

Attention and Perception

Lecture 2: A Robust Test of Prejudice

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Recall

Caplin & Martin (2015), "A Testable Theory of Imperfect Perception."

- ▶ Question: Can we assume that a decision maker is **updating beliefs correctly** (using Bayes' Rule) and **maximizing utility** for unobservable private information?
 - ▶ Key assumptions behind many, if not most, models of perception
 - ▶ Includes: drift-diffusion model, race model, signal detection theory

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- ▶ Question: Can we assume that a decision maker is **updating beliefs correctly** (using Bayes' Rule) and **maximizing utility** for unobservable private information?
 - ▶ Key assumptions behind many, if not most, models of perception
 - ▶ Includes: drift-diffusion model, race model, signal detection theory
- ▶ Use choice data (observable) to understand private information (unobservable)
 - ▶ Choice data are summarized by $P(a, \omega)$, the joint distribution of actions and states
 - ▶ Call this "**state-dependent stochastic choice data**" (**SDSC**)

Definition

Utility function u satisfies the No Improving Action Switches (**NIAS**) condition with respect to P if,

$$\sum_{\omega \in \Omega} P(a, \omega) u(x(a, \omega)) \geq \sum_{\omega \in \Omega} P(a, \omega) u(x(b, \omega)),$$

for all $a, b \in A$.

Intuition: Cannot improve utility by making a *wholesale* switch from any chosen action

Theorem

P has a Bayesian Expected Utility (BEU) representation if and only if there exists $u : X \rightarrow \mathbb{R}$ satisfying the NIAS inequalities.

Moving to Application

- ▶ Many possible applications of NIAS
- ▶ Key steps:
 1. Determine the data set $P(a, \omega)$ for that application
 2. Then connect back to theory (what does BEU imply in this application?)
- ▶ For example:
 - ▶ $P(\text{bundle}, \text{price})$ NIAS = consumers with price uncertainty
 - ▶ $P(\text{report}, \text{evidence})$ NIAS = beliefs with bad memory
 - ▶ $P(\text{hire/not}, \text{productivity})$ NIAS across groups = statistical discrimination with subjective perception

Statistical Discrimination with Subjective Perception

- ▶ Hiring is rife with subjective perception: hiring managers partially read CVs, partially read cover letters, etc.
- ▶ **Intuitive question:** Could it be that differences in choices across groups is due to statistical discrimination with subjective perception?
- ▶ Statistical discrimination with subjective perception = information structure $\pi(\gamma|\omega)$ changes with group
- ▶ **Technical version:** Can changes in $\pi(\gamma|\omega)$ across groups explain changes in the data $P(a, \omega)$ across groups?

Decision-Problem Dependence

- ▶ New idea: The DM might face several different “decision problems” $i \in D$
- ▶ Many things can change with the decision problem
 - ▶ Actions A_i
 - ▶ Prizes $x_i(a, \omega)$
 - ▶ Utility $u_i(a, \omega)$
 - ▶ Objective prior $P_i(\omega)$
 - ▶ Subjective prior μ_i
 - ▶ Information structure $\pi_i(\gamma|\omega)$
 - ▶ Decision rule σ_i
- ▶ And so might get different SDSC $P_i(a, \omega)$ in each decision problem $i \in D$

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- ▶ And so might get different SDSC $P_i(a, \omega)$ in each decision problem $i \in D$
- ▶ In this application, i indicates the protected category (gender, race, etc.) of the person that the decision is being made about

Martin & Marx (2022), "A Robust Test of Prejudice."

- ▶ Two main explanations for discrimination are prejudice (utility-based) and statistical (belief-based)
- ▶ Question: Can we identify when someone is prejudiced?
- ▶ Challenge: Don't know the decision maker's utility or their perception!
- ▶ Idea: **NIAS provides the limits of what can be explained by statistical discrimination, so if violated, this provides strong evidence of prejudice**
- ▶ Example setting: Reuben et al. (2014)
 - ▶ One randomly selected subject is the "employer" and must decide whether to "hire" subjects of different genders
 - ▶ Information provided in each treatment: appearance, past performance, and/or candidate predictions for future performance

Statistical Discrimination with Subjective Perception

- ▶ Actions: hire or not hire, States: H or L (higher and lower productivity)
- ▶ Data: SDSC for both groups (P_w and P_m)
- ▶ For members of group w , NIAS requires that for action hire:

$$P_w(\text{hire}, H)u(\text{hire}, H) + P_w(\text{hire}, L)u(\text{hire}, L) \geq P_w(\text{hire}, H)u(\text{not hire}, H) + P_w(\text{hire}, L)u(\text{not hire}, L)$$

- ▶ Or dividing off the action probability:

$$P_w(H|\text{hire})u(\text{hire}, H) + (1 - P_w(H|\text{hire}))u(\text{hire}, L) \geq P_w(H|\text{hire})u(\text{not hire}, H) + (1 - P_w(H|\text{hire}))u(\text{not hire}, L)$$

Statistical Discrimination with Subjective Perception

- ▶ Likewise, for action not hire:

$$P_w(\text{not hire, H})u(\text{not hire, H}) + P_w(\text{not hire, L})u(\text{not hire, L}) \geq \\ P_w(\text{not hire, H})u(\text{hire, H}) + P_w(\text{not hire, L})u(\text{hire, L})$$

- ▶ And dividing off the action probability:

$$(1 - P_w(L|\text{not hire}))u(\text{not hire, H}) + P_w(L|\text{not hire})u(\text{not hire, L}) \geq \\ (1 - P_w(L|\text{not hire}))u(\text{hire, H}) + P_w(L|\text{not hire})u(\text{hire, L})$$

Utility Bounds

- ▶ These NIAS inequalities place bounds on the utility function u
- ▶ Normalizing the utility of mistakes in each state to 0 ($u(\text{hire}, L) = 0$ and $u(\text{not hire}, H) = 0$), it must be that for w :

$$\frac{P_w(L|\text{not hire})}{1 - P_w(L|\text{not hire})} \geq \frac{u(\text{hire}, H)}{u(\text{not hire}, L)} \geq \frac{(1 - P_w(H|\text{hire}))}{P_w(H|\text{hire})}$$

- ▶ The same bounds hold for m :

$$\frac{P_m(L|\text{not hire})}{1 - P_m(L|\text{not hire})} \geq \frac{u(\text{hire}, H)}{u(\text{not hire}, L)} \geq \frac{(1 - P_m(H|\text{hire}))}{P_m(H|\text{hire})}$$

A Robust Test of Prejudice

- ▶ This holds if and only if

$$P_m(H|\text{hire}) \geq P_w(H|\text{not hire})$$

and the analogous condition with w and m swapped

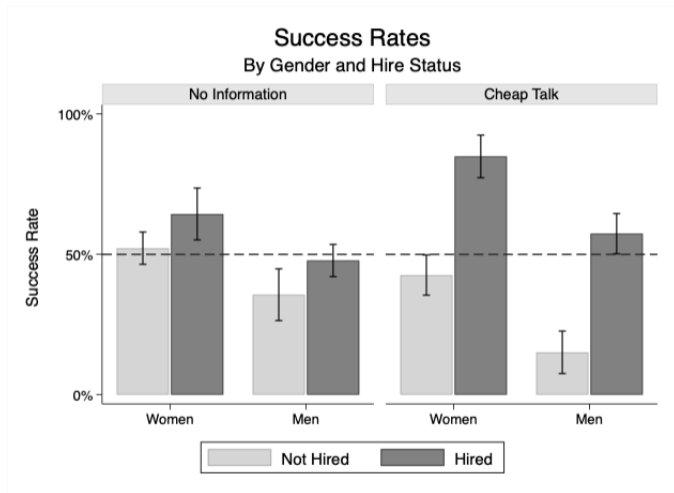
- ▶ Thus, choice data are not consistent with statistical discrimination if:

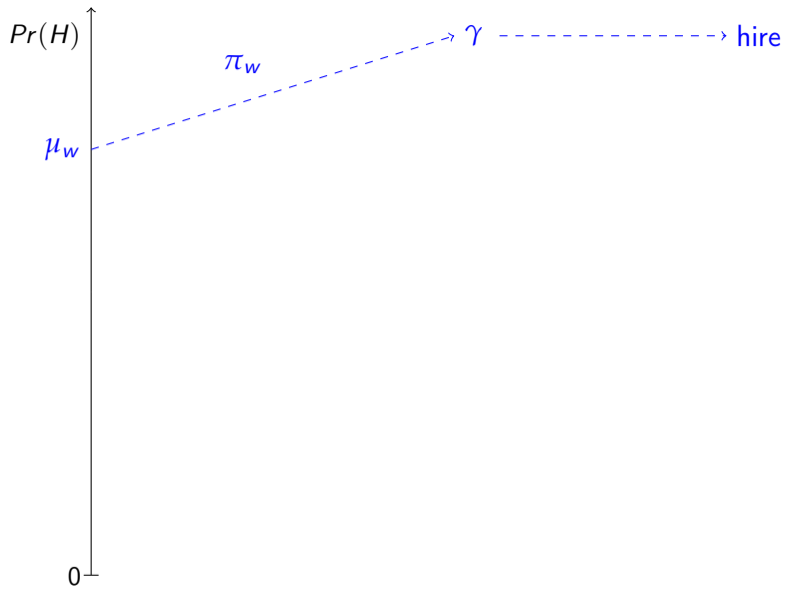
$$P_w(H|\text{not hire}) > P_m(H|\text{hire})$$

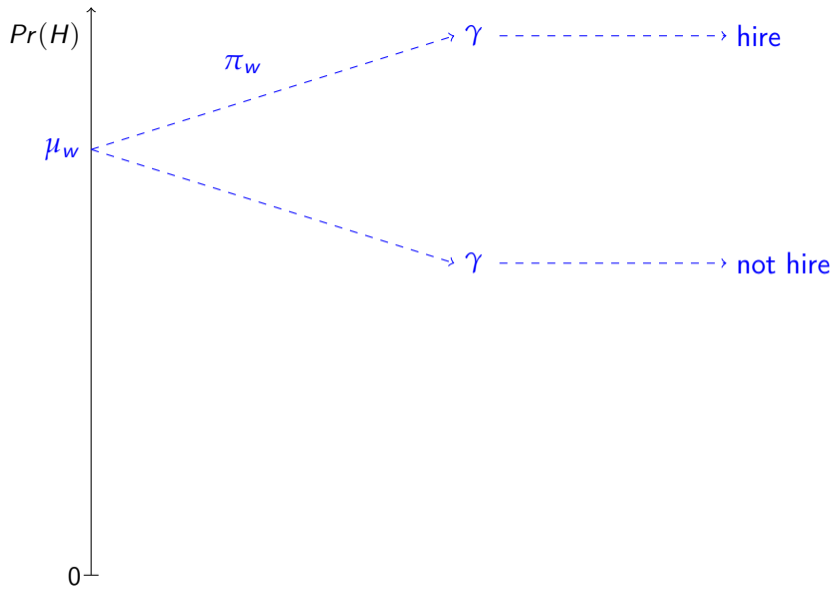
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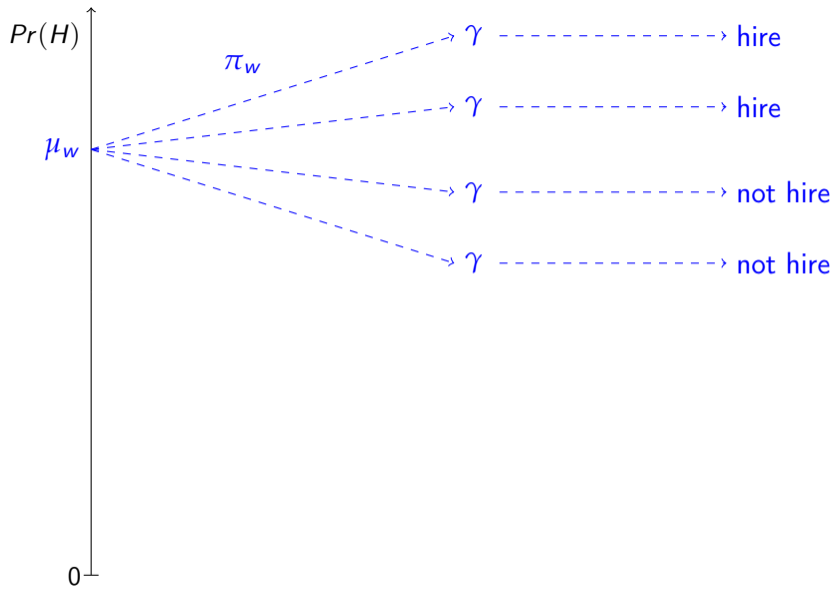
- ▶ A simple and robust outcome test of prejudice!

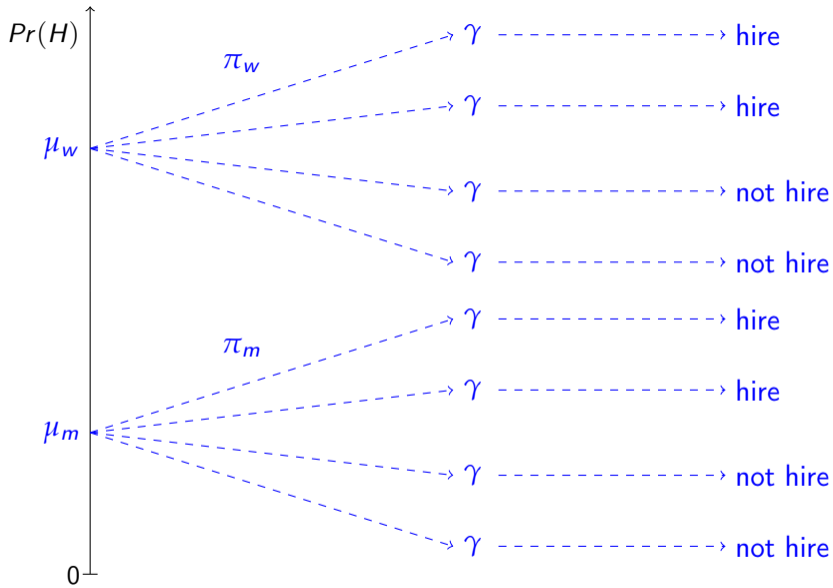
Lab experiment of Reuben et al. (2014)

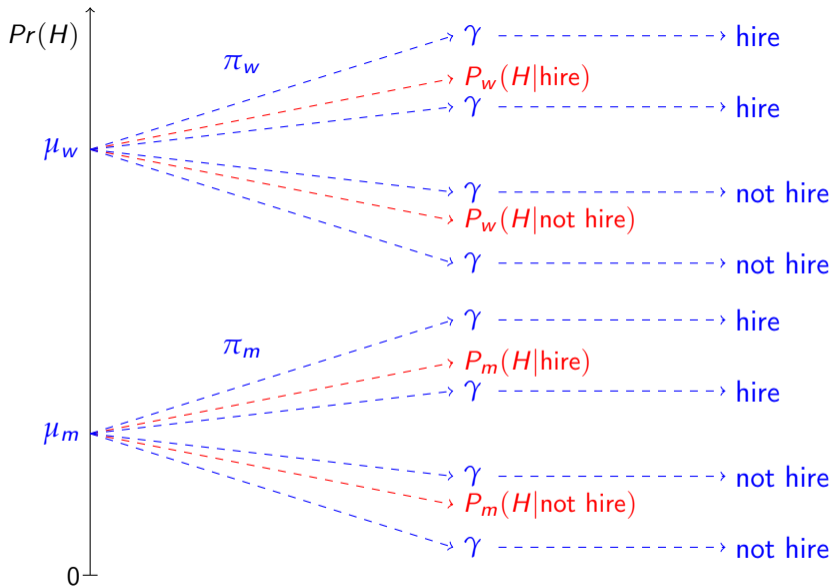


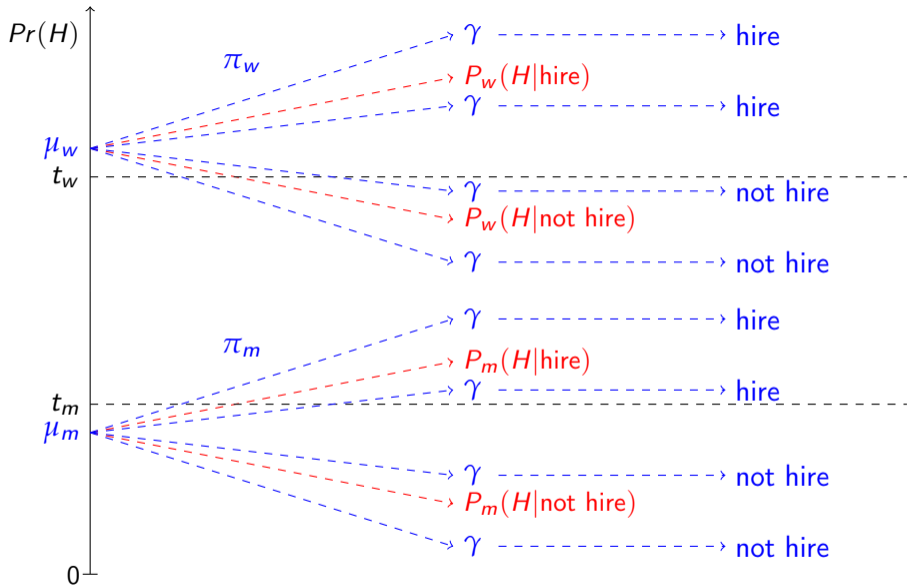












Selection Motives

- ▶ Another possibility is **prejudice in the selection motive**
 - ▶ When the decision-maker positively selects for a trait in one group and negatively selects for the same trait in another group
- ▶ Demonstrate using the correspondence field experiment of Bertrand & Mullainathan (2004)
 - ▶ Names that strongly signal gender and race were randomly added to fictitious resumes of subjectively high and low quality
 - ▶ They observed a strong disparity in job callbacks depending on the race of the name that was added to a resume

Our Test

- ▶ Proposition 2 shows there is prejudice in the selection motive against group m if

$$P_m(H|\text{call back}) < P_m(H|\text{not call back})$$

- ▶ Equivalently, if high quality candidates are called back **less often** than low quality candidates in that group:

$$P_m(\text{call back}|H) < P_m(\text{call back}|L)$$

- ▶ Why might this happen? Many possible reasons!
- ▶ To the best of our knowledge, this form of prejudice is new to the discrimination literature

Bertrand and Mullainathan (2004)

- ▶ Proposition 3 shows our test remains true as long as observed outcomes correlate sufficiently with true outcomes
 - ▶ Allows us to leverage exogenous variation in resume quality
- ▶ Based on variation in resume quality, Martin & Marx (2022) find robust evidence of prejudice in selection motive at the [intersection of gender and race](#)
- ▶ Show the probability of a callback for an African-American male *decreases* with resume quality: from 7.4% for low-quality resumes to 4.3% for high-quality resumes

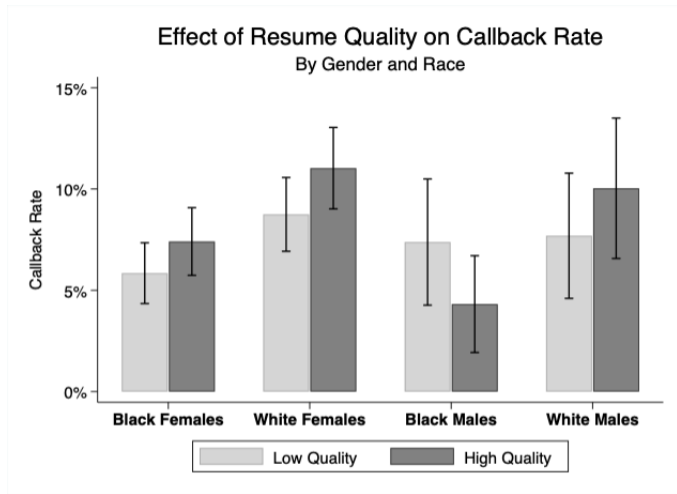


Figure 1: Similarly to their Table 5, standard errors are corrected for clustering at the employment-ad level in a probit regression.

Bertrand and Mullainathan (2004)

- ▶ Same pattern for all job types (manager, sales representative, retail)
- ▶ Martin & Marx (2022) appear to be the first to document this pattern
- ▶ This pattern implies that:
 1. Employers are paying attention to resume details
 2. Employers are prejudiced in their selection motive regardless of what information they gleaned from the resumes they received

Contributions

1. Martin & Marx (2022) provide a test of prejudice that is **general and simple**
 - ▶ Demonstrate with two well-known experiments: Reuben et al. (2014) and Bertrand & Mullainathan (2004)
2. It is **very robust** to selective attention and unobservable learning
 - ▶ Makes no assumptions about how informativeness varies across unobservables or how informativeness varies across decision-makers
 - ▶ We relax assumptions of correct subjective prior in the paper (important for recent discrimination literature)
3. Can be applied to **average outcomes**
 - ▶ Becker (1957) showed that a decision-maker is prejudiced if there are differences in outcomes across groups *for marginal decisions*
 - ▶ Limitation: Requires knowing which decisions are marginal

References I

- Becker, G. S. (1957), *The Economics of Discrimination*, University of Chicago Press, Chicago.
- Bertrand, M. & Mullainathan, S. (2004), 'Are emily and greg more employable than lakisha and jamal? a field experiment on labor market discrimination', *American Economic Review* **94**(4), 991–1013.
- Caplin, A. & Martin, D. (2015), 'A testable theory of imperfect perception', *The Economic Journal* **125**(582), 184–202.
- Martin, D. & Marx, P. (2022), 'A robust test of prejudice for discrimination experiments', *Management Science* **68**(6), 4527–4536.
- Reuben, E., Sapienza, P. & Zingales, L. (2014), 'How stereotypes impair women's careers in science', *Proceedings of the National Academy of Sciences of the United States of America* **111**(12), 4403–4408.