Discrimination and learning

Heidi L. Williams
MIT 14.662
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Outline

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1 Preliminaries: Farber and Gibbons (1996)

The statistical models of discrimination we covered previously were static models. In contrast, Altonji and Pierret (2001) use a dynamic model of employer learning to develop a test of statistical discrimination by firms. The theoretical underpinnings of their paper build closely on the paper by Farber and Gibbons (1996). Before discussing Altonji and Pierret (2001), we are first going to walk through the Farber and Gibbons (1996) model in detail, and from there we will be able to discuss the Altonji and Pierret (2001) in more depth.

The starting point of the Farber and Gibbons (1996) paper is the following. When a worker enters the labor market, her education and some other characteristics are observable by employers, but it is likely that these observable characteristics convey only partial information to the employer about the worker's productive abilities. However, over time - as the worker accumulates experience in the labor market - further information is likely to be revealed. One of the key insights of the Farber-Gibbons paper was to realize that, at least in some datasets, the econometrician may observe variables measuring productivity that are *not* observed by employers - such as AFQT scores. It is then possible to ask how employers learn about these (unobserved to employers) productivity measures as they gather information about the worker's productivity over time. Farber and Gibbons are interested in the question of what implications this type of employer learning has for wage dynamics. This paper was very influential, in part because it developed a tractable framework with empirically testable implications that were supported by the data.

1.1 Theory: Time-invariant worker characteristics

Let η_i and s_i denote worker i's innate (time-invariant) ability and (time-invariant) schooling. Assume that η_i is not observed directly by employers. Let X_i denote a vector of time-invariant worker attributes other than schooling which are observable by employers and included in the data - such as race and gender. Let Z_i denote a vector of time-invariant worker characteristics that are observed by employers but not included in the data - such as the quality of the school attended by the worker. The key difference between Z_i and η_i is that employers observe the former but must learn about the latter. Finally, let B_i denote a vector of time-invariant background variables on workers that are included in the data but not directly observed by employers - such as AFQT score. Farber and Gibbons allow for an arbitrary joint distribution $F(\eta_i, s_i, X_i, Z_i, B_i)$ of η_i, s_i, X_i, Z_i, and B_i.

Let y_{it} denote the output of worker i in the worker's t^{th} period in the labor market. Assume that outputs $\{y_{it} : t = 1, ..., T\}$ are independent draws from the conditional distribution $G(y_{it}|\eta_i, s_i, X_i, Z_i)$. Note that B_i does not appear in this conditional distribution: in order to distinguish the background variables B_i from the worker's ability, Farber and Gibbons assume that B_i has no direct affect on output (although B_i can affect output through other variables such as η_i).

Assume that all employers know the joint distribution $F(\eta_i, s_i, X_i, Z_i, B_i)$ and the conditional distribution $G(y_{it}|\eta_i, s_i, X_i, Z_i)$; observe schooling s_i and other worker characteristics X_i and Z_i; and observe the sequence of outputs $\{y_{i1}, ..., y_{it}\}$ through period t. Note that the third part is a first strong assumption of the model: Farber and Gibbons refer to this as the "public learning" feature of the model, and discuss in the introduction of their paper some other work that examines alternative assumptions.

The wage paid to a worker in period t is her expected output given all information available at t about the worker:

$$w_{it} = E(y_{it}|s_i, X_i, Z_i, y_{i1}, ..., y_{it-1}) \tag{1}$$

This spot-market model of wage determination rules out long-term contracts; this is a second strong assumption of the model. Farber and Gibbons note that it could be that long-term contracts are not useful, or that they are useful but impossible to enforce.

This model yields three predictions about coefficients that can be estimated in an earnings regression:

1. The estimated effect of schooling on the level of wages should be independent of experience
2. Time-invariant worker characteristics correlated with ability but unobserved by employers should be increasingly correlated with wages as experience increases
3. Wage residuals should be a martingale

We'll discuss each of these predictions in more detail.

1.1.1 Prediction #1: The effect of schooling on wages

Consider a panel data set covering a single cohort of workers that all enter the labor market in the same year. The data provide s_i and X_i for each worker in the cohort, as well as the wage (but not the output) of each worker in each year of the panel ($t = 1, 2, ..., T$). Using wage data from year t, we can estimate the following earnings regression:

$$w_{it} = \alpha_t + \beta_t s_i + X_i \gamma_t + \varepsilon_{it} \tag{2}$$

Note that this regression does not include Z_i, because Z_i is by construction not included in the data (so can't be included in the regression). Note also that Farber and Gibbons are careful to match their theory to the data: because the theory gives predictions about the level of earnings rather than the log of earnings, they follow this and specify their regression equation for wages in levels, not logs.

Let $E^*(\cdot)$ denote a linear projection and $E(\cdot)$ denote a conditional expectation. The estimated coefficients from the regression outlined above ($\hat{\alpha_t}$, $\hat{\beta}_t$, $\hat{\gamma_t}$) are the coefficients from the linear projection $E^*(w_{it}|s_i, X_i)$ of w_{it} on s_i and X_i:

$$E^*(w_{it}|s_i, X_i) = \hat{\alpha_t} + \hat{\beta}_t s_i + X_i \hat{\gamma_t} \tag{3}$$

Farber and Gibbons then apply a version of the law of iterated expectations: $E^*(E(y|x, z)|x) = E^*(y|x)$.[1] Recall from above that $w_{it} = E\left(y_{it}|s_i, X_i, Z_i, y_{i1}, ..., y_{it-1}\right)$. Substituting this expression for w_{it} and applying this version of the law of iterated expectations generates the following:

$$\begin{aligned} E^*\left(w_{it}|s_i, X_i\right) &= E^*\left(E\left(y_{it}|s_i, X_i, Z_i, y_{i1}, ..., y_{it-1}\right)|s_i, X_i\right) && (4) \\ &= E^*\left(y_{it}|s_i, X_i\right) && (5) \end{aligned}$$

Recall that s_i and X_i are both time-invariant. Given our assumption above that the y_{it} are independent and identically distributed draws, we know that $E^*\left(y_{it}|s_i, X_i\right)$ is independent of t. This implies that the effect of schooling on wages is independent of experience. Farber and Gibbons note that the same argument also implies that the estimated effect of any other time-invariant worker characteristics (such as race and gender) on wages should be independent of experience.

The intuition here is that because wages are assumed to equal expected output and because outputs are independent and identically distributed draws, not only is the first period wage w_{i1} the expectation of first period output given s_i and X_i, but also no part of the innovation in wages between the first and second periods ($w_{i2} - w_{i1}$) can be forecast from the information used to determine w_{i1}. Thus, w_{i2} equals w_{i1} plus a term that depends on y_{i1} but is orthogonal to s_i and X_i. This implies that the estimated coefficients on s_i and X_i are the same in the first and second and all subsequent periods.

[1]See Wooldridge (2010) page 35, property (LP.5) for one proof of this property. More generally, Section 2.A.3 of Wooldridge covers a useful review of properties of linear projections, and Section 2.A.1 covers a useful review of properties of conditional expectations.

1.2 Prediction #2: Unobserved characteristics

Recall that B_i is a vector of background variables observed in the data but not observed by employers. Note that other variables observable to employers (s_i, X_i, and Z_i) could be correlated with B_i. To create a vector of variables that are orthogonal to employers' information when the worker enters the labor market, define B_i^* to be the residual from a regression of B_i on all the other variables in the data (s_i, X_i) and the worker's initial wage w_{i1}:

$$B_i^* \quad = \quad B_i - E^* \left(B_i | s_i, X_i, w_{i1} \right) \tag{6}$$

By including w_{i1} in this regression, we are conditioning out everything about B_i that employers can observe at the time of market entry. Note that regressing B_i on the worker's initial wage purges B_i^* of the correlation between Z_i and B_i, provided there is no measurement error in the observed initial wage. Now add B_i^* as a regressor to our wage equation:

$$w_{it} \quad = \quad \alpha_t + \beta_t s_i + X_i \gamma_t + B_i^* \pi_t + \varepsilon_{it} \tag{7}$$

The question here is how π_t will vary with experience. For ease of exposition, Farber and Gibbons specialize to the case where B is a scalar. Since B^* is by construction orthogonal to the other regressors, we know that $\hat{\pi}_t$ is given by $\frac{cov(B_i^*, w_{it})}{var(B_i^*)}$. We can write:

$$\begin{aligned} w_{it} &= w_{it-1} + \zeta_{it} && (8) \\ &= w_{i1} + \sum_{\tau=2}^{t} \zeta_{i\tau} && (9) \end{aligned}$$

where ζ_{it} is the innovation in wages in each period. Since B_i^* is orthogonal to w_{i1} by construction, we know that $\hat{\pi}_1 = 0$ and:

$$\begin{aligned} cov\left(B_i^*, w_{it}\right) &= cov\left(B_i^*, w_{i1} + \sum_{\tau=2}^{t} \zeta_{i\tau}\right) && (10) \\ &= cov\left(B_i^*, w_{i1}\right) + cov\left(B_i^*, \sum_{\tau=2}^{t} \zeta_{i\tau}\right) && (11) \\ &= 0 + cov\left(B_i^*, \sum_{\tau=2}^{t} \zeta_{i\tau}\right) && (12) \\ &= \sum_{\tau=2}^{t} cov\left(B_i^*, \zeta_{i\tau}\right) && (13) \end{aligned}$$

Farber and Gibbons argue that for most common distributions of the joint distribution $F\left(\eta_i, s_i, X_i, Z_i, B_i\right)$ and the conditional distribution $G\left(y_{it} | \eta_i, s_i, X_i, Z_i\right)$, $cov\left(B_i^*, w_{it}\right)$ will be positive for every τ;[2] if that is true, then $\hat{\pi}_t$ will increase with t. That is, if B_i^* is correlated with ability, then the estimated effect of B_i^* on wages should increase with experience because wages progressively incorporate output signals and output is correlated with ability.

[2] The paper doesn't go into detail on this point, they just impose this as an assumption.

It is helpful to compare the effect of worker characteristics the market cannot observe (B_i^*) with the effect of characteristics the market can observe (s_i, X_i). By construction, the former play no role in wage determination, but their estimated effect increases over time as the market learns about ability by observing output. The latter play a declining role in the market's inference process but have a constant estimated effect. Whereas prediction #1 follows very closely from the assumptions of the model, there is more distance between the model assumptions and prediction #2.

1.3 Prediction #3: Wage residuals

Because $E\left(\zeta_{it}|w_{it-1}\right) = 0$, wages are a martingale: $E\left(w_{it}|w_{it-1}\right) = w_{it-1}$. You may be thinking: what is a martingale? Because this third prediction is not central to understanding the Altonji-Pierret paper, I'm not going to spend time discussing this prediction. You can see the paper for details.

Note that in the end, the empirical fact that measured wage growth increases with experience implies that wages are *not* a martingale, so their empirical work focuses on the related prediction that wage residuals (rather than wages) are a martingale.

1.4 Theory: Time-variant worker characteristics

The model thus far has ruled out that productivity may grow with experience. Farber and Gibbons extend the model to allow for productivity to grow with labor market experience. Specifically, they assume that the i^{th} worker's total output in period t is:

$$Y_{it} = y_{it} + h(t) \tag{14}$$

where y_{it} is the part of output due to innate ability and $h(t)$ is the part due to acquired skill. Continue to assume that $\{y_{i1}, ..., y_{iT}\}$ are independent and identically distributed draws from $G\left(y_{it}|\eta_i, s_i, X_i, Z_i\right)$.

Assume that total output grows with labor market experience according to $h(t)$, due for example to on-the-job training. For simplicity take $h(t)$ to be deterministic and linear. Farber and Gibbons then write down a new wage equation that conditions on trends in schooling at experience:

$$w_{it} \quad = \quad \alpha_0 + \alpha_1 t + \beta_0 s_i + \beta_1 s_i t + \varepsilon_{it} \tag{15}$$

1.5 Empirical analysis

Farber and Gibbons use the National Longitudinal Survey of Youth (NLSY) data, a panel dataset focused on younger workers (for whom employer learning about worker quality is likely most important). Rather than inferring experience (typically inferred as age - education - 6), the

NLSY data can measure labor market experience more precisely. The panel dimension allows them to observe wage dynamics for individuals, and the AFQT score variable will be a useful measure of B_i, given that this test score is likely correlated with a worker's ability but not directly observed by employers.

Many of the determinants of B_i are observable by the market, but we can condition out other observables and the first period wage in order to construct a measure B_i^* that is not observed by employers:

$$B_i^* = B_i - X_i\hat{\gamma} - \hat{\delta}w_{i0} \tag{16}$$

In the model the wage at time t incorporates all information the market has about that worker's ability. However, if the wage is measured with error or otherwise doesn't perfectly correspond to productivity, then this B_i^* term will not be completely purged of attributes observed by the market. Farber and Gibbons construct this residualized variable for AFQT score as well as an indicator for whether anyone in the home had a library card when the individual was age 14 (a measure of "household intellectual environment" or family background).

Table 2 tests Farber and Gibbons' first and second predictions:

1. The estimated effect of schooling on the level of wages should be independent of experience
2. Time-invariant worker characteristics correlated with ability but unobserved by employers should be increasingly correlated with wages as experience increases

TABLE II
REGRESSION ANALYSIS OF EARNINGS FUNCTION

Independent variable	(1) Mean [sd]	(2) Wage (level)	(3) Wage (level)	(4) Wage (level)	(5) Wage (Level)	(6) Wage (log)
Constant	1.0	−3.5579	−3.8086	−6.0321	−2.7034	0.0873
		(0.785)	(0.788)	(0.928)	(0.388)	(0.124)
Experience	5.1804	0.4428	0.5054	0.5366	0.2697	0.1012
	[2.502]	(0.102)	(0.103)	(0.100)	(0.069)	(0.013)
Experience squared	33.0953	−0.0178	−0.0185	−0.0178	−0.0198	−0.0027
	[29.947]	(0.003)	(0.003)	(0.003)	(0.003)	(0.000)
Education	13.0450	0.6745	0.6938	0.6719	0.4602	0.0989
	[2.349]	(0.061)	(0.061)	(0.059)	(0.024)	(0.007)
Education × experience	67.5424	−0.0004	−0.0049	−0.0041	0.0172	−0.0026
	[35.014]	(0.008)	(0.008)	(0.007)	(0.005)	(0.001)
AFQT residual/100	0.0024	—	0.6494	0.8734	0.7841	0.1880
	[0.148]		(0.307)	(0.291)	(0.292)	(0.044)
AFQT resid/100 × experience	0.0189	—	0.1938	0.1848	0.1922	0.0187
	[0.856]		(0.064)	(0.060)	(0.060)	(0.008)
Lib card residual/10	−0.0002	—	0.2583	0.2130	−0.0579	0.1440
	[0.043]		(1.035)	(0.988)	(0.989)	(0.146)
Lib card resid × experience/10	−0.00011	—	0.6035	0.6169	0.6448	0.0588
	[0.248]		(0.205)	(0.192)	(0.192)	(0.026)
Year		yes	yes	yes	no	yes
Education × year		yes	yes	yes	no	yes
Other demographic		no	no	yes	yes	yes
R^2		0.215	0.224	0.294	0.289	0.296

The dependent variable is real hourly earnings on the current job (in levels in columns (2)–(5) and in logs in column (6). The mean of the level of earnings is 6.91 (s.d. = 3.30). The mean of the log of earnings is 1.83 (s.d. = 0.448). The numbers in parentheses are White/Huber standard errors computed accounting for the fact that there are multiple observations for each worker. There are 28,984 wage observations on 4970 individuals. Where included, there are ten year dummies for 1981–1990 and interactions of education with each of the ten year dummies. The base year is 1991. The other demographic characteristics, where included, consist of age at entry, a dummy variable for part-time, the interaction of part-time with education, and dummy variables for collective bargaining coverage, race, sex, marital status, and the interaction of sex and marital status.

Column (1) reports the means and standard deviations of the key regressors. Column (2) is a basic earnings regression, and Column (3) adds the AFQT and library card residuals. As previewed earlier, the wage function is specified in levels rather than logs, but the implied return to education (evaluating the proportional effect of education at the mean level of earnings) is approximately 9 percent - a number that lines up with typical estimates.

Consistent with the model, there is no evidence that the relationship between earnings and education varies with experience: the estimated coefficient on the interaction is not statistically different from zero. However, this finding is sensitive to the inclusion of controls for changes in the returns to education over time: Column (5) omits the education-by-year interactions that are included in the earlier columns, and here the interaction of education and experience is positive. Given the increase in the return to education over this period, and the fact that experience is growing over time, it isn't surprising that the return to education would appear to grow with experience (age) if the return to education is not allowed to vary by calendar year.

Also consistent with the model, the estimated coefficients of the interactions of the AFQT residuals with experience are positive (Columns (3) and (4)). Because AFQT is correlated with ability but unobserved by employers, this supports the notion that AFQT and wages should be increasingly correlated with wages as experience increases. The library card residuals show a similar trend. Farber and Gibbons are concerned that these interactions could be related to an increase in the return to ability over the sample period (time effects). But the estimates are robust to including AFQT residual-by-year interactions.

Farber and Gibbons also analyze their model's third prediction:

3. Wage residuals should be a martingale

Because the test of this third prediction is somewhat involved and not critical to understanding the Altonji-Pierret paper, I'm not going to go over that section of the paper.

2 Testing statistical discrimination: Altonji and Pierret (2001)

2.1 Overview of the model

Altonji and Pierret are motivated by the following questions: do employers statistically discriminate among young workers on the basis of easily observable characteristics such as education and race, and as they learn over time do they rely less on such variables? Like Farber and Gibbons, Altonji and Pierret examine a model of employer learning where information is common across firms and the labor market is competitive. The focus of Altonji and Pierret is on variables that employers do observe and which are correlated with variables in the data but not observed by employers - such as race, which employers observe and could be correlated with AFQT scores. They key idea is that statistical discrimination in a model of employer learning should imply that the coefficient on AFQT will rise with experience whereas (conditional on AFQT) the coefficient on race will fall.

The model laid out in Altonji and Pierret's paper is very similar to the Farber-Gibbons model, so I won't go through it in detail. There are a few key differences (see footnote 7 on page 319):

1. The Altonji-Pierret model is specified in logs rather than levels (this comes out as a function of some additional restrictions on one of the joint distributions)

2. Whereas Farber-Gibbons orthogonalize B_i with respect to X_i and w_{i0}, Altonji-Pierret do *not* do this - they are exactly interested in how changes in the relationship between B_i and wages over time affects the coefficients on X_i's such as race and schooling. This is a key difference between the two models.

The key result is summarized in Proposition 1, the key idea of which is the following. Assume schooling s is correlated with the initially unobserved variable z (AFQT score). If we include z in the wage regression with a time-varying coefficient, then as employers learn about the productivity of workers the observable variable s (schooling) will get less of the credit for an association with productivity as z can claim the shifting credit.

2.2 Do employers statistically discriminate on the basis of education?

Like Farber and Gibbons, Altonji and Pierret use the National Longitudinal Survey of Youth (NLSY) data. Table 1 reports results for education (ignore the race coefficients for now).

TABLE I
THE EFFECTS OF STANDARDIZED AFQT AND SCHOOLING ON WAGES
Dependent Variable: Log Wage; OLS estimates (standard errors).

Panel 1—Experience measure: potential experience				
Model:	(1)	(2)	(3)	(4)
(a) Education	0.0586	0.0829	0.0638	0.0785
	(0.0118)	(0.0150)	(0.0120)	(0.0153)
(b) Black	−0.1565	−0.1553	0.0001	−0.0565
	(0.0256)	(0.0256)	(0.0621)	(0.0723)
(c) Standardized AFQT	0.0834	−0.0060	0.0831	0.0221
	(0.0144)	(0.0360)	(0.0144)	(0.0421)
(d) Education * experience/10	−0.0032	−0.0234	−0.0068	−0.0193
	(0.0094)	(0.0123)	(0.0095)	(0.0127)
(e) Standardized AFQT * experience/10		0.0752		0.0515
		(0.0286)		(0.0343)
(f) Black * experience/10			−0.1315	−0.0834
			(0.0482)	(0.0581)
R^2	0.2861	0.2870	0.2870	0.2873

Panel 2—Experience measure: actual experience instrumented by potential experience				
Model:	(1)	(2)	(3)	(4)
(a) Education	0.0836	0.1218	0.0969	0.1170
	(0.0208)	(0.0243)	(0.0206)	(0.0248)
(b) Black	−0.1310	−0.1306	0.0972	0.0178
	(0.0261)	(0.0260)	(0.0851)	(0.1029)
(c) Standardized AFQT	0.0925	−0.0361	0.0881	0.0062
	(0.0143)	(0.0482)	(0.0143)	(0.0572)
(d) Education * experience/10	−0.0539	−0.0952	−0.0665	−0.0889
	(0.0235)	(0.0276)	(0.0234)	(0.0283)
(e) Standardized AFQT * experience/10		0.1407		0.0913
		(0.0514)		(0.0627)
(f) Black * experience/10			−0.2670	−0.1739
			(0.0968)	(0.1184)
R^2	0.3056	0.3063	0.3061	0.3064

Experience is modeled with a cubic polynomial. All equations control for year effects, education interacted with a cubic time trend, Black interacted with a cubic time trend, AFQT interacted with a cubic time trend, two-digit occupation at first job, and urban residence. For these time trends, the base year is 1992. For the model in Panel 1 column (1) the coefficient on AFQT and Black are .0312 and −.1006, respectively, when evaluated for 1983. In Panel 2 the instrumental variables are the corresponding terms involving potential experience and the other variables in the model. Standard errors are White/Huber standard errors computed accounting for the fact that there are multiple observations for each worker. The sample size is 21,058 observations from 2976 individuals.

The basic specification estimates log wages as a function of schooling, race, AFQT, and interactions of those variables with experience. Column (1) includes education, black, AFQT and an education-experience interaction. AFQT has a strong association with earnings even conditional on education. Education also has a strong association with earnings, but the effect of education declines (statistically insignificantly) over time.

Column (2) adds an AFQT-experience interaction. The effect of AFQT rises from essentially 0 when experience is 0 to 0.0692 when experience is 10. This supports the hypothesis that employers learn about productivity over time. The coefficient on the education-experience interaction declines sharply once this AFQT-experience interaction is added. This result supports the idea that employers statistically discriminate on the basis of education. In early periods, employers use easily observed variables like education to predict productivity (and hence wages). However, as experience accumulates wages become more strongly related to variables that are likely to be correlated with productivity but which are hard for the employer to observe directly.

Tables II and III show analogous results using sibling's wage and father's education as alternative (initially unobserved) correlates of underlying productivity.

2.3 Do employers statistically discriminate on the basis of race?

A statistically discriminating firm might use race along with education and other information to predict the productivity of new workers. With experience, the productivity of the worker would become apparent, and compensation would be based on all the information available rather than just the information available at the time of hire. Consequently, if statistical discrimination on the basis of race is important, then adding interactions between t and z variables such as AFQT and father's education to the wage equations should lead to a positive (or less negative) coefficient on Black $\cdot t/10$ and should lead to an increase in the race intercept. On the other hand, if firms do not use or only partially use race as information, than Black behaves as a z variable: the race intercept when experience is 0 will be smaller than when firms use race to discriminate. The gap should widen with experience if race is negatively related to productivity, and adding a second z variable that is negatively related to race will reduce the race gap in experience slopes and possibly make the race intercept more negative.

In Table 1 column (1), the Black coefficient is -0.1565. When Black $\cdot t/10$ is added in column (3), the coefficient on Black drops to 0.0001, implying that the race gap when t equals 0 is essentially 0; the coefficient on Black $\cdot t/10$ suggests that the race gap rises sharply with experience. Together, these facts are consistent with the hypothesis of no or very limited statistical discrimination on the basis of race. These facts are inconsistent with the hypothesis that firms make full use of race as information.

In Column (4), Altonji and Pierret add a second variable related to productivity (AFQT score) and its interaction with experience to the model. If firms do not statistically discriminate on race and race is negatively related to productivity, then adding AFQT score to the model will reduce the race difference in the experience profile. They find support for this prediction: adding an AFQT-experience interaction decreases the Black-experience interaction coefficient from -0.1315 to -0.0834. One interpretation of these findings is that employers are obeying the law and not statistically discriminating on the basis of race.

Altonji and Pierret stress that the simple model of statistical discrimination cannot explain the large negative coefficient on Black $\cdot t/10$ unless firms do not make full use of race as information. The fact that the race gap is so small at low experience levels suggests either that there is not much difference in the productivity of black and white men at the time of labor market entry, or that firms do not statistically discriminate very much. The accumulation of additional information during a career that can legally be used to differentiate among workers would imply a widening of the race gap with experience (if there is a productivity gap), which is consistent with their estimates. However, the authors stress that there are other discrimination-related explanations of the race differences in the experience slope that could be relevant; the authors discuss some potential explanations in the paper (see p.338).

Although I won't have time to go over it in class, Autor and Scarborough (2008) provide an alternative test of statistical discrimination.

3 Affirmative action

3.1 Overview and empirics

Fryer and Loury (2005) provide a recent overview of affirmative action policies, which they define as regulations on the allocation of scarce positions in education, employment, or business contracting so as to increase the representation in those positions of people belonging to certain population subgroups. Table 1 of Holzer and Neumark (2000) provides a list of key executive orders, regulations, and court decisions regarding affirmative action in the labor market, and reviews a number of empirical studies that have investigated the effects of affirmative action policies, such as Leonard (1984) on the affirmative action policy mandated by Executive Order no. 11246 in 1965, and Chay (1998) on the Equal Employment Opportunity Act of 1972. McCrary (2007)'s investigation of the effects of a series of court-ordered racial hiring quotas in municipal police departments is one more recent well-known paper.

3.2 Coate and Loury (1993)

The use of affirmative action policies has been very controversial. One key question is whether the labor market gains from affirmative action policies can continue without these policies becoming a permanent fixture in the labor market. Coate and Loury (1993) tackle one component of this question - namely how affirmative action impacts employers' stereotypes about the capabilities of minority workers.

If affirmative action serves to break down negative stereotypes, then to the extent that these stereotypes underlie discrimination a temporary program of affirmative action should lead to permanent gains for minorities. But if negative views about a minority group are not eroded or are worsened by affirmative action, then the policy would need to be maintained permanently for the minority group's gains to be protected. Coate and Loury (1993) offer a framework in which to analyze this set of issues.

As they note in the introduction of their paper, popular debates over affirmative action often focus exactly on this issue: advocates say that preferential policies break down negative views about minority workers by allowing them to demonstrate their capabilities, whereas critics say that affirmative action forces employers to lower standards - with the consequence that subsequent poor performance by preferred workers will only reinforce negative stereotypes. I won't go through this model in as much detail as I did with Farber and Gibbons (1996), but rather just want to give you a flavor of how their model is set up.

3.2.1 Model set-up

Assume a large number of identical employers and a larger population of workers who are randomly matched to employers. Workers belong to one of two groups: B or W, where λ is the fraction of the population that is W.

The sole action of an employer is to assign each of her workers to one of two possible jobs: job 0 or job 1. All workers can perform satisfactorily in job 0, but a given worker may or may not be capable of satisfactory performance in job 1 (which is more demanding and more rewarding). Workers get a gross benefit ω if assigned to task 1; employers get a net return of $x_q > 0$ if they assign a qualified worker to task 1, and a net return of $-x_u < 0$ if they assign an unqualified worker to task 1. Define $r = x_q/x_u$ to be the ratio of net gain to loss. Workers' gross returns and employers' net returns from an assignment to task zero are normalized to zero.

Employers are unable to observe (prior to assignment) whether a worker is qualified for task 1. Employers observe each worker's group identity $\in [B, W]$ and a noisy signal $\theta \in [0, 1]$ of the worker's qualification level (say, the result of a test or an interview). The distribution of θ depends, in the same way for each group, on whether or not a worker is qualified.

Let $F_q(\theta)$ be the probability that the signal does not exceed θ given that the worker is qualified. Similarly, let $F_u(\theta)$ be the probability that the signal does not exceed θ given that the worker is unqualified. Let $f_q(\theta)$ and $f_u(\theta)$ be the density functions. Define $\varphi = \frac{f_u(\theta)}{f_q(\theta)}$ to be the likelihood ratio at θ. Assume that $\varphi(\cdot)$ is non-increasing on $\theta \in [0, 1]$, which implies that $F_q(\theta) \leq F_u(\theta)$ for all θ. Thus, higher values of the signal are more likely if the worker is qualified, and for a given prior, the posterior likelihood that a worker is qualified is larger if his signal takes a higher value.

Employers' assignment policies will be characterized by the choice of threshold "standards" for each group, such that only those workers with a signal observed to exceed the standard are assigned to the more demanding task. Workers are qualified to perform task 1 only if they have made some costly *ex ante* investment (e.g. working hard in high school). The cost of becoming qualified varies across workers. Suppose that the cost distribution is the same for each group. Let c be a worker's investment cost and let $G(c)$ be the fraction of workers with investment cost no greater than c.

In this framework, an equilibrium is defined as a set of employer beliefs (about workers' qualifications in each group W and B) and workers' investments that are self-confirming. That is, in equilibrium workers will not have an incentives to change their investments, and employers will not have an incentive to change their hiring decisions. Coate and Loury define a discriminatory equilibrium as one in which workers from one group (say, B) are believed less likely to be qualified.

3.2.2 Employers' decision rule

Consider a worker from group W or B, the representative member of which has probability $\pi \in (0,1)$ of being qualified. Conditional on the worker's signal θ, the employer's posterior probability that the worker is qualified is:

$$\begin{aligned} \xi(\pi,\theta) &= \frac{\pi f_q(\theta)}{\pi f_q(\theta) + (1-\pi) f_u(\theta)} \\ &= \frac{1}{[1 + ((1-\pi)/\pi)\varphi(\theta)]} \end{aligned}$$

The expected benefit of assigning a worker to Task 1 is therefore:

$$\xi(\pi,\theta) x_q - [1 - \xi(\pi,\theta)] x_u$$

implying that an employer will assign a worker to task 1 if and only if:

$$\begin{aligned} r &= \frac{x_q}{x_u} \geq \frac{1-\xi(\pi,\theta)}{\xi(\pi,\theta)} \\ r &\geq \left[\frac{1-\pi}{\pi}\right]\varphi(\theta) \end{aligned}$$

Given our assumptions on φ, the employer will choose a threshold value of the signal $s^*(\pi)$ (i.e. a standard) and to adopt the policy "assign a worker from a group whose representative member has prior probability π of being qualified to task 1 if and only if that worker's signal is no less than the standard $s^*(\pi)$," where:

$$s^*(\pi) = \min\left\{\theta \in [0,1] \quad r \geq \left[\frac{1-\pi}{\pi}\right]\varphi(\theta)\right\}$$

More optimistic beliefs about a group will be reflected in easier standards, since s^* is decreasing in π.

3.2.3 Workers' investment decisions

Workers invest if the cost of doing so does not exceed the expected benefit. For a given standard s, the expected benefit to obtaining the qualification is the product of the gross return from being assigned to task 1 (ω) and the increased probability of assignment due to investing:

$$\beta(s) = \omega[F_u(s) - F_q(s)]$$

where s is the passing standard. Note that $\beta(s)$ is a single-peaked function of s that satisfies $\beta(0) = \beta(1) = 0$. Workers invest if and only if $\beta(s) \geq c$, so the share of workers that become qualified is $G(\beta(s))$.

3.2.4 Equilibrium

An equilibrium is a pair of beliefs (π_b, π_w) such that:

$$\pi_i = G\left(\beta\left(s^*\left(\pi_i\right)\right)\right) \qquad i = B, W.$$

A discriminatory equilibrium (say, one with $\pi_b < \pi_w$) can occur whenever this equilibrium equation has multiple solutions, for then it is possible that employers believe - consistent with their experience - that B's are less likely to be qualified than W's. Proposition 1 provides a set of conditions such that there are at least two nonzero solutions. In the paper, Coate and Loury discuss why stereotypes are not only discriminatory but are also inefficient.

3.2.5 Affirmative action

Given the model outlined above, Coate and Loury then consider the effects of affirmative action. They model affirmative action as a government-mandated constraint on employers requiring them to assign workers from each group to the more rewarding job at the same rate. They then ask whether the introduction of such a constraint is sufficient to induce employers, in the resulting equilibrium, to believe that workers' productivities are uncorrelated with their group identity. They find that under some circumstances, affirmative action will successfully eliminate negative stereotypes. However, there are also circumstances under which minority workers continue to be (correctly) perceived as less capable.

Coate and Loury conclude by saying that their results give "credence to both the hopes of advocates of preferential policies and the concerns of critics." There are circumstances under which affirmative action will eliminate negative stereotypes, but equally plausible circumstances under which it fail to do so or even worsen stereotypes.

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