Learning." *Journal of Labor Economics*, 25(1), 651-691.

Lundberg, Shelly J. and Richard Startz. 1983. "Private Discrimination and Social Intervention in Competitive Labor Markets," *American Economic Review*, 73(3, June), 340-347.

Moro, Andrea. 2003. "The Effect of Statistical Discrimination on Black–White Wage Inequality: Estimating a Model with Multiple Equilibria," *International Economic Review*, 44(2), 467-500.

Neal, Derek. 2004. "The Measured Black-White Wage Gap among Women Is Too Small." *Journal of Political Economy*, 112(1): S1–28.

Neumark, David. 1999. "Wage Differentials by Race and Sex: the Roles of Taste Discrimination and Labor Market Information." *Industrial Relations*, 38(3), 414-442.

Oettinger, Gerald S. 1996. "Statistical Discrimination and the Early Career Evolution of the Black-White Wage Gap." *Journal of Labor Economics*, 14(1, Jan.), 52-78.

Pinkston, Joshua C. 2003. "Screening Discrimination and the Determinants of Wages." *Labour Economics*, 10(6, November), 643-658.

Pinkston, Joshua C. 2006. "A Test of Screening Discrimination with Employer Learning." *Industrial and Labor Relations Review*, 59(2, January), 267-284.

Ritter, Joseph A. and Lowell J. Taylor. 2011. "Racial Disparity in Unemployment." *Review of Economics and Statistics*, 93(1), 30-42.