9. Labour market discrimination

KAT.TAL.322 Advanced Course in Labour Economics

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Same level of **productivity**, **different** outcomes based on **nonproductive** characteristics

- **Employers** may discriminate in hiring/firing decisions
- **Co-workers** may discriminate in collaboration activity
- **Customers** may discriminate in purchase decisions

Today

- Taste discrimination
- Statistical discrimination
- Systemic discrimination
- Empirical results

Taste discrimination

Taste discrimination

First formalized by Becker (1957)

- There are two types of workers A and B
- Perfect substitutes: $F(A + B) \Rightarrow F_A = F_B$

A firm decides how many workers to employ to maximise the utility

$$\max_{A,B} PF(A + B) - w_A A - w_B B - dB$$

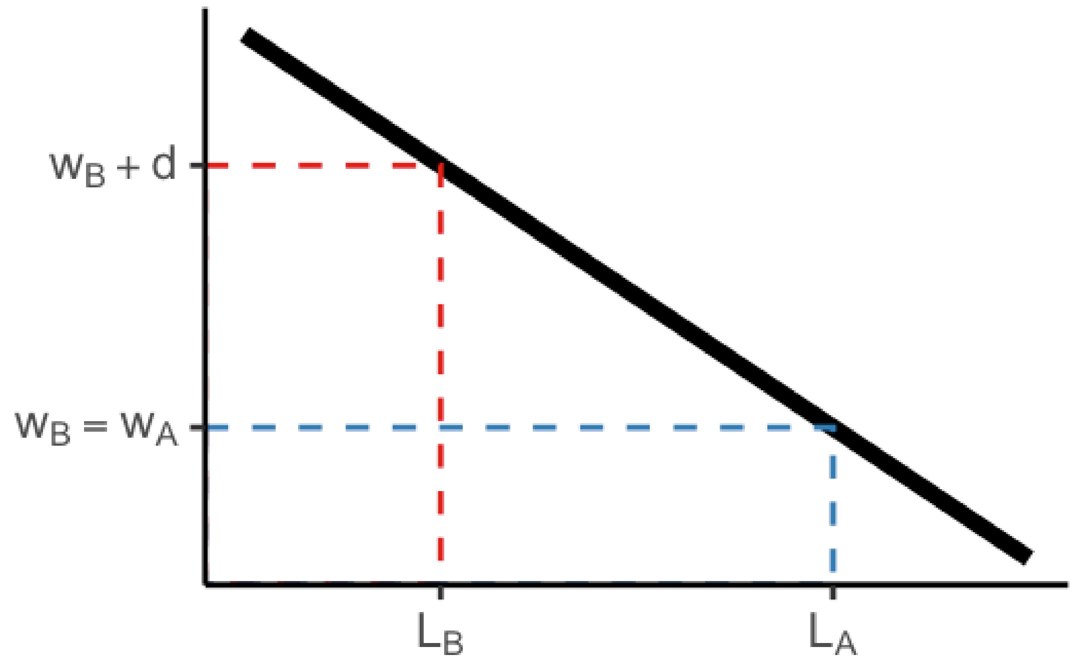
where $d \geq 0$ is the disutility employer gets from worker B

Taste discrimination

FOCs:

$$PF_A(A+B) = w_A$$
$$PF_B(A+B) = w_B + d$$

Hire B iff $w_B + d \leq w_A$



Taste discrimination

Perfect competition and free entry

Non-discriminating firms $d = 0$ enters the market

Pay competitive wages to both groups $w_A = w_B = PF_L(L)$

Therefore,

- discriminating firms hire A workers at w_A
- non-discriminating firms hire everyone at $w_A = w_B = w$

Taste discrimination cannot persist under perfect competition

Taste discrimination

Imperfect competition

1. **Monopsonistic employer**

   Lower wages and lower employment of discriminated group

2. **Market frictions (Black 1995)**

   Job search costs:

   - Existence of employers with $d > 0$ lowers reservation wage
   - Wages of discriminated workers at non-discriminating firms are also lower
   - Longer unemployment until meet non-discriminating firm

Statistical discrimination

Statistical discrimination

Overview

Key feature: **unobservable** productivity

- Suppose firms meets workers A_i and B_j such that $F_{Ai} = F_{Bi}$
- Firm doesn't see F_{Ai} or F_{Bi}, only group identities A and B
- If firms believe that $\mathbb{E}(F_A) \geq \mathbb{E}(F_B)$, then $\uparrow w_A$ and $\uparrow L_A$

Statistical discrimination

- Two types of workers: high $h^+ > 0$ and low $h^- = 0$
- Employers know the overall share of efficient workers $\pi(h^+) \equiv \pi$
- Employers use costless test to infer worker types and hire if passed
  - → $\Pr(\text{pass}|h^+) = 1$
  - → $\Pr(\text{pass}|h^-) = p$ where $p \in [0, 1]$
- Average productivity of workers passing the test ($\equiv w$)

$$w \equiv \mathbb{E}(h|\text{pass}) = h^+ \frac{\pi}{\pi + p(1 - \pi)}$$

Statistical discrimination

Self-fulfilling prophecies

Workers choose education to $\max_{e \in \{0,1\}} U(w, e) = \max_e w - e$

If $e = 1 \Rightarrow$ achieve productivity h^+, otherwise, h^-

$$w^+ \equiv \mathbb{E}(h|\text{pass}) = h^+ \frac{\pi}{\pi + p(1-\pi)}$$

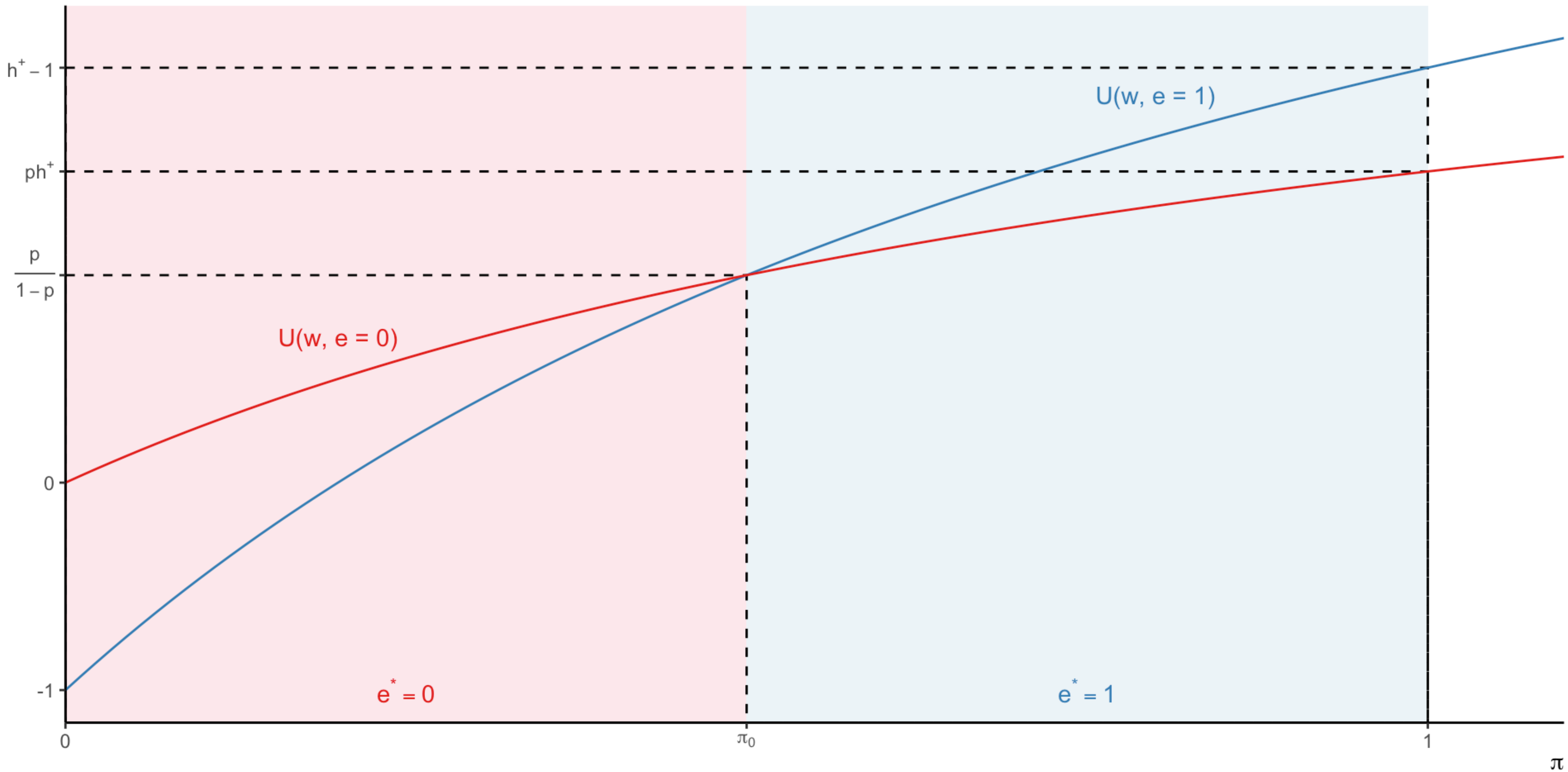
$$\mathbb{E}(w|e=0) = pw^+$$

Optimal decision

$$e = 1 \Leftrightarrow w^+ - 1 \geq \mathbb{E}(w|e=0) \Rightarrow p \leq \pi\left[\left(h^+ - 1\right)(1-p)\right]$$

Statistical discrimination

Multiple equilibria and persistent inequalities



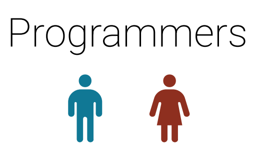
Source: Figure 5.7 (Cahuc 2004)

Systemic discrimination

Systemic discrimination (Bohren, Hull, and Imas 2025)

Discrimination in one area has spillover effects on other areas

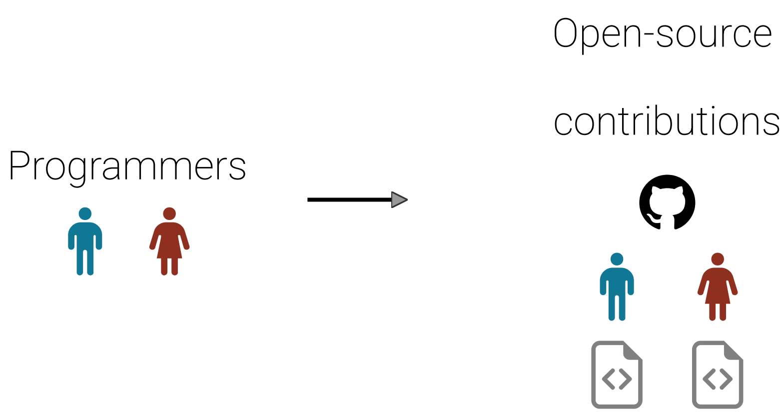
Let’s consider two programmers: male (**M**) and female (**F**)



Systemic discrimination (Bohren, Hull, and Imas 2025)

Discrimination in one area has spillover effects on other areas

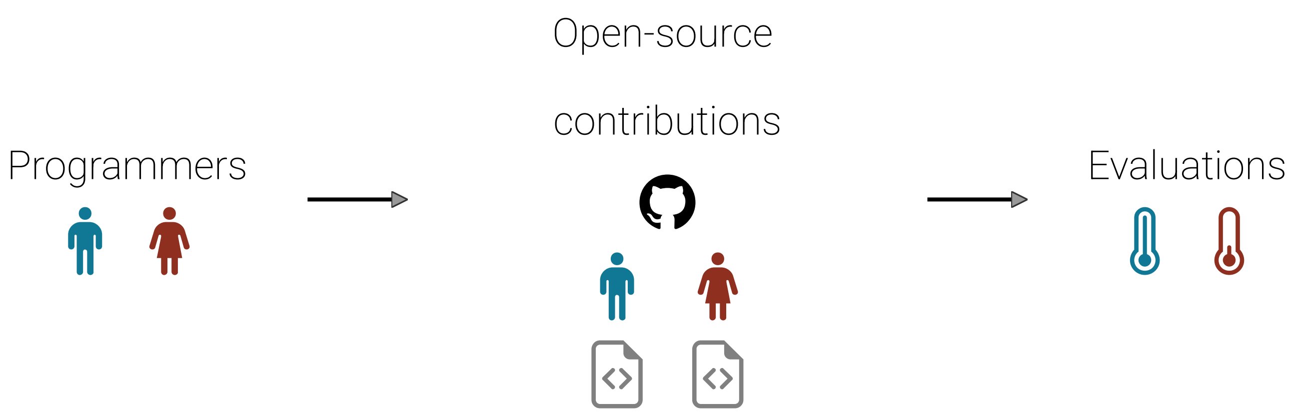
They submit codes $C_{0M} \equiv C_{0F}$ to open-source software



Systemic discrimination (Bohren, Hull, and Imas 2025)

Discrimination in one area has spillover effects on other areas

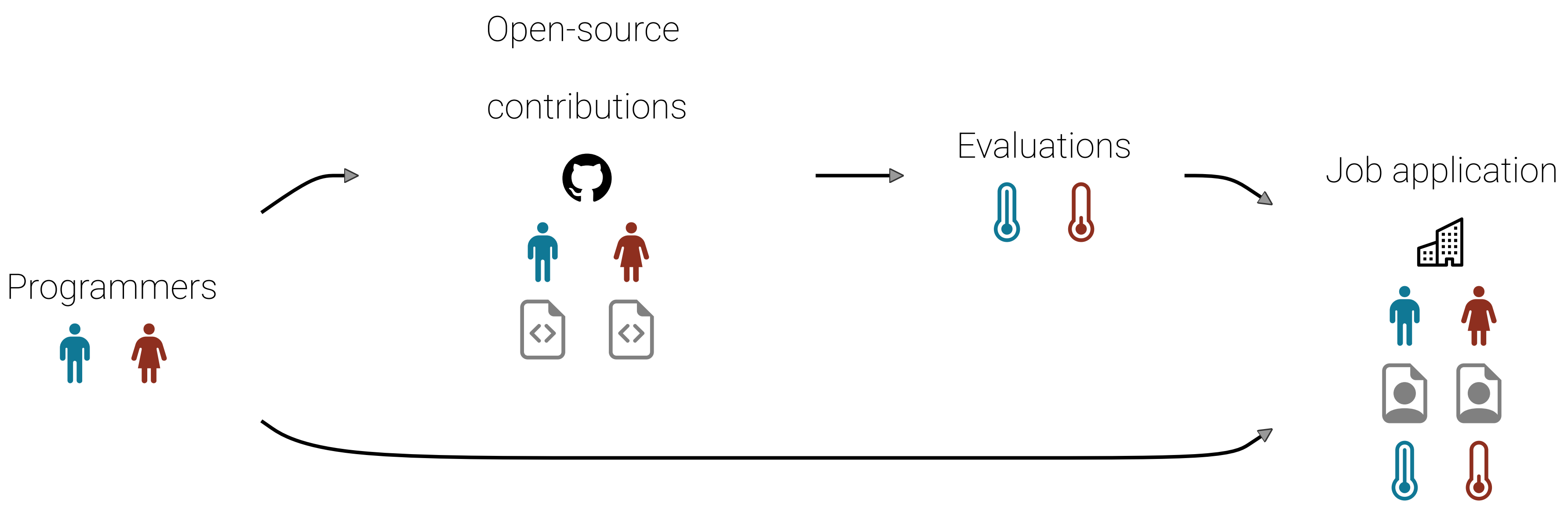
They receive performance ratings P_M and P_F



Systemic discrimination (Bohren, Hull, and Imas 2025)

Discrimination in one area has spillover effects on other areas

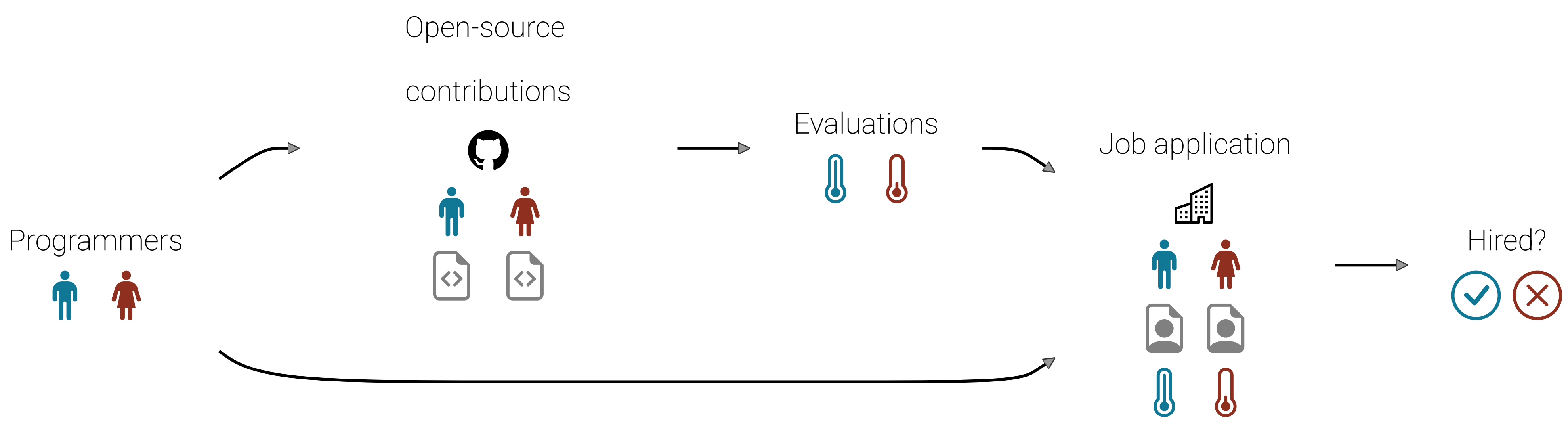
Apply for jobs with signals $S_M = (P_M, R_M)$ and $S_F = (P_F, R_F)$



Systemic discrimination (Bohren, Hull, and Imas 2025)

Discrimination in one area has spillover effects on other areas

Employer's hiring decision $A_M(M, S_M)$ and $A_F(F, S_F)$



Decomposition (Bohren, Hull, and Imas 2025)

Direct discrimination

For a given signal S, $\delta(S) \equiv A(M,S) - A(F,S) \neq 0$

Total discrimination

Let $G(A|C_0,i)$ be distribution over all possible actions given identity i and initial condition C_0.

$$\Delta^T(C_0) \equiv \mathbb{E}_G\left[A|C_0,M\right] - \mathbb{E}_G\left[A|C_0,F\right] \neq 0$$

Systemic discrimination

Let $\tilde{G(A|C_0,i)}$ be distribution over actions under original signal distribution but $A(-i,S)$

$$\Delta^S(C_0,M) \equiv \mathbb{E}_G\left[A|C_0,M\right] - \mathbb{E}_{\tilde{G}}[A,C_0,F]$$

$$\Delta^S(C_0,F) \equiv \mathbb{E}_{\tilde{G}}[A|C_0,M] - \mathbb{E}_G\left[A,C_0,F\right]$$

Decomposition

Let $\Sigma(S|C_0,i)$ be distribution over all possible signals given identity i and initial condition C_0

$$\Delta^T(C_0) = \mathbb{E}_\Sigma\left[\delta(S)|C_0,M\right] + \Delta^S(C_0,F)$$

$$\Delta^T(C_0) = \mathbb{E}_\Sigma\left[\delta(S)|C_0,F\right] + \Delta^S(C_0,M)$$

Empirical results

Measuring discrimination

Δ Wage by non-productive characteristics given same productivity.

Empirical challenges

- What constitutes a productive vs non-productive characteristic?
- Is Δ wage attributable to discrimination alone or worker preferences?
- Does the discrimination arise from tastes or unobserved information?

Types of studies

- Observational
- Audit and correspondence studies
- Lab and field experiments
- Quasi-random variation

Kitagawa-Oaxaca-Blinder[1] decomposition

Wages in two groups ($\boldsymbol{A}$ and $\boldsymbol{B}$) can be written

$$\begin{aligned} \ln w_A &= \mathbf{x}_A \boldsymbol{\beta}_A + \varepsilon_A, \quad && \mathbb{E}(\varepsilon_A) = 0 \\ \ln w_B &= \mathbf{x}_B \boldsymbol{\beta}_B + \varepsilon_B, \quad && \mathbb{E}(\varepsilon_B) = 0 \end{aligned}$$

Then, average wage differential

$$\Delta \equiv \mathbb{E}(\ln w_A) - \mathbb{E}(\ln w_B) = \left[\mathbb{E}(\mathbf{x}_A) - \mathbb{E}(\mathbf{x}_B)\right] \boldsymbol{\beta}_A + \mathbb{E}(\mathbf{x}_B)(\boldsymbol{\beta}_A - \boldsymbol{\beta}_B)$$

decomposed into **explained** and **unexplained** components.

Kitagawa-Oaxaca-Blinder decomposition

Interpretation

- **Common support**: $\mathbf{x}_A$ and $\mathbf{x}_B$ contain same set of variables with similar value
- **Conditional mean independence**: $\mathbb{E}(\varepsilon_A | \mathbf{x}_A) = \mathbb{E}(\varepsilon_B | \mathbf{x}_B) = 0$
- **Invariance of conditional distributions**: distribution of $w_A | \mathbf{x}_A$ remains unchanged if B workers receive returns $\boldsymbol{\beta}_A$

These are very strict assumptions, so the decomposition is a correlational (not causal) measure.

Kitagawa-Oaxaca-Blinder decomposition

Decomposition of the gender wage gap among the NLSY cohort, ages 35–43 in 2000. All coefficients are significant at the 10% level.

Decomposition of the wage gap $\overline{\ln w_A} - \overline{\ln w_B}$	Using male	Using female	Weighted	Pooled
	(1)	(2)	(3)	(4)
Unadjusted mean log wage gap	.233	.233	.233	.233
Composition effect, controlling for:				
Age, city, region, race	.012	.009	.011	.010
Education	−.012	−.008	−.010	−.010
AFQT	.011	.011	.011	.011
L.T. withdrawal due to family responsibilities	.033	.035	.034	.028
Lifetime work experience	.137	.087	.112	.092
Industrial sectors	.017	.003	.010	.009
Total “explained” by model	.197	.136	.167	.142
Total “unexplained” by model (incl. cst)	.036	.097	.066	.092

Note: OLS regressions. L.T. = Long Term.

Source: Table 8.5 (Cahuc 2004)

Audit (correspondence) studies

- Send fictitious CVs nearly identical except in group membership
- Measure callback (interview invitations, offers) received
- RCT $\Rightarrow$ group differences can be interpreted as discrimination

Challenges

- CVs may not convey all relevant productive characteristics
- Cannot disentangle taste discrimination from statistical
- Harder to generalize

Bertrand and Mullainathan (2004)

Created templates for CVs of jobseekers in Boston and Chicago

- high and low quality types based on experience, skills, career profiles
- randomly assign distinctively White or African-American name
- track callback/email rates in race/sex/city/quality cell

	White names	**African-American**
College degree	0.720	0.720
	(0.450)	(0.450)
Years of experience	7.860	7.830
	(5.070)	(5.010)
Computer skills?	0.810	0.830
	(0.390)	(0.370)
Obs.	2 435	2 435

Source: Table 3 (Bertrand and Mullainathan 2004)

Bertrand and Mullainathan (2004)

TABLE 1—MEAN CALLBACK RATES BY RACIAL SOUNDINGNESS OF NAMES

	Percent callback for White names	Percent callback for African-American names	Ratio	Percent difference (p-value)
Sample:				
All sent resumes	9.65	6.45	1.50	3.20
	[2,435]	[2,435]		(0.0000)
Chicago	8.06	5.40	1.49	2.66
	[1,352]	[1,352]		(0.0057)
Boston	11.63	7.76	1.50	4.05
	[1,083]	[1,083]		(0.0023)
Females	9.89	6.63	1.49	3.26
	[1,860]	[1,886]		(0.0003)
Females in administrative jobs	10.46	6.55	1.60	3.91
	[1,358]	[1,359]		(0.0003)
Females in sales jobs	8.37	6.83	1.22	1.54
	[502]	[527]		(0.3523)
Males	8.87	5.83	1.52	3.04
	[575]	[549]		(0.0513)

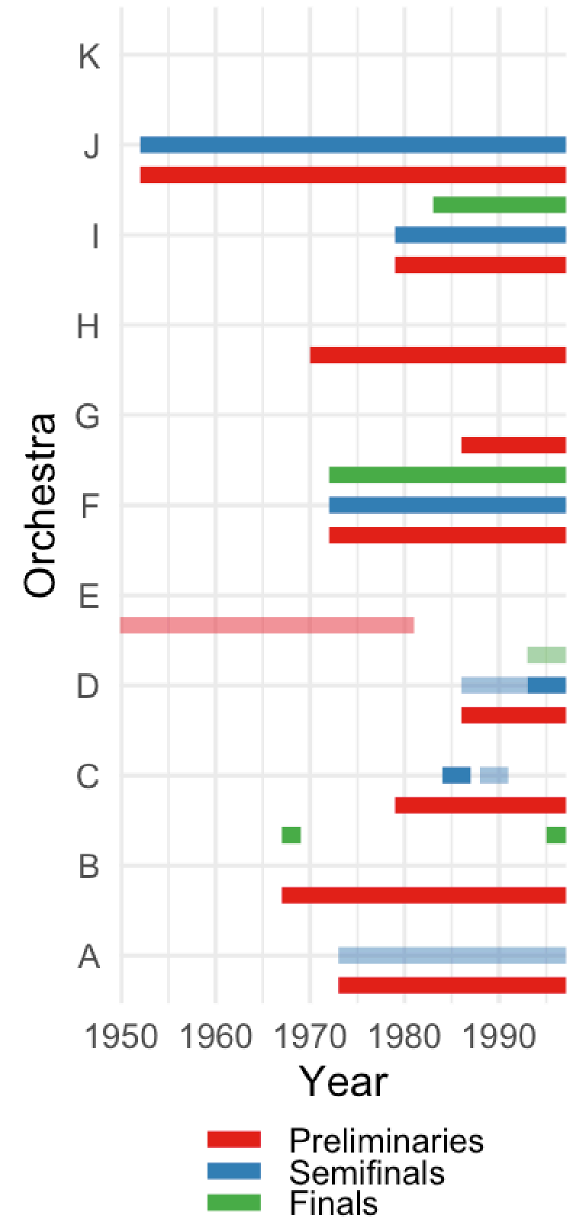
Goldin and Rouse (2000)

Pre-1970s, musicians handpicked by the director

In 1970s-80s, auditions

- “open and routinized”
- blind (some stages)

Staggered adoption of screen: DiD method



Goldin and Rouse (2000)

Results

	Preliminaries			
	Without semifinals	**With semifinals**	**Semifinals**	**Finals**
Female x Blind	0.111	-0.025	-0.235	0.331
	(0.067)	(0.251)	(0.133)	(0.181)
Obs.	5 395	6 239	1 360	1 127
R2	0.775	0.697	0.794	0.878

Source: Table 6 (Goldin and Rouse 2000)

Mobius and Rosenblat (2006)

Lab experiment: taste discrimination based on beauty

Participants randomly assigned as workers (5) and employers (5).

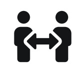
1. Workers answer survey and solve simplest maze game

   Survey + practice time = digital CV
2. Confidence: predict # mazes solved in 15 min (private)

   $100A_j - 40|C_j - A_j|$, where A_j actual and C_j predicted performance

Mobius and Rosenblat (2006)

3. Workers randomly matched to employers (5×5)

B	CV only	(baseline)
V	CV + 	(visual)
O	CV + 	(oral)
VO	CV +  + 	(visual and oral)
FTF	CV +  + 	(face-to-face)

4. Employers set wages w_{ij} = # mazes could solve in 15 min

$$\Pi_i = 4000 - 40 \sum_{j=1}^{5} |w_{ij} - A_j|$$

5. Workers complete 15 min “employment”: realised A_j

Mobius and Rosenblat (2006)

6. Payoffs
   a. Firms receive Π_i as on previous slide
   b. Workers receive $\Pi_j = 100A_j - 40|C_j - A_j| + \sum_{i=1}^{5} W_{ij}$ where

$$W_{ij} = \begin{cases} 100w_{ij} & \text{with probability } 80\% \\ \bar{w}_j & \text{with probability } 20\% \end{cases}$$

Employers know if $W_{ij} = 100w_{ij}$ **before** setting it!

Mobius and Rosenblat (2006)

Results

1. Beauty does not affect actual performance, but ↑ confidence
2. Beauty premia, but no taste-based discrimination

	B	V	O	VO	FTF
BEAUTY	0.017	0.131**	0.129**	0.124**	0.167**
	(0.040)	(0.042)	(0.034)	(0.036)	(0.043)
SETWAGE	-0.010	-0.072	0.098*	-0.046	0.033
	(0.055)	(0.052)	(0.046)	(0.048)	(0.057)
SETWAGE x BEAUTY	-0.058	-0.099+	0.005	-0.022	-0.044
	(0.057)	(0.053)	(0.048)	(0.050)	(0.058)
N	163	161	163	162	163

Source: Table 4 (Mobius and Rosenblat 2006)

3. Beauty premium: 15-20% due to confidence, 40% - stereotype

Rao (2019)

Field and lab experiments eliciting taste-based discrimination

Δ policy in India: elite schools offer free places to poor students

Exploit staggered implementation using DiD

1. more charitable
2. changes fundamental notions of fairness and generosity
3. reduce discrimination (teammate choice in race)
    - high stakes: only 6% choose slower rich over faster poor student
    - low stakes: 33% discriminate against poor students
    - past exposure $\downarrow$ taste discrimination WTP by 12pp

Doleac and Hansen (2020)

Quasi-random policy experiment measuring statistical discrimination

Ban-the-box (BTB) policy

- Banning prior criminal convictions box on job applications
- Hawaii in 1998 $\longrightarrow$ 34 states + DC in 2015

BTB "does nothing to address the average job readiness of ex-offenders".

Therefore, statistical discrimination may $\uparrow$

Use DiD to measure effect of **BTB on employment of minorities**

Doleac and Hansen (2020)

	Full sample	BTB-adopting
White x BTB	-0.003	-0.005
	(0.006)	(0.008)
Black x BTB	-0.034**	-0.031**
	(0.015)	(0.014)
Hispanic x BTB	-0.023*	-0.020
	(0.013)	(0.015)
Obs.	503,419	231,933
Pre-BTB baseline		
White	0.8219	0.8219
Black	0.677	0.677
Hispanic	0.7994	0.7994

Source: Table 4 (Doleac and Hansen 2020)

Glover, Pallais, and Pariente (2017)

Capturing self-fulfilling prophecy of statistical discrimination

Quasi-random assignment of new cashiers to managers in French stores

Do minority cashiers perform worse with biased managers?

Measure manager bias using Implicit Association Test (IAT)

- 66% moderate to severe bias
- 20% slight bias

Outcomes: absences, time worked, scanning speed, time between customers

Glover, Pallais, and Pariente (2017)

	Absences	Overtime (min)	Scan per min	Inter-customer time (sec)
Minority x Mngr bias	0.012***	-3.237*	-0.249**	1.360**
	(0.004)	(1.678)	(0.111)	(0.665)
Obs.	4,371	4,163	3,601	3,287
Dep var mean	0.0162	-0.068	18.53	28.7

Sources: Tables III and IV (Glover, Pallais, and Pariente 2017)

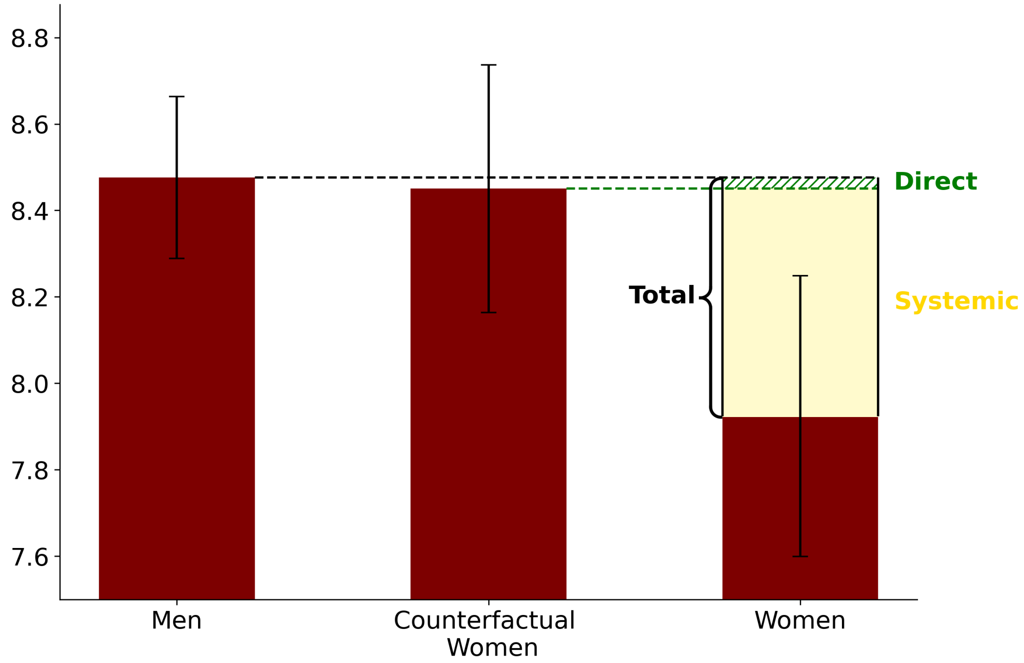
Bohren, Hull, and Imas (2025)

Role of gendered recommendation letters on hiring

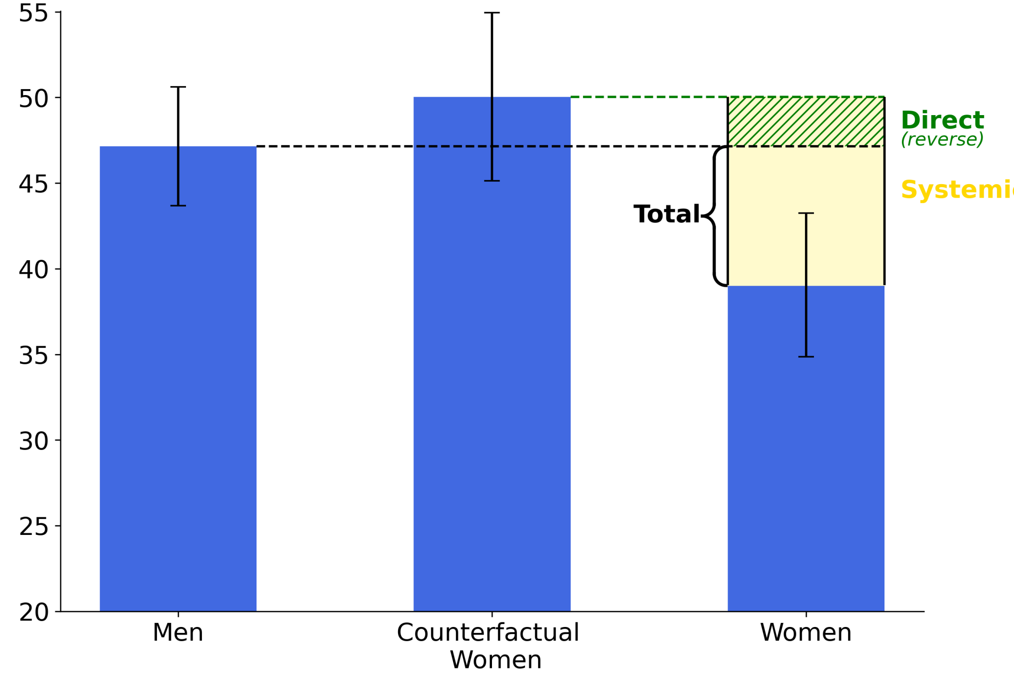
- LLM: “female” and “male” recommendation letters
- Fictitious CVs with “male” and “female” names
- Survey 396 hiring managers

	Recommendation gender	
CV name	CV	CV
	CV	CV

Bohren, Hull, and Imas (2025)



Hiring likelihood



Prospective wage

Summary

- Two main frameworks with different implications for labour markets
  - → Taste-based discrimination
  - → Statistical discrimination
- Systemic discrimination accumulating over time
- Simple decomposition to measure unexplained gap
- Vast experimental and quasi-experimental literature

Next lecture: Intergenerational mobility on 24 Sep

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