

---

## Empirical Implications of Statistical Discrimination on the Returns to Measures of Skill

Andrea Moro and Peter Norman

(U. of Minnesota - U. of Wisconsin, Madison)

June 2003

---

0

---

## Topic of interest

Quantitatively measure of how different sources of discrimination contribute to wage inequality

## Today

Present a simple model of statistical discrimination.

Estimate the model using NLSY data

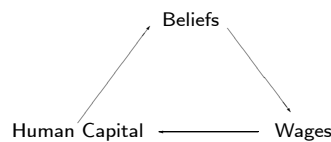
How much does statistical discrimination contribute to wage inequality?

---

1

---

## Statistical discrimination as self fulfilling stereotypes



- Incomplete information is crucial (we don't observe human capital investment).
  - In equilibrium, minority workers have lower incentives to acquire human capital.
- 

2

---

## A standard argument

- We observe measures of skill (e.g. AFQT, education), and minorities have lower average skill
  - Use returns to skill as a proxy for returns to human capital investment.
  - Test : look at difference in returns to skill between groups: if they are insignificant, then statistical discrimination is rejected
- 

3

---

## Examples

- Derek Neal and William Johnson (JPE 1996) on racial differences: returns to AFQT are not significantly different between black and white workers.
  - Nicola Persico, Andrew Postlewaite, and Dan Silverman (2002) on height wage differences (a similar test).
- 

4

---

## Problem with the argument (Moro and Norman, 2003)

- Measures of skill are not perfectly correlated with ability or productivity.
  - The econometrician cannot observe the same signals that employers have
  - The econometrician's estimate of the returns to his signal of productivity is a biased measure of the return to the firms' signal
  - The bias is different across groups
- 

5

## A model of statistical discrimination

Continuous human capital	$h$
Cost of $h$	$C(h, i) = \frac{h}{i}, \ln(i) = N(\mu_i, \sigma_i)$
Firms' observe signal	$x = \ln(h) + \varepsilon, \varepsilon \sim N(0, \sigma_\varepsilon)$
Preferences	$u(w, h) = \ln(w) - c(h, i)$
Technology	production = $h$
Perfectly competitive labor mkts.	

6

## Equilibrium

Assume  $\ln(h) \sim N(\mu_h, \sigma_h)$  (later verify this is the case)

Firms' signal  $x = \ln(h) + \varepsilon$

$$\Rightarrow f(\ln(h)|x) = N\left(\mu_h \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_h^2} + x \frac{\sigma_h^2}{\sigma_\varepsilon^2 + \sigma_h^2}, \frac{\sigma_h \sigma_\varepsilon}{(\sigma_\varepsilon^2 + \sigma_h^2)^{\frac{1}{2}}}\right)$$

$$w(x) = E(h|x) = \exp\left(\mu_h \frac{\sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_h^2} + x \frac{\sigma_h^2}{\sigma_\varepsilon^2 + \sigma_h^2} + \frac{1}{2} \frac{\sigma_h^2 \sigma_\varepsilon^2}{\sigma_\varepsilon^2 + \sigma_h^2}\right)$$

Log wages are linear in  $x$ :

$$\ln(w(x)) = \alpha + \beta \cdot x$$

7

## Workers' problem

$u(w, h) = \ln(w) - c(h, i) \Rightarrow$  Expected utility linear in  $\ln(h)$ :

$$\begin{aligned} E_x[\ln(w(x)) | h] &= E_x[\alpha + \beta x | h] = \alpha + \beta E_x(x | h) \\ &= \alpha + \beta \ln(h) \end{aligned}$$

Workers's choice of human capital:

$$\begin{aligned} &\max_{h \geq 0} \alpha + \beta \ln(h) - \frac{h}{i} \\ \Rightarrow h(i) &= \beta \cdot i \\ \Rightarrow \ln(h(i)) &= \ln(\beta) + \ln(i) \end{aligned}$$

8

With  $h(i) = \beta \cdot i$  human capital is indeed lognormal

$\ln(h) \sim N(\mu_i + \ln(\beta), \sigma_i)$ , hence consistency requires:

$$\begin{aligned} \sigma_h &= \sigma_i \\ \mu_h &= \mu_i + \ln \beta = \mu_i + \ln\left(\frac{\sigma_i^2}{\sigma_\varepsilon^2 + \sigma_i^2}\right). \end{aligned}$$

Note:

$$\beta = \frac{\sigma_i^2}{\sigma_\varepsilon^2 + \sigma_i^2}$$

9

## Summary

- We can compute only one equilibrium (there may be others)
- Our approach: use exogenous differences to rationalize difference in behavior

$$\text{e.g. } \sigma_\varepsilon^B > \sigma_\varepsilon^W \Rightarrow E^B(h) < E^W(h)$$

10

## Econometricians observe a different signal

True d.g.p:

$$\ln[w_i^J(x)] = \alpha^J + \beta^J x_i$$

$$x_i = \ln(h_i) + \varepsilon_i, \varepsilon_i \sim N(0, \sigma_\varepsilon)$$

But the investigator observes

$$z_i = \ln(h_i) + \delta_i$$

$$\delta_i \sim N(0, \sigma_\delta)$$

11

## Data

NLSY 79, 1990 wages and test scores of young males aged less than 18 when they took the test (1980)

Test: AFQT (verbal, math and arithmetic skills)

	Black	White
Observations	466	825
$\bar{w}^j = \text{Average}(\log(w))$	6.64	6.89
$\sigma_w^j \equiv \text{Stdev}(\log(w))$	.46	.43
$\sigma_z^j \equiv \text{Stdev}(\log(z))$	.82	.93
$\hat{\beta}_{LS}^j$	0.19 (.02)	0.18 (.02)

12

## Likelihood Function

Hence given a dataset  $D = \{w_i, z_i\}_{i=1}^N$  our log likelihood is

$$\begin{aligned} l(\sigma_i, \sigma_\varepsilon, \mu_h, \sigma_\delta | D) &= \sum_{i=1, N} \log [f(\ln w_i, z_i)] \\ &= \sum_{i=1, N} \log f(\ln w_i | z_i) + \log f(z_i) \end{aligned}$$

13

## Results

		Black	Whites
(cost parameters)	$\mu_i$	4.103871 (.0905601)	5.062817 (.0560569)
	$\sigma_i$	13.61844 (.0742783)	12.18787 (.0602092)
(firms' signal)	$\sigma_\varepsilon$	862.3624 (76.65127)	781.4184 (38.2517)
(econometrician's signal)	$\sigma_\delta$	~0 (~0)	~0 (~0)

14

## Simulations

Question: what happens if there were no informational differences, i.e. if the employers had a "race-neutral" test?

	Average Wage	Black	Whites	$\Delta$
Data		853.4	1075.6	222.2
Experiment 1 $\sigma_\varepsilon^b = \sigma_\varepsilon^w$		940.2	1075.6	135.4
Experiment 2 $\sigma_\varepsilon^b = \sigma_\varepsilon^w = \frac{\hat{\sigma}_\varepsilon^w + \hat{\sigma}_\varepsilon^b}{2}$		894.7	1023.3	128.6

I.e. "Statistical discrimination" accounts for about 40% of the wage differential

15

The bias of OLS regression

$$\hat{b} = \frac{\text{Cov}_N(z_i, \ln(w_i))}{\text{Var}_N(z_i)}$$

$$\begin{aligned} \text{Cov}_N(z_i, \ln(w_i)) &= \text{Cov}_N(\ln h_i + \delta_i, \alpha + \beta(\ln h_i + \varepsilon_i)) \\ &= \beta \text{Cov}_N(\ln h_i, \ln h_i) + \beta \text{Cov}_N(\ln h_i, \varepsilon_i) \\ &\quad + \beta \text{Cov}_N(\delta_i, \ln h_i) + \beta \text{Cov}_N(\delta_i, \varepsilon_i) \end{aligned}$$

$$p \lim(\hat{b}) = \beta \left( \frac{\sigma_i^2}{\sigma_\delta^2 + \sigma_i^2} \right) = \frac{\sigma_i^2}{\sigma_\delta^2 + \sigma_i^2} \cdot \frac{\sigma_i^2}{\sigma_\delta^2 + \sigma_i^2}$$

16