Testing for Asymmetric Employer Learning and Statistical Discrimination*

Suqin Ge   Andrea Moro   Beibei Zhu

Virginia Tech   Vanderbilt   Slack

SaMMF online workshop
June 26, 2020

*This study was prepared with funding from the U.S. Department of Labor. The views expressed are those of the authors and should not be attributed to the Federal Government or the Department of Labor.

Statistical Discrimination with Employer Learning

- Empirical research documents a large and persistent black-white wage gap in the U.S. (Neal and Johnson 1996; Altonji and Blank 1999; Lang and Lehmann 2012), but the racial wage gap does not provide a direct test for discrimination.

- *Wage dynamics* can be used to test for statistical discrimination using the EL-SD framework: Farber and Gibbons (1996), Altonji and Pierret (2001).

- Employer Learning (EL): employers observe signals of productivity and update their beliefs over time.

- Statistical Discrimination (SD): employers have incomplete information and use group average as a predictor of productivity.

How to Identify EL and SD?

- Employers have incomplete information at hiring but receive signals of productivity over time.
- Econometricians observe a variable that is correlated with productivity (AFQT).
- Over time, employers rely more on hard-to-observe correlates of productivity (AFQT) and rely less on group average productivity.
- Wage coefficients on AFQT should rise with experience. Coefficients on group dummies should decrease.

How to Identify EL and SD?

- Employers have incomplete information at hiring but receive signals of productivity over time.
- Econometricians observe a variable that is correlated with productivity (AFQT).
- Over time, employers rely more on hard-to-observe correlates of productivity (AFQT) and rely less on group average productivity.
- Wage coefficients on AFQT should rise with experience. Coefficients on group dummies should decrease.
- Altonji and Pierret(2001) find strong evidence on employer learning, but little evidence for race-based statistical discrimination.

Asymmetric Learning and Statistical Discrimination

- One key assumption of this literature is that employer learning is *symmetric* between current employer and outside employers.

- What if employer learning is *asymmetric*, that is, outside employers have less information than current employer?

- Position in the literature using the EL-SD framework:

	Symmetric EL	Asymmetric EL
No SD	Farber and Gibbons (1996)	Schönberg (2007) Pinkston (2009) Kahn (2013)
SD	Altonji and Pierret (2001) Lange (2007) Alcidiacono et al. (2010)	THIS PAPER

This Paper

- Tests for statistical discrimination based on race when employer learning can occur asymmetrically.

- Tenure and experience have different impact if outside firms have asymmetric information. These differences also generate implications for racial discrimination.

- We test these implications using NLSY79 data.

This Paper

- Tests for statistical discrimination based on race when employer learning can occur asymmetrically.
- Tenure and experience have different impact if outside firms have asymmetric information. These differences also generate implications for racial discrimination.
- We test these implications using NLSY79 data.
- We find evidence of asymmetric learning and statistical discrimination against blacks among non-college graduates.
- We also find that employers directly observe most of the productivity of college graduates at hiring, and learn very little over time about these workers.

A Simple Model

- Productivity $q \sim N(\mu, \sigma^2)$
- Employer's first signal in period 1 : $s_1 = q + \epsilon_1$
- Noise $\epsilon_t \sim N(0, \sigma_\epsilon^2)$
- Expected productivity (wage) after first signal:

$$E(q|s_1) = (1 - \theta_1)\mu + \theta_1 s_1$$

- Learning parameter:

$$\theta_1 = \frac{\sigma^2}{\sigma^2 + \sigma_\epsilon^2}$$

- When the signal is perfectly informative ($\sigma_\epsilon = 0$), the population mean is ignored; when the signal is pure noise ($\sigma_\epsilon = \infty$), expected ability is equal to the population mean.

Multiple Signals

- Employer's signal in period t :

$$s_t = q + \epsilon_t$$

- Expected productivity (wage) at time t :

$$E(q|s_1, \ldots, s_t) = (1 - \theta_t)\mu + \theta_t \left(\frac{\sum s_t}{t} \right)$$

- Learning parameter:

$$\theta_t = \frac{t\theta_1}{1 + (t-1)\theta_1}$$

- Expected productivity remains a weighted average of the population average productivity and the signals.

- Learning increases over time: $t \to \infty$, $\theta_t \to 1$. The worker's expected productivity gets closer to her true productivity over time.

Empirical Implication of Employer Learning

- A researcher observes wages and a one-time signal of productivity, r, that is not observed by the employer, such that

$$r = q + \epsilon_r, \epsilon_r \sim N(0, \sigma_r^2).$$

- Follow the literature, AFQT score is used as one such signal. The covariance of this signal (AFQT) with expected productivity (wage) is

$$\begin{aligned} & Cov(r, E(q|s_1, \dots, s_t)) \\ = \;& Cov\left(q + \epsilon_r, (1-\theta_t)\mu + \theta_t \left(\frac{\sum(q+\epsilon_t)}{t}\right)\right) \\ = \;& \theta_t Var(q), \text{ which increases in } t. \end{aligned}$$

Empirical Implication of Employer Learning

- A researcher observes wages and a one-time signal of productivity, r, that is not observed by the employer, such that

$$r = q + \epsilon_r, \epsilon_r \sim N(0, \sigma_r^2).$$

- Follow the literature, AFQT score is used as one such signal. The covariance of this signal (AFQT) with expected productivity (wage) is

$$\begin{aligned} & Cov(r, E(q|s_1, \ldots, s_t)) \\ = \; & Cov\left(q + \epsilon_r, (1-\theta_t)\mu + \theta_t \left(\frac{\sum(q+\epsilon_t)}{t}\right)\right) \\ = \; & \theta_t Var(q), \text{ which increases in } t. \end{aligned}$$

- Implication: Wage covaries more and more with AFQT over time because of learning.

Learning with Multiple Jobs

Consider a worker hired by a new employer in period t

$$E(q|s_1, \ldots, s_t) = (1 - \theta_t)\mu + \theta_t \left(\frac{\sum s_t}{t} \right)$$

- If learning is symmetric, the new employer has the same information about the worker's productivity as the current employer. The learning parameter θ_t evolves as if the worker stays with the same employer.
- If learning is asymmetric, the new employer has less information than the current employer. The learning parameter θ_t is reset to θ_1 when the worker changes job.

Learning with Multiple Jobs

Consider a worker hired by a new employer in period t

$$E(q|s_1, \ldots, s_t) = (1-\theta_t)\mu + \theta_t \left(\frac{\sum s_t}{t} \right)$$

- If learning is symmetric, the new employer has the same information about the worker's productivity as the current employer. The learning parameter θ_t evolves as if the worker stays with the same employer.
- If learning is asymmetric, the new employer has less information than the current employer. The learning parameter θ_t is reset to θ_1 when the worker changes job.
- Implication: Employer learning takes place over experience when learning is symmetric; and it takes place over tenure when learning is asymmetric.

Statistical Discrimination

- Other covariates, X, and race, R, if used by employer, affect the unconditional mean μ :

$$E(q|s_1, \ldots, s_t) = (1 - \theta_t)\mu(X, R) + \theta_t \left(\frac{\sum s_t}{t} \right)$$

- Statistical discrimination (agnostic about why):

$$\mu(X, Blacks) < \mu(X, Whites)$$

- As time passes, employers rely more and more on signal series, and less on other variables, including race.

Statistical Discrimination

- Other covariates, X, and race, R, if used by employer, affect the unconditional mean μ :

$$E(q|s_1, \ldots, s_t) = (1 - \theta_t)\mu(X, R) + \theta_t \left(\frac{\sum s_t}{t} \right)$$

- Statistical discrimination (agnostic about why):

$$\mu(X, Blacks) < \mu(X, Whites)$$

- As time passes, employers rely more and more on signal series, and less on other variables, including race.

- Implication: If blacks are statistically discriminated against, the coefficient on black dummy is negative, but its interaction with time is positive because of learning.

Regression Model: Learning

$$\ln w = ... + \alpha AFQT + \beta AFQT \cdot t + \gamma Black + \delta Black \cdot t$$

- $t =$ Experience or Tenure
- $\alpha > 0$: employers have some initial info
- $\beta > 0$: they learn over time

Regression Model: Learning

$$\ln w = ... + \alpha AFQT + \beta AFQT \cdot t + \gamma Black + \delta Black \cdot t$$

- $t =$ Experience or Tenure
- $\alpha > 0$: employers have some initial info
- $\beta > 0$: they learn over time
- with asymmetric learning: $\beta(t = Tenure) > \beta(t = Experience)$
- with symmetric learning: $\beta(t = Experience) > \beta(t = Tenure)$

Regression Model: Statistical Discrimination

$$\ln w = ... + \alpha AFQT + \beta AFQT \cdot t + \gamma Black + \delta Black \cdot t$$

- $t =$ Experience or Tenure
- $\gamma < 0$: employers statistically discriminate against blacks
- $\delta > 0$: they discriminate less as they learn over time

Regression Model: Statistical Discrimination

$$\ln w = ... + \alpha AFQT + \beta AFQT \cdot t + \gamma Black + \delta Black \cdot t$$

- $t =$ Experience or Tenure
- $\gamma < 0$: employers statistically discriminate against blacks
- $\delta > 0$: they discriminate less as they learn over time
- with asymmetric learning and statistical discrimination:

$$\delta(t = Tenure) > \delta(t = Experience) > 0$$

- with symmetric learning and statistical discrimination:

$$\delta(t = Experience) > \delta(t = Tenure) > 0$$

Data

- We use the 2008 release of the National Longitudinal Survey of Youth 1979 (NLSY79).
- Sample is restricted to black and white male workers with at least 8 years of education.
- We construct individual monthly employment status using NLSY79 work history data and follow workers over time.
- We standardize the AFQT score to have a mean zero and standard deviation one for each three-month age cohort.
- The sample consists of 2,592 whites and 1,133 blacks with 317,988 person-month observations.

Data: Descriptive Statistics

	Whites			Blacks		
	All	Non-col	Col	All	Non-col	Col
AFQT	0.50	0.20	1.35	-0.57	-0.73	0.48
	(0.96)	(0.89)	(0.57)	(0.80)	(0.65)	(0.90)
Education	13.35	12.14	16.74	12.69	12.12	16.60
	(2.39)	(1.31)	(1.19)	(2.00)	(1.35)	(1.06)
Hourly wage	12.91	11.10	17.99	10.15	9.23	16.41
	(8.14)	(5.89)	(10.97)	(6.14)	(4.98)	(8.96)
No. of ind.	2,592	1,906	686	1,133	987	146
No. of obs.	224,304	165,480	58,824	93,684	81,660	12,024

Benchmark Specifications

Experience X

$$\ln w_i = \beta_0^X + \beta_{AFQT}^X AFQT_i + \beta_{AFQT,X}^X (AFQT_i \times X_i) \\ + \beta_{Black}^X Black_i + \beta_{Black,X}^X (Black_i \times X_i) + \beta_\Omega^X \Omega_i + H(X_i) + \epsilon_i^X,$$

Tenure T

$$\ln w_i = \beta_0^T + \beta_{AFQT}^T AFQT_i + \beta_{AFQT,T}^T (AFQT_i \times T_i) \\ + \beta_{Black}^T Black_i + \beta_{Black,T}^T (Black_i \times T_i) + \beta_\Omega^T \Omega_i + H(X_i) + \epsilon_i^T.$$

Benchmark Specifications

Experience X

$$\ln w_i = \beta_0^X + \beta_{AFQT}^X AFQT_i + \beta_{AFQT,X}^X (AFQT_i \times X_i) + \beta_{Black}^X Black_i + \beta_{Black,X}^X (Black_i \times X_i) + \beta_\Omega^X \Omega_i + H(X_i) + \epsilon_i^X,$$

Tenure T

$$\ln w_i = \beta_0^T + \beta_{AFQT}^T AFQT_i + \beta_{AFQT,T}^T (AFQT_i \times T_i) + \beta_{Black}^T Black_i + \beta_{Black,T}^T (Black_i \times T_i) + \beta_\Omega^T \Omega_i + H(X_i) + \epsilon_i^T.$$

Main interest: coefficients on AFQT and Black, and coefficients on experience/tenure interactions with AFQT

Replicating Altonji and Pierret (2001)

	1979-1992	1979-1992	1979-2008	1979-2008
	(1)	(2)	(3)	(4)
AFQT	0.022	0.035*	0.057***	0.036**
	(0.042)	(0.014)	(0.012)	(0.013)
AFQT×Experience	0.052	0.069***	0.037***	0.071***
	(0.034)	(0.018)	(0.009)	(0.014)
Black	-0.057	-0.030	-0.037	-0.039
	(0.072)	(0.026)	(0.022)	(0.025)
Black×Experience	-0.083	-0.084**	-0.053***	-0.053*
	(0.058)	(0.031)	(0.015)	(0.026)
R^2	0.287	0.273	0.346	0.322
No. of obs.	21,058	177,288	317,988	212,640

Note: Column (1) reproduced from AP's Table 1.

Testing SD with Symmetric Learning

- AFQT becomes increasingly more important in explaining wage over time. This is consistent with the idea that employers learn about productivity over time.
- There is no evidence for statistical discrimination on race, conditional upon being hired in the first place (discrimination may have meant others in the group did not get hired). Employers on average do not use race to infer productivity at time of hire.

College vs Non-college

- The employer learning literature assumes that productivity is equally unobservable for *all* potential employees.
- There is evidence that college graduation plays a role in signaling/revealing ability to the labor market (Arcidiacono, Bayer, Hizmo 2010), because of the information contained in resumes, such as grades, majors and the college attended.
- We test the EL-SD model for non-college graduates and college graduates, respectively.

Results with Non-College Samples

	Actual Experience	Job Tenure
AFQT	0.051***	0.054***
	(0.012)	(0.010)
AFQT$\times$Experience/120	0.036***	
	(0.011)	
AFQT$\times$Tenure/120		0.065***
		(0.018)
Black	-0.046*	-0.127***
	(0.021)	(0.019)
Black$\times$Experience/120	-0.042*	
	(0.020)	
Black$\times$Tenure/120		0.049
		(0.037)
R^2	0.258	0.253

Results with College Samples

	Actual Experience	Job Tenure
AFQT	0.123***	0.156***
	(0.026)	(0.024)
AFQT × Experience/120	0.038	
	(0.024)	
AFQT × Tenure/120		-0.036
		(0.041)
Black	0.138**	0.104*
	(0.047)	(0.046)
Black × Experience/120	-0.091*	
	(0.038)	
Black × Tenure/120		-0.155*
		(0.077)
R^2	0.268	0.262

Results with Non-College and College Samples

Non-college market

- Evidence of asymmetric learning. Initial AFQT effects are not statistically different when experience or tenure are used in the wage regression. Employers learn faster over tenure.
- Evidence that black non-college workers are statistically discriminated at time of hire.

College market,

- Employers observe the productivity of college graduates almost perfectly at time of hire and learn very little over time.
- Less evidence of statistical discrimination on black college workers. In fact, black college graduates earn a wage premium conditional on AFQT at time of hire.

Robustness Checks

1. We allow outside firms to have some but not all information about worker productivity compared to the current firm. We add both tenure and experience measures in the wage regressions and find evidence that outside firms have little information.

2. Is racial wage gap driven by blacks and whites being sorted into jobs of different skill levels? We include initial occupation and industry in the wage regressions. We find that the observed racial wage gap cannot be attributed to racial differences in initial occupation or industry sorting.

Robustness: Both Tenure and Experience

	(1)	(2)
AFQT	0.054***	0.046***
	(0.010)	(0.012)
AFQT×Tenure/120	0.065***	0.050*
	(0.018)	(0.022)
AFQT×Experience/120		0.018
		(0.013)
Black	-0.127***	-0.059**
	(0.019)	(0.021)
Black×Tenure/120	0.049	0.097*
	(0.037)	(0.043)
Black×Experience/120		-0.065**
		(0.023)
R^2	0.253	0.277

Robustness: Initial Occupation

	Non-college Graduates		College Graduates	
	(1)	(2)	(3)	(4)
AFQT	0.034**	0.033**	0.091***	0.141***
	(0.013)	(0.012)	(0.027)	(0.025)
AFQT × Experience/120	0.038***		0.040	
	(0.011)		(0.024)	
AFQT × Tenure/120		0.075***		-0.077
		(0.020)		(0.041)
Black	-0.066**	-0.140***	0.133**	0.105*
	(0.025)	(0.023)	(0.048)	(0.047)
Black × Experience/120	-0.033		-0.109**	
	(0.021)		(0.040)	
Black × Tenure/120		0.067		-0.221**
		(0.041)		(0.075)
Initial occupation	Yes	Yes	Yes	Yes
R^2	0.276	0.271	0.318	0.310

Robustness: Initial Industry

	Non-college Graduates		College Graduates	
	(1)	(2)	(3)	(4)
AFQT	0.042^{**}	0.042^{***}	0.108^{***}	0.150^{***}
	(0.013)	(0.012)	(0.026)	(0.025)
AFQT $\times$ Experience/120	0.036^{***}		0.042	
	(0.011)		(0.024)	
AFQT $\times$ Tenure/120		0.068^{***}		-0.052
		(0.020)		(0.043)
Black	-0.072^{**}	-0.146^{***}	0.124^{**}	0.101^{*}
	(0.024)	(0.023)	(0.047)	(0.047)
Black $\times$ Experience/120	-0.036		-0.097^{*}	
	(0.020)		(0.040)	
Black $\times$ Tenure/120		0.057		-0.201^{**}
		(0.041)		(0.077)
Initial Industry	Yes	Yes	Yes	Yes
R^2	0.286	0.281	0.317	0.305

Implications on Job Mobility

- If learning is asymmetric, when changing employer, high skill workers are pooled with lower skill workers in the new employers' evaluation of expected productivity. Therefore, the probability of a job change decreases with skill.

- For minority (black non-college) workers, they get discriminated each time they switch jobs. Therefore, the probability of a job change is lower for minority workers.

- We estimate a probit model that examines the effects of AFQT and race on workers' job change probability:

$$Pr(J_{i,t} = 1) = \Phi(\beta_0 + \beta_1 AFQT_i + \beta_2 Black_i + \beta_\Omega \Omega_{i,t}),$$

  where $J_{i,t}$ is a dummy variable for job change..

- Under asymmetric learning and statistical discrimination, we expect $\beta_1 < 0$ and $\beta_2 < 0$.

Racial Difference in Job Change Probabilities

	Non-college Graduates		College Graduates	
	(1)	(2)	(3)	(4)
AFQT	-0.0058***		-0.0049***	
	(0.0006)		(0.0013)	
Black	-0.0056***	-0.0006	0.0026	0.0069**
	(0.0010)	(0.0009)	(0.0025)	(0.0021)
Education	0.0009**	-0.0006*	0.0000	-0.0005
	(0.0003)	(0.0003)	(0.0007)	(0.0006)
Experience/120	-0.0250***	-0.0247***	-0.0310***	-0.0305***
	(0.0014)	(0.0014)	(0.0029)	(0.0029)

Conclusions

- Employers statistically discriminate black workers in the non-college market where learning appears to be mostly asymmetric.
- No evidence of black college graduates being statistically discriminated. Perhaps employers have better signals of productivity of college graduates.
- Policy question: how to rectify information asymmetry in the labor market, especially for non-college workers?
- Remaining challenge: an equilibrium model of asymmetric learning and statistical discrimination.