Studying Discrimination (1)

Socio-Demography: Mind the Gap

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Outline

1. Intro: What is discrimination?
2. Types of D (theory)
    1. Taste based D
    2. Statistical D
    3. Consumer-driven D
    4. Implicit-bias
3. The limitations of observational data to study LMD
    - The Oaxaca-Blinder decomposition method
4. Q&A

Discrimination

- Discrimination (D) is both unjust and inefficient. It hurts people, it heightens inequality and it hampers economic growth
- Discriminatory behaviours take many forms, but they all involve unequal treatment + (often) some form of exclusion or rejection
- Many basis for D→ e.g. age, gender, sexual orientation, religion, ethnicity, phenotype, looks, etc
- Many realms and agents of D
- …but researchers concerned with socio-economic inequality typically focus on…
  1. D in access to crucial assets/resources (e.g. D against minority children in schools, housing market, etc)
  2. D in the labor market (DLM) (e.g. access to employment, promotion opportunities and pay)

!

D in the labour market (LMD) is the main focus of today's talk

!

D is only but one possible explanation of LM gaps

!

As we will see, estimating **D** is a complex task

2. Types of labour market **D**

Theory

!

Theories of LMD focus on discriminatory practices by firms (employers, managers & directors) in hiring, promoting and paying workers from specific social groups (e.g. women, ethnic/racial minorities)

Types of LMD

1. Discrimination by taste (Becker 1993[1964])

- Firms discriminate against particular groups (e.g. women/minorities) due to
    1. the firms' (i.e. employers) dislike for them
    2. the firms' employees' dislike for them
    3. The firm's customers dislike for them
- In the literature DbT is often used as referring only to 1) but Becker spoke of the three forms (I follow the conventional view and treat consumer-driven D as a different case below)
- Because D by taste is based on prejudice, it is **irrational** from an economic point of view

  → In equilibrium competitive markets should penalize firms that discriminate by taste → This is actually not the case in consumer-driven D

Types of LMD

2. Statistical discrimination (Arrow 1971; Phelps 1972; Aigner and Cain 1977)

- Under incomplete/asymmetric information, rational employers might still discriminate against individuals from some groups if such groups are believed to be…

  1) *on average* less productive (e.g. some international migrants in communicational-intensive tasks) –or having a higher average probability of interrupting their careers (e.g. women) OR…
  2) If the *variance* in the distribution of unobserved skills is expected to differ by group (e.g. more dispersion in motivation) OR…
  3) If the signal employers receive for judging expected productivity is noisier for some groups (e.g. test scores from foreign schools)

Types of LMD

2. Statistical discrimination (Phelps 1972; Arrow 1973; Aigner and Cain 1977)

- Statistical D is based on information deficits, not taste
- Yet employers' assessments of the distribution of unobserved qualities are often based on biased beliefs (stereotypes)

  → Processes of status categorization typically involved in stereotypes (i.e. beliefs about performance, behaviours, capabilities→ e.g. "gypsies are lazy"; "women can't handle pressure"…)

  Stereotypes are widely shared by members of the in-group/dominant culture/majority population

  D reinforces stereotyping because people interpret differences in outcomes as proof of their prior stereotypical beliefs

- IMPLICATION: Yet for stat-D theory, reducing information deficits should always reduce D

Types of LMD

3. Customer-driven discrimination

- Rational firms might still discriminate against particular individuals to comply with customers/clients own prejudiced preferences
  - Example: British Oil companies working in the Persian Gulf did not hire women not to upset their main clients
- This is a situation where firms rationally adapt to their costumers' irrational tastes (this is why it is considered distinct from DbT)
- Recent experiments with employers suggest customer-driven discrimination plays a significant role in shaping employers' decisions (Baert & De Pauw 2014)

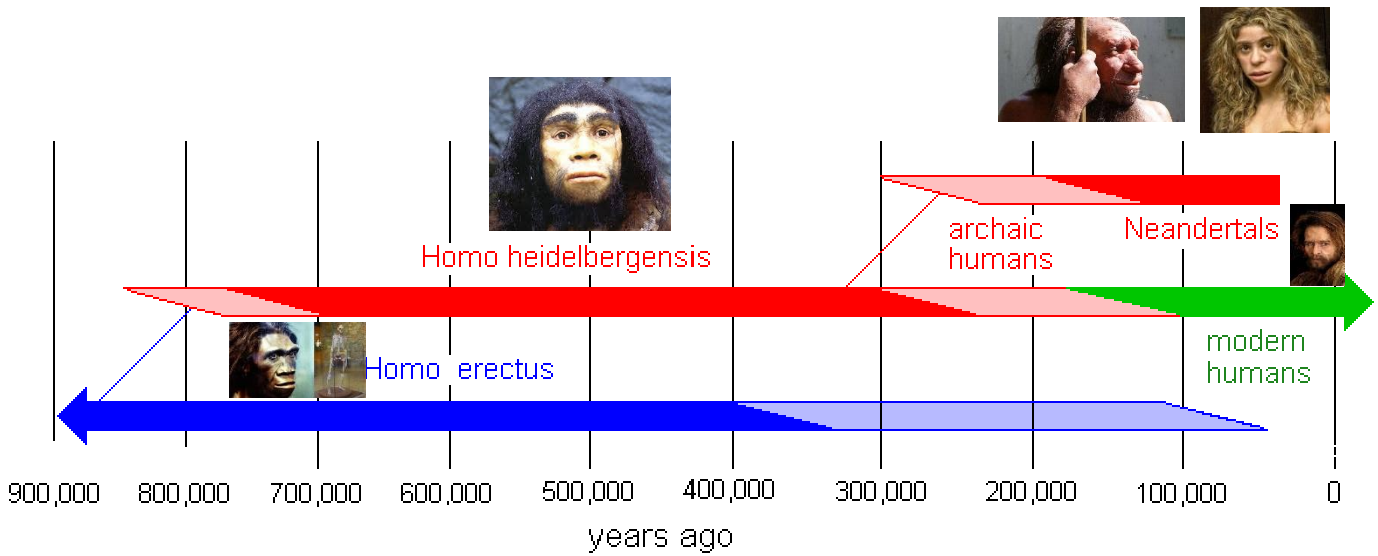
Types of LMD

4. Implicit bias

- Note both DbT and Stat D imply conscious assessments of the applicants' qualities by employers
- But research in cognitive and social psychology shows people often categorize, stereotype and D others on the basis of implicit mental associations of which they are largely (if not fully) unaware (see e.g. Richeson and Sommers 2015; Phelps and Thomas 2003; Reskin 2000)
- Evolutionary psychologists argue that the "computational machinery" that triggers race, sex and age categorization & stereotyping of others is a universal feature of human cognition, which can be explained by its adaptive function (see e.g. discussion in Kurzban et al. 2001; Neuberg and Schaller 2016)
  - Age, gender, and race would be "primitive" dimensions which the mind activates in an automatic and mandatory fashion when encountering others

IMPLICATION: D might be harder to eradicate

A very long human evolution



IMPLICATIONS

- Human males and females transmitted their genes under different reproductive circumstances. Genetic adaptation in prehistory led to sexual dimorphism → **sex-specific traits** (i.e. nurturance vs aggressiveness and competition)
- The capacity to recognize outgroup members and to predict their behaviour was crucial for survival under extremely harsh and competitive conditions→ **outgroup recognition**
- The ability to recognize healthy and potentially fertile mates→ **age recognition**

→ Age, sexual and phenotypic categorization are "primitive" dimensions of cognition operating in the 'automatic' area of our brains (where thinking fast takes place)→ Little conscious control over age, sex, and phenotypic categorization→ Strong forces leading to implicit bias (but see e.g. Reskin 2000; Vaisey 2009; for a "cultural" version of implicit bias)

3. The limitations of observational data

?

Can we measure D quantitatively using observational data (i.e. surveys)?

?

NO, we cannot *because*…

!

…surveys do not contain all the characteristics that employers observe when hiring, promoting, or setting wages…

!

Hence we can never be
sure that the minority and non-minority
workers compared are truly similar

!

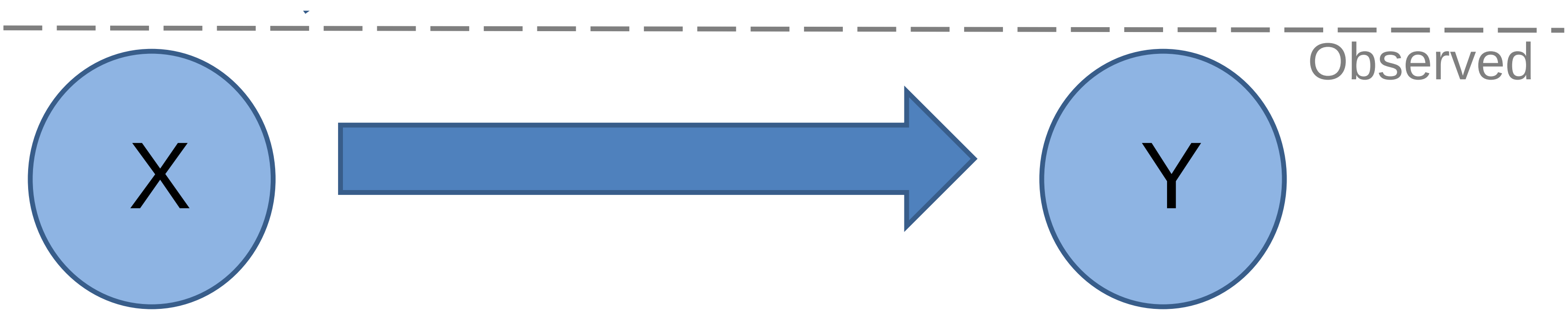
In other words, we face the problem of **unobserved confounders** (also known as unobserved heterogeneity) and this **hinders causal identification**

A graphical representation of OVB

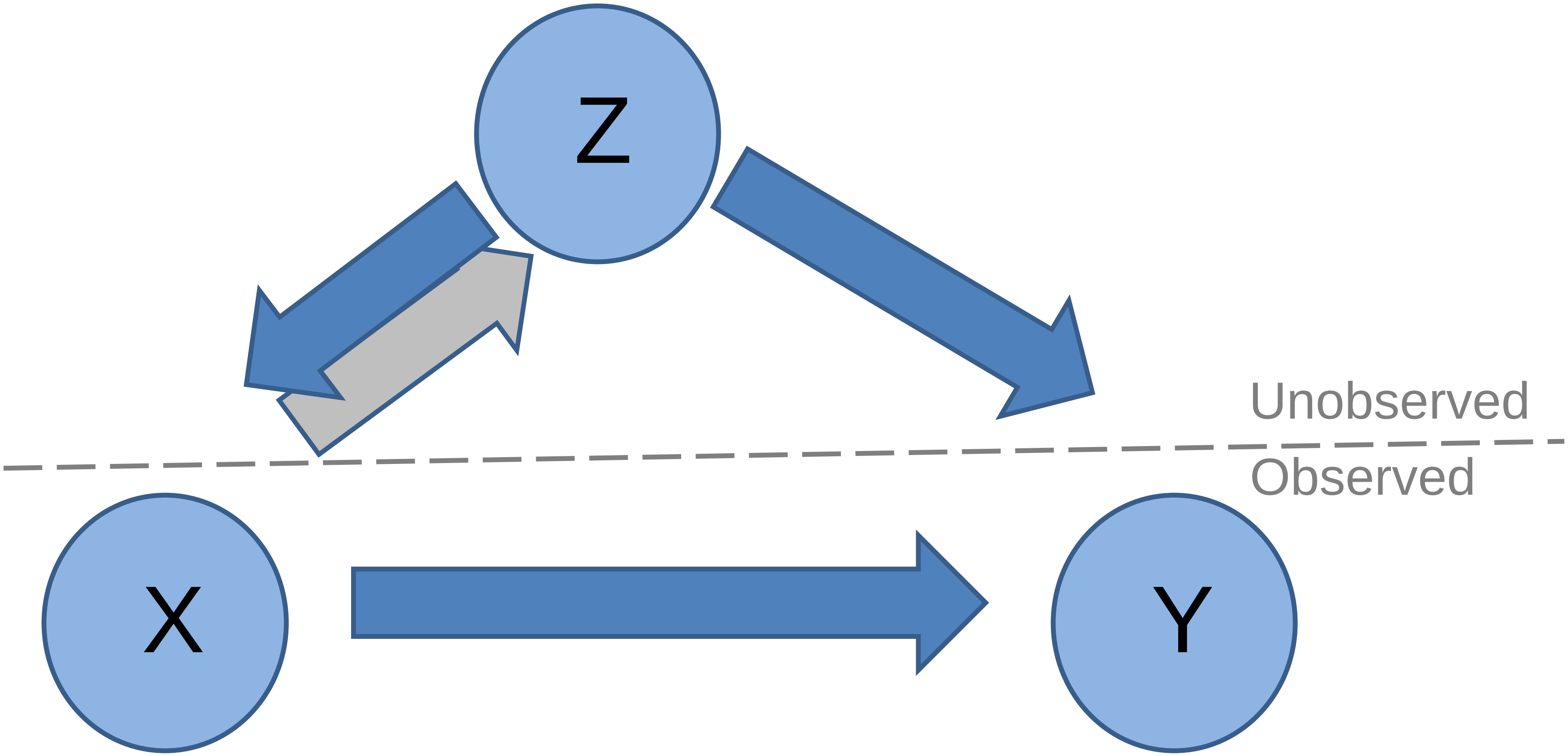
$Y = \alpha + \beta X + \mathbf{G}\gamma + \varepsilon$

Remember **ε** captures all other unobserved factors affecting Y

Key ID assumption: $Cov(X, \varepsilon) = 0$



A graphical representation of OVB



Now the effect of Z on Y is “hidden” in the effect of X on Y…

This means Cov(X, ε)≠0

The ID logic in observational research

- We attempt to ID by **controlling** for as many counfounders as we can possibly think of (i.e. to convert Zs is Gs in our graphic example)
- When we control for confounders we are **blocking** their effects on X

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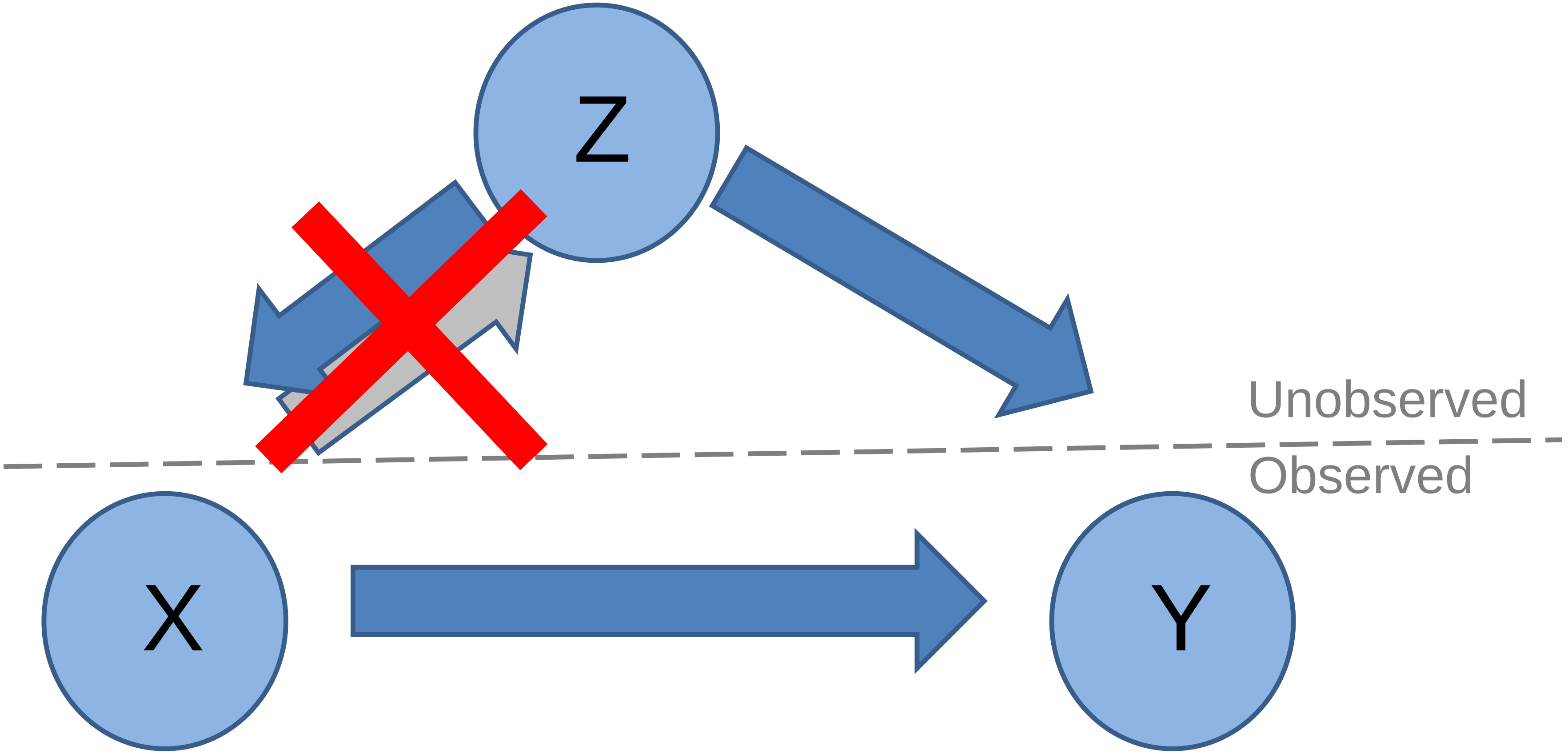

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The ID logic in observational research

- We attempt to ID by **controlling** for as many counfounders as we can possibly think of (i.e. to convert Zs is Gs in our graphic example)
- When we control for confounders we are **blocking** their effects on X
- So ID is "achieved" by "netting out" the effect of X from the effect of potential confounders
- Problem is many confounders cannot be observed, and others we cannot think of
- So **ID is problematic** (note IV approaches must also make assumptions about the exogeneity of the instrument)
- ID of hiring D with observational data is also particularly problematic because we typically sample the "wrong" subjects (employees)

!

Standard LM surveys typically focus on the supply-side (i.e. employees) but it is employers who make hiring decisions

→ i.e. researchers often test demand-side theories with supply-side data!

An illustration of the limitations of observational data

The Oaxaca-Blinder decompostion method*

*I use the example of the gender age gap nut the method can be (and has been) applied in multiple studies of ethnic and racial pay gaps.

Wage decomposition (Oaxaca-Blinder)

Men's factual earnings→ $S_i^{\text{♂}} = \beta_i^{\text{♂}} X_i^{\text{♂}} + e_i^{\text{♂}}$ (i.e. the wages men really get in the LM)

Women's factual earnings→ $S_i^{\text{♀}} = \beta_i^{\text{♀}} X_i^{\text{♀}} + e_i^{\text{♀}}$ (i.e. the wages women really get in the LM)

Women's counterfactual earnings→ $S^{*}{}_i^{\text{♀}} = \beta_i^{\text{♂}} X_i^{\text{♀}} + e_i^{\text{♀}}$ (i.e. what women would get in a neutral LM)

$$\underbrace{S_i^{\text{♂}} - S_i^{\text{♀}}} = \underbrace{\beta_i^{\text{♂}}(X_i^{\text{♂}} - X_i^{\text{♀}})} + \underbrace{(\beta_i^{\text{♂}} - \beta_i^{\text{♀}})X_i^{\text{♀}}}$$

Gross wage gap= Differences in assests + Differences in returns

Explained component + Unexplained component

(This has often been interpreted as capturing discrimination)

The problem is…

- The effect of any unobserved characteristic affecting wage differences that is not captured by the explained component will necessarily appear in the residual component!!

An example from Farkas & Vicknair (1996)

Table 1. Coefficients from Regression of (ln) Hourly Wage on Selected Independent Variables, and Percent of Wage Gap Explained: Full-Time Black Male Workers, Ages 26 to 33 in 1991

	Mean Difference	Coefficients		Percent of Wage Gap Explained	
Independent Variable	(Black minus White)	Model 1	Model 2	Model 1	Model 2
Cognitive skill (1980)	−1.000	—	.109***	—	40.43
Years of school	−.627	.069***	.045***	16.11	10.41
Work experience (weeks)	−75.861	.001***	.001***	22.48	22.48
Mother's education (years)	−1.255	.013*	.010	6.18	4.56
Age in 1979	−.110	−.002	−.007	−.07	−.29
Lives in rural area	−.122	−.019	−.016	−.86	−.74
Lives in the South	.320	−.168**	−.166**	19.91	19.68
Health limitation	−.005	−.038	−.050	−.07	−.10
Married	−.219	.179***	.164***	14.52	13.30
Grew up in South	.341	−.014	.014	1.80	−1.73
Number of children under age 18	.304	−.012	−.007	1.36	.81
Has preschool child	.045	.022	.006	−.36	−.09
R^2 (adjusted)	—	.274	.295	—	—
Total	—	—	—	80.99	108.72

100-(Total)= % unexplained

Note: The mean of the dependent variable for this sample is 6.75. The dependent variable is ln(100 × dollars per hour). The sample size is 602.

*$p < .05$ **$p < .01$ ***$p < .001$ (two-tailed tests)

The problem is…

- The effect of any unobserved characteristic affecting wage differences that is not captured by the explained component will necessarily appear in the residual component!!

D cannot be properly identified with observational data

Qs

1. List a few relevant confounders in the study of gender pay gaps
2. And what confounders you think might be relevant in the study of native/migrant gaps?
3. Are all unobserved variables correlated with gender/ethnicity “confounders”? How can you differentiate a confounder from a mechanism?

That's all

Many thanks for your attention!

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