Employer Learning and Statistical Discrimination

Joseph G. Altonji & Charles R. Pierret. (2001).
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I. Introduction

II. Implications of Statistical Discrimination and Employer Learning for Wages

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II.1 A Model of Employer Learning and Wages

- Our research builds on some previous work, particularly Farber and Gibbons (1996), (hereinafter FG).
- Our model is similar to FG.
- Let y_{it} be the log of labor market productivity of worker i with t_i years of experience:

known only to the firm

$$y_{it} = rs_i + \alpha_1 q_i + \Lambda z_i + \eta_i + H(t_i). \tag{1}$$

not

known to the firm & the analyst

known by both

known only to the analyst!

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- In (1) we separate the determinants of productivity into four categories:
- s_i represents variables that are observed by both the employer and the econometrician;
- q_i includes variables observed by the employer but not seen (or not used) by the econometrician;
- z_i consists of correlates of productivity that are not observed directly by employers but are available to and used by the econometrician;
- and η_i is an index of other determinants of productivity and is not directly observed by the employers and not observed (or observed but not used) by the econometrician.

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- Normalize z_i so that all the elements of the conformable coefficient vector Λ are positive.
- In addition, $H(t_i)$ is the experience profile of productivity.
- For now we assume that the experience profile of productivity does not depend on s_i, z_i, q_i, or η_i.

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- In the absence of knowledge of z and η, firms form the conditional expectations $E(z|s,q)$ and $E(\eta|s,q)$, which we assume are linear in q and s.
- Consequently,

$$
\begin{aligned}
z = E(z|s,q) + v &= \gamma_1 q + \gamma_2 s + v \\
\eta = E(\eta|s,q) + e &= \alpha_2 s + e,
\end{aligned} \tag{2}
$$

- Vector v and the scalar e have mean 0 and are uncorrelated with q and s by definition of an expectation.
- Links from s to z and η may be due in part to a causal effect of s.

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- Equations (1) and (2) imply that $\Lambda\nu + e$ is the error in the employer's belief about the log of productivity of the worker at the time the worker enters the labor market.
- The sum $\Lambda\nu + e$ is uncorrelated with q and s. (Assume independence)

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The firm observe noisy signal of productivity

- $\xi_t = y + \epsilon$, where $y = y_t - H(t)$.
- ϵ_t reflects transitory variation in the performance of worker i and the effects of variation in the firm environment that are hard for the firm to control for in evaluating the worker.
- Employers know q and s.

- Observing ξ_t is equivalent to observing $d_t = \xi_t - E(y|s, q) = \Lambda\nu + e + \epsilon_t$ which is the sum of the noise ϵ_t and the error $\Lambda\nu + e$ in the employer's belief about initial log productivity.
- The vector $D_t = \{d_l, d_2, \ldots, d_t\}$ summarizes the worker's performance history.
- Let μ_t be the difference between $\Lambda\nu + e$ and $E(\Lambda\nu + e|D_t)$.
- μ_t is uncorrelated with D_t, q, and s.
- μ_t is distributed independently of D_t, q, and s.
- q, s, and D_t are known to all employers, as in FG.

↑ Crucial!

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- Substituting and taking logs, we arrive at the log wage process:

$$w_t = (r + \Lambda\gamma_2 + \alpha_2)s + H^*(t) + (\alpha_1 + \Lambda\gamma_1)q + E(\Lambda\nu + e|D_t) + \zeta_t, \quad (3)$$

- $w_t = \log(W_t)$ and $H^*(t) = H(t) + \log(E(\exp^{\mu_t}))$.
- $E(\Lambda\nu + e|D_t)$ in (3) shows that wages change over time not just because productivity changes with experience, but also because firms learn about errors in their initial assessment of worker productivity.

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- Examine the parameters of the conditional expectation of w_t given s, z, t, and the experience profile $H^*(t)$.
- Begin with the case in which z and s are scalars and then turn to the more general cases.
- Consider the conditional expectation function when $t = 0, \ldots, T$, with

$$E(w_t | s, z, t) = b_{st} s + b_{zt} z + H^*(t). \tag{4}$$

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- To simplify the algebra but without any additional assumptions, we reinterpret s, z, and q as the components of s, z, and q that are orthogonal to $H^*(t)$.
- Given that the wage evolves according to (3), the omitted bias formula for least squares regression implies that

Changes w/ time!

$$b_{st} = b_{s0} + \Phi_{st} = [r + \Lambda\gamma_2 + \alpha_2] + \Phi_{qs} + \Phi_{st} \tag{5}$$
$$b_{zt} = b_{z0} + \Phi_{zt} = \Phi_{qz} + \Phi_{zt},$$

- where Φ_{qs} and Φ_{qz} denote the coefficients of the auxiliary regressions of $(\alpha_1 + \Lambda\gamma_1)q$ on s and z, respectively, and Φ_{st} and Φ_{zt} are the coefficients of the regression of $E(\Lambda v + e|D_t)$ on s and z.

FWL type of an argument

$$b_{st} = \frac{cov(\tilde{s}, \tilde{w})}{Var(\tilde{s})} = \frac{cov(\tilde{s}, w)}{var(\tilde{s})} =$$

$$\frac{cov(\tilde{s}, \beta_s S + \beta_q q_z + \mathbb{E}[\Lambda v + e \mid 0] + q_b)}{Var(\tilde{s})} =$$

$$\beta_s + \frac{cov(q, s)}{var(\tilde{s})}\beta_q + \frac{cov(\tilde{s}, \mathbb{E}[\Lambda v + e \mid 0])}{var(\tilde{s})} =$$

the coefficient from $\beta_q q \sim S, Z$

$\tilde{S}$ – residuals

$$cov(z, \mathbb{E}[\quad]) \geq 0$$

$$cov(v, \mathbb{E}[\quad]) \geq 0$$

$$\rightarrow \frac{cov(\tilde{s}, \mathbb{E}[\Lambda v + e \mid 0])}{var(\tilde{s})} =$$

$$\frac{cov(s - gz, \mathbb{E}[\Lambda v + e \mid 0])}{Var(\tilde{s})} =$$

$$-g \frac{cov(Z, \mathbb{E}[\Lambda v + e \mid 0])}{Var(\tilde{s})}$$

$$g = \frac{cov(s, z)}{var(s)}$$

Driven by the $cov(s, z)$ – as employers learn more on z, $cov(z, \mathbb{E}(\Lambda v + e \mid 0))$ increases and b_{st} falls!

- Using the facts that $\text{cov}(s, E(\Lambda v + e|D_t)) = 0$ and $\text{cov}(z, E(\Lambda v + e|D_t)) = \text{cov}(v, E(\Lambda v + e|D_t))$ and the least squares regression formula, one may express Φ_{st} and Φ_{zt} as

$$\Phi_{st} = \theta_t \Phi_s \tag{6}$$
$$\Phi_{zt} = \theta_t \Phi_z,$$

the true correlation between s, z & E(Λv+e|D)

- where Φ_s and Φ_z are the coefficients of the regression of $\Lambda v + e$ on s and z and

$$\theta_t = \frac{\text{cov}(E(\Lambda v + e|D_t), z)}{\text{cov}(\Lambda v + e, z)} = \frac{\text{cov}(E(\Lambda v + e|D_t), v)}{\text{cov}(\Lambda v + e, v)}. \tag{7}$$

How much informative z is

Λv + e ~ s, z

Proposition 1. Under the assumptions of the above model,

- (a) the regression coefficient b_{zt} is nondecreasing in t, and
- (b) the regression coefficient b_{st} is nonincreasing in t.

Proposition 2. Under the assumptions of the above model,

$$\frac{\partial b_{st}}{\partial t} = -\Phi_{zs} \frac{\partial b_{zt}}{\partial t}.$$

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- However, a matrix version of Proposition 2 still holds

$$\frac{\partial b_{st}}{\partial t} = -\frac{\partial b_{zt}}{\partial t}\Phi_{zs},$$

- where Φ_{zs} is now the $K \times J$ matrix of coefficients of the regression of z on s.

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II.2. Statistical Discrimination on the Basis of Race

III. Data and Econometric Specification

→ NLSY

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IV. Results for Education

IV.1. AFQT as a z Variable

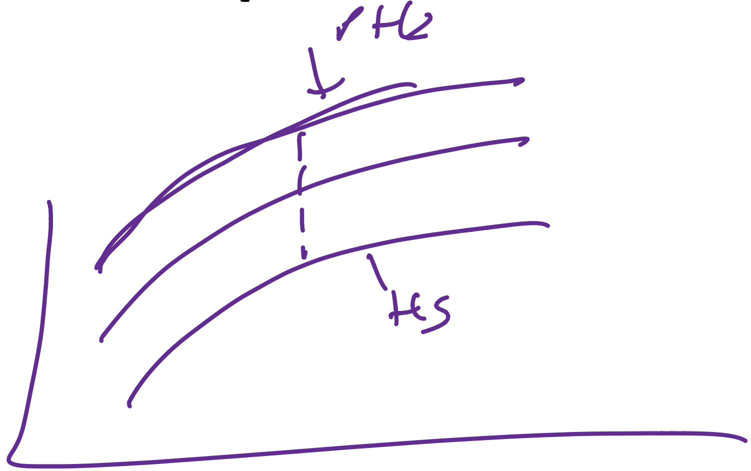

Figure 1: The Effects of Standardized AFQT and Schooling on Wages

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/l0			-0.1315	-0.0834
			(0.0482)	(0.0581)
R^2	0.2861	0.2870	0.2870	0.2873

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Figure 2: The Effects of Standardized AFQT and Schooling on Wages

Dependent Variable: Log Wage; OLS estimates (standard errors)

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 *	-0.0539	-0.0952	-0.0665	-0.0889
experience/10	(0.0235)	(0.0276)	(0.0234)	(0.0283)
(e) Standardized AFQT *		0.1407		0.0913
experience/10		(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

IV.2. The Sibling Wage and Father's Education as z Variables

Figure 3: The Effects of Father's Education, Sibling Wages, and Schooling on Wages

Dependent Variable: Log Wage; Experience Measure: Potential Experience

OLS estimates (standard errors)

Model:	(1)	(2)	(3)	(4)
(a) Education	0.0511	0.0630	0.0568	0.0659
	(0.0160)	(0.0166)	(0.0163)	(0.0167)
(b) Black	-0.2074	-0.2076	-0.0509	-0.0878
	(0.0276)	(0.0276)	(0.0846)	(0.0871)
(c) Log of sibling's wage	0.1802	-0.0260	0.1817	0.0010
	(0.0328)	(0.0913)	(0.0329)	(0.0940)
(d) Father's education/10				
(e) Education * experience/10	0.0107	0.0012	0.0065	-0.0008
	(0.0131)	(0.0136)	(0.0133)	(0.0136)
(f) Log of sibling's wage * experience/10		0.1796		0.1571
		(0.0749)		(0.0770)
(g) Father's education * experience/100				
(h) Black * experience/10			-0.1311	-0.1004
			(0.0686)	(0.0704)
R^2	0.3183	0.3196	0.3191	0.3200
Observations	10746	10746	10746	10746
Individuals	1441	1441	1441	1441

Figure 4: The Effects of Father's Education, Sibling Wages, and Schooling on Wages

Dependent Variable: Log Wage; Experience Measure: Potential Experience

OLS estimates (standard errors)

Model:	(5)	(6)	(7)	(8)
(a) Education	0.0666	0.0730	0.0704	0.0734
	(0.0129)	(0.0140)	(0.0130)	(0.0140)
(b) Black	-0.2212	-0.2209	-0.0705	-0.0793
	(0.0250)	(0.0250)	(0.0668)	(0.0692)
(c) Log of sibling's wage				
(d) Father's education/10	0.0826	-0.0187	0.0829	0.0314
	(0.0366)	(0.1000)	(0.0364)	(0.1030)
(e) Education *	0.0023	-0.0029	-0.0002	-0.0027
experience/10	(0.0104)	(0.0113)	(0.0105)	(0.0113)
(f) Log of sibling's wage *				
experience/10				
(g) Father's education *		0.0867		0.0441
experience/100		(0.0813)		(0.0841)
(h) Black * experience/10			-0.1270	-0.1194
			(0.0541)	(0.0563)
R^2	0.2748	0.2750	0.2755	0.2756
Observations	18523	18523	18523	18523
Individuals	2594	2594	2594	2594

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Figure 5: The Effects of Standardized AFQT, Father's Education, Sibling Wage, and Schooling on Wages

Dependent Variable: Log Wage; Experience Measure: Potential Experience

OLS estimates (standard errors)

Model:	(1)	(2)	(3)	(4)
(a) Education	0.0505	0.0832	0.0563	0.0780
	(0.0118)	(0.0151)	(0.0120)	(0.0155)
(b) Black	-0.1333	-0.1296	0.0454	-0.0284
	(0.0255)	(0.0257)	(0.0609)	(0.0704)
(c) Standardized AFQT	0.0792	-0.0206	0.0789	0.0065
	(0.0145)	(0.0361)	(0.0144)	(0.0413)
(d) Log of sibling's wage	0.1602	0.0560	0.1617	0.0604
	(0.0208)	(0.0352)	(0.0207)	(0.0351)
(e) Father's education/10	0.0362	0.0154	0.0385	0.0295
	(0.0356)	(0.0963)	(0.0354)	(0.0968)
(f) Education *	0.0005	-0.0269	-0.0035	-0.0220
experience/10	(0.0093)	(0.0123)	(0.0094)	(0.0128)
(g) Standardized AFQT		0.0843		0.0614
* experience/10		(0.0285)		(0.0333)
(h) Log of sibling wage *		0.1194		0.1151
experience/10		(0.0393)		(0.0393)
(i) Father's education *		0.0176		0.0055
experience/100		(0.0789)		(0.0794)
(j) Black * experience/10			-0.1500	-0.0861
			(0.0474)	(0.0570)
R^2	0.2991	0.3014	0.3002	0.3016

IV.3. The Experience Profile of the Effects of AFQT and Education on Wages

V. Do Employers Statistically Discriminate on the Basis of Race?

VI. Models with Training

Figure 6: The Effects of Standardized AFQT, Father's Education, Sibling Wage, Schooling, and Training on Wages

Dependent Variable: Log Wage; Experience Measure: Potential Experience
Training Measure: Predicted before 88, Actual After; OLS estimates (standard errors)

Model:	(1)	(2)	(3)	(4)
(a) Education	0.0606	0.0802	0.0651	0.0746
	(0.0119)	(0.0151)	(0.0121)	(0.0155)
(b) Black	-0.1159	-0.1135	0.0241	-0.0028
	(0.0265)	(0.0267)	(0.0616)	(0.0722)
(c) Standardized AFQT	0.0334	-0.0199	0.0338	0.0102
	(0.0150)	(0.0363)	(0.0150)	(0.0420)
(d) Log of sibling's wage	0.1594	0.0716	0.1611	0.0759
	(0.0213)	(0.0357)	(0.0213)	(0.0356)
(e) Father's education/10	0.0460	0.0211	0.0482	0.0353
	(0.0356)	(0.0974)	(0.0354)	(0.0977)
(f) Education *	-0.0231	-0.0392	-0.0260	-0.0339
experience/10	(0.0095)	(0.0123)	(0.0096)	(0.0128)
(g) Standardized AFQT *		0.0460		0.0207
experience/10		(0.0287)		(0.0339)
(h) Log of sibling's wage *		0.1041		0.1001
experience/10		(0.0402)		(0.0402)
(i) Father's education *		0.0205		0.0084
experience/100		(0.0803)		(0.0805)
(j) Black * experience/10			-0.1180	-0.0945
			(0.0476)	(0.0583)
(k) Training: R_t	-0.1143	-0.1095	-0.1115	-0.1091
	(0.0200)	(0.0199)	(0.0199)	(0.0199)
(1) Cumulative training: Σ	0.1881	0.1830	0.1854	0.1827
R_T	(0.0139)	(0.0139)	(0.0139)	(0.0139)
R^2	0.3188	0.3199	0.3195	0.3202

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Figure 7: Estimates of the Effects of AFQT, Father's Education, Sibling Wage, and Schooling on Wage Growth with Controls for Training

Dependent Variable: Δ log Wage; Experience Measure: Potential Experience

Coefficient estimates (standard errors)

Model:	(1)	(2)	(3)	(4)
Education *	-0.0060	-0.0694	-0.0106	-0.0729
Δexperience/10	(0.0833)	(0.0960)	(0.0832)	(0.0959)
AFQT * Δexperience/10		0.3025		0.2975
		(0.1613)		(0.1614)
Log of sibling wage *		0.2153		0.2107
Δexperience/10		(0.1477)		(0.1477)
Father's education *		-0.4306		-0.4215
Δexperience/10		(0.5034)		(0.5034)
Black * Δexperience/10	-0.0504	-0.0425	-0.0503	-0.0426
	(0.0484)	(0.0485)	(0.0483)	(0.0484)
Training: $R_t/10$			0.2468	0.2429
			(0.1024)	(0.1025)
Lag training: $R_{t-1}/10$			-0.0194	-0.0230
			(0.1108)	(0.1108)
S.E.E.	.2965	.2965	.2965	.2964

VII. Conclusions and a Research Agenda