



Discrimination

EC 350: Labor Economics

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Spring 2021

Discrimination



What is it?

Labor market discrimination occurs when two or more **equally productive individuals** are **treated differently** on the basis of some other characteristic that is unrelated to productivity.

- **Examples?** Age, race, gender, *etc.*

Why should we care?

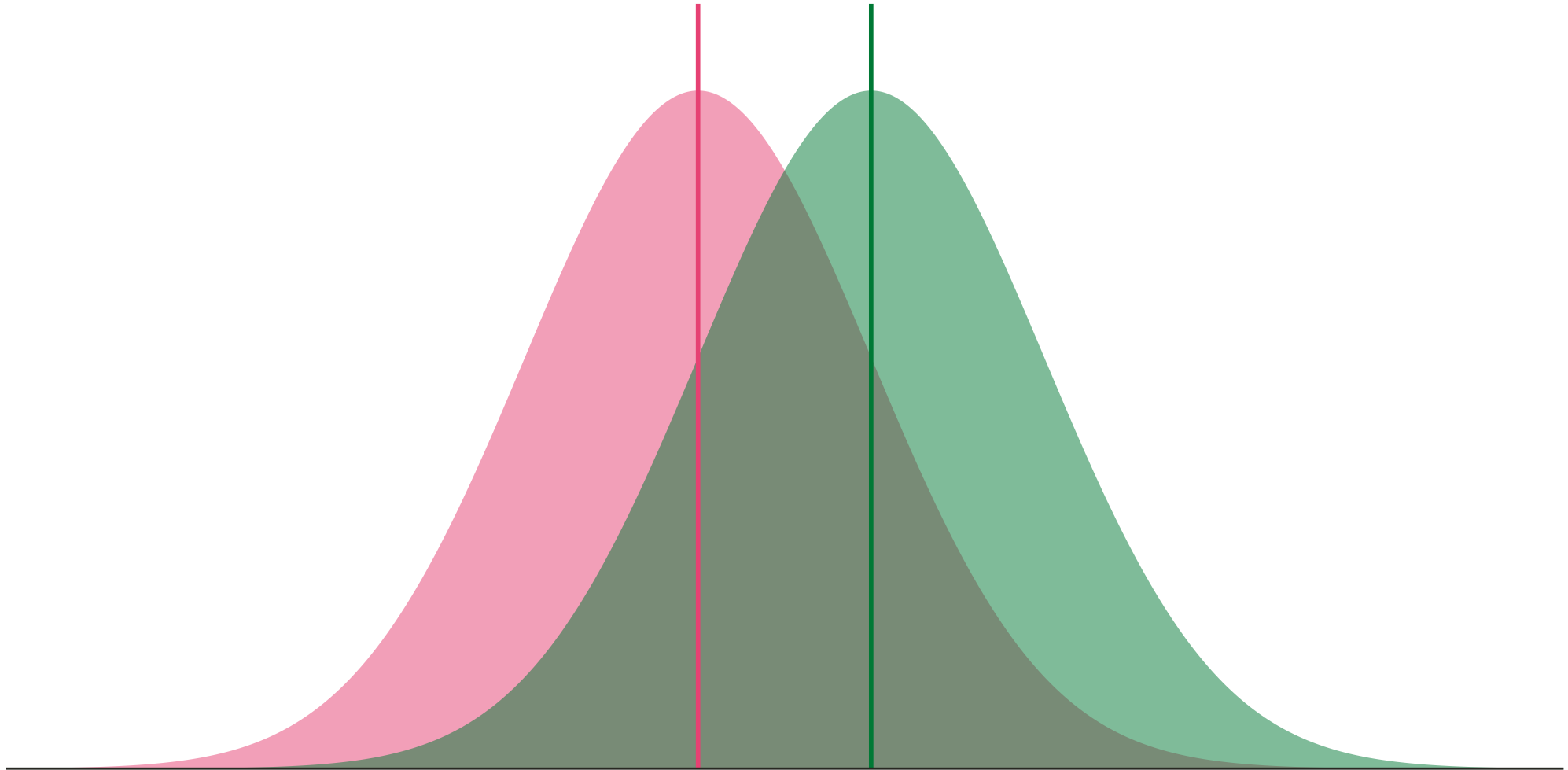
Discrimination is...

- Morally objectionable.
- Illegal.
- A cause of inequality.
- Common.

Understanding group differences



Q: What do we mean when we say "**Group A** earns less than **Group B**, on average?"



Earnings gaps



Data

The source? Current Population Survey (via **IPUMS**).

The sample? Nationally representative sample of employed working-age adults aged 16+.

- We will further restrict the sample to those who self-identify as Asian, Black, Hispanic (of any race), or White (non-Hispanic).
- We will first analyze the 2021 data (43,119 survey respondents), then incorporate data going back to 2010 (1,711,699 survey respondents).

The outcome? Weekly earnings.

Earnings gaps



Approach

Run regressions of the form

$$\log(\text{Earnings}_i) = \alpha + \beta \text{Group}_i + X' \Phi + \varepsilon_i$$

- Group_i is an indicator variable denoting race or gender.
- β is the earnings gap, interpreted as a percentage difference.
- X' is a vector of control variables.



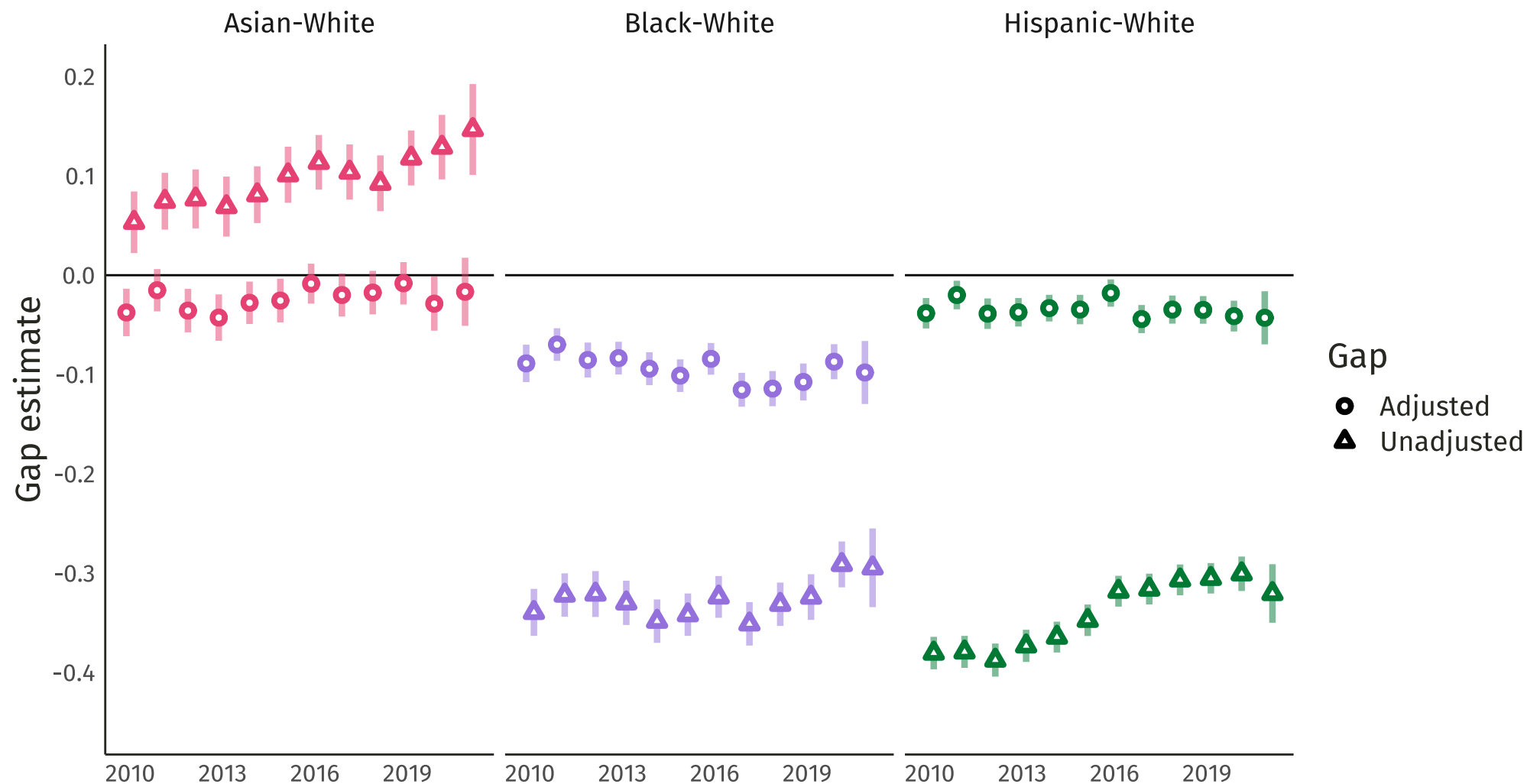
Racial earnings gaps among men (2021)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---------------------|---------|---------|---------|---------|---------|---------|----------------|
| <i>Asian</i> | 0.147 | -0.007 | -0.001 | -0.027 | -0.009 | -0.039 | -0.017 |
| | (0.023) | (0.020) | (0.020) | (0.019) | (0.018) | (0.019) | (0.017) |
| <i>Black</i> | -0.295 | -0.213 | -0.199 | -0.16 | -0.101 | -0.097 | -0.098 |
| | (0.020) | (0.019) | (0.018) | (0.018) | (0.017) | (0.017) | (0.016) |
| <i>Hispanic</i> | -0.32 | -0.095 | -0.069 | -0.06 | -0.016 | -0.034 | -0.043 |
| | (0.015) | (0.015) | (0.014) | (0.014) | (0.014) | (0.015) | (0.014) |
| <i>Education</i> | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| <i>Experience</i> | | | ✓ | ✓ | ✓ | ✓ | ✓ |
| <i>Industry</i> | | | | ✓ | ✓ | ✓ | ✓ |
| <i>Occupation</i> | | | | | ✓ | ✓ | ✓ |
| <i>State</i> | | | | | | ✓ | ✓ |
| <i>Hours worked</i> | | | | | | | ✓ |

Notes: Outcome variable = log(weekly earnings). Standard errors in parentheses. Reference category = White men.



Racial earnings gaps among men (2010-2021)



Notes: Outcome variable = log(weekly earnings). Vertical bars outline 95% confidence intervals. Reference category = White men.



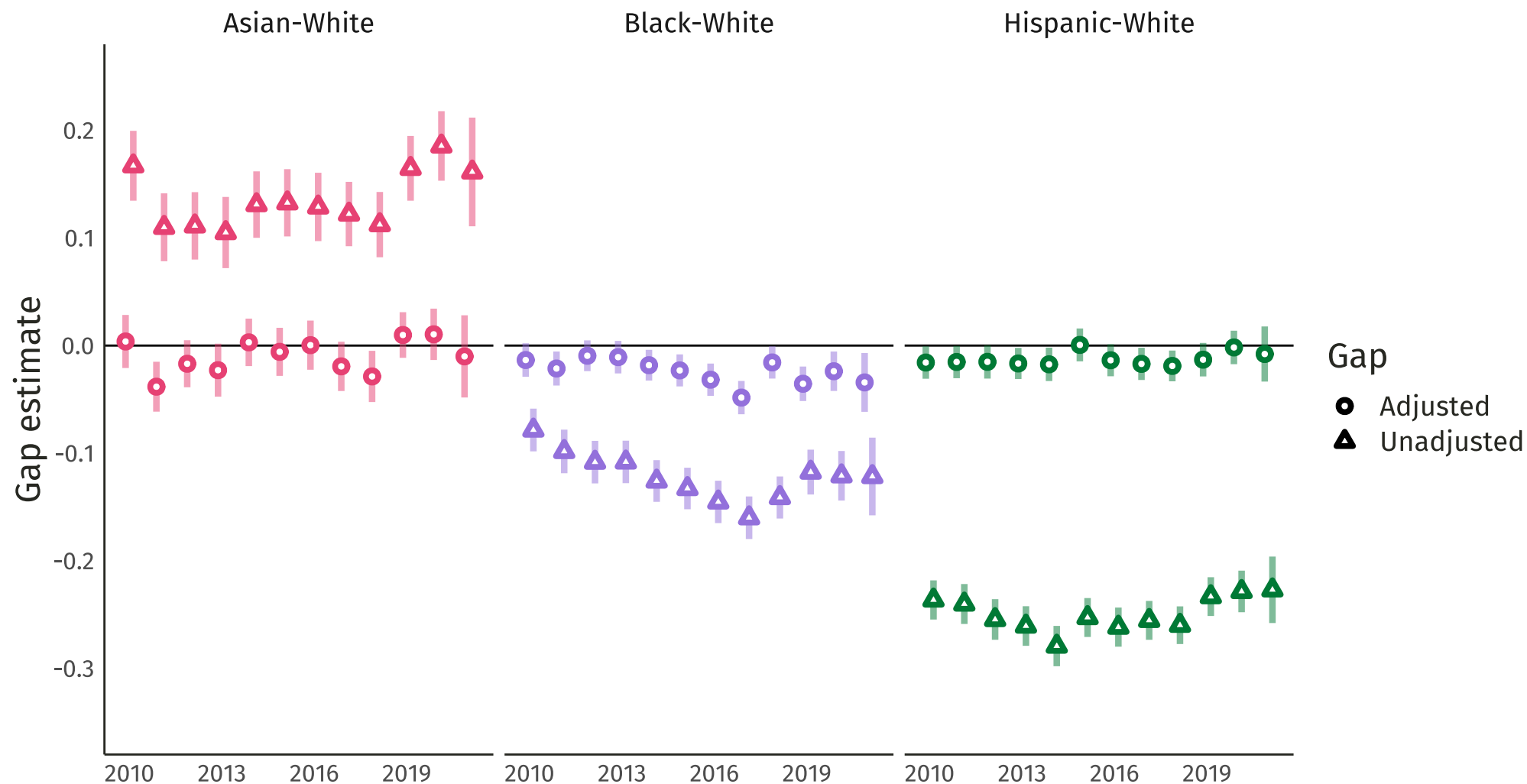
Racial earnings gaps among women (2021)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---------------------|---------|---------|---------|---------|---------|---------|----------------|
| <i>Asian</i> | 0.161 | 0.06 | 0.057 | 0.021 | 0.034 | -0.025 | -0.01 |
| | (0.026) | (0.022) | (0.022) | (0.021) | (0.021) | (0.022) | (0.019) |
| <i>Black</i> | -0.122 | -0.035 | -0.028 | -0.044 | -0.008 | -0.014 | -0.034 |
| | (0.018) | (0.016) | (0.016) | (0.015) | (0.015) | (0.016) | (0.014) |
| <i>Hispanic</i> | -0.227 | 0.005 | 0.021 | 0.034 | 0.071 | 0.028 | -0.008 |
| | (0.016) | (0.015) | (0.015) | (0.014) | (0.013) | (0.015) | (0.013) |
| <i>Education</i> | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| <i>Experience</i> | | | ✓ | ✓ | ✓ | ✓ | ✓ |
| <i>Industry</i> | | | | ✓ | ✓ | ✓ | ✓ |
| <i>Occupation</i> | | | | | ✓ | ✓ | ✓ |
| <i>State</i> | | | | | | ✓ | ✓ |
| <i>Hours worked</i> | | | | | | | ✓ |

Notes: Outcome variable = log(weekly earnings). Standard errors in parentheses. Reference category = White women.



Racial earnings gaps among women (2010-2021)



Notes: Outcome variable = log(weekly earnings). Vertical bars outline 95% confidence intervals. Reference category = White women.



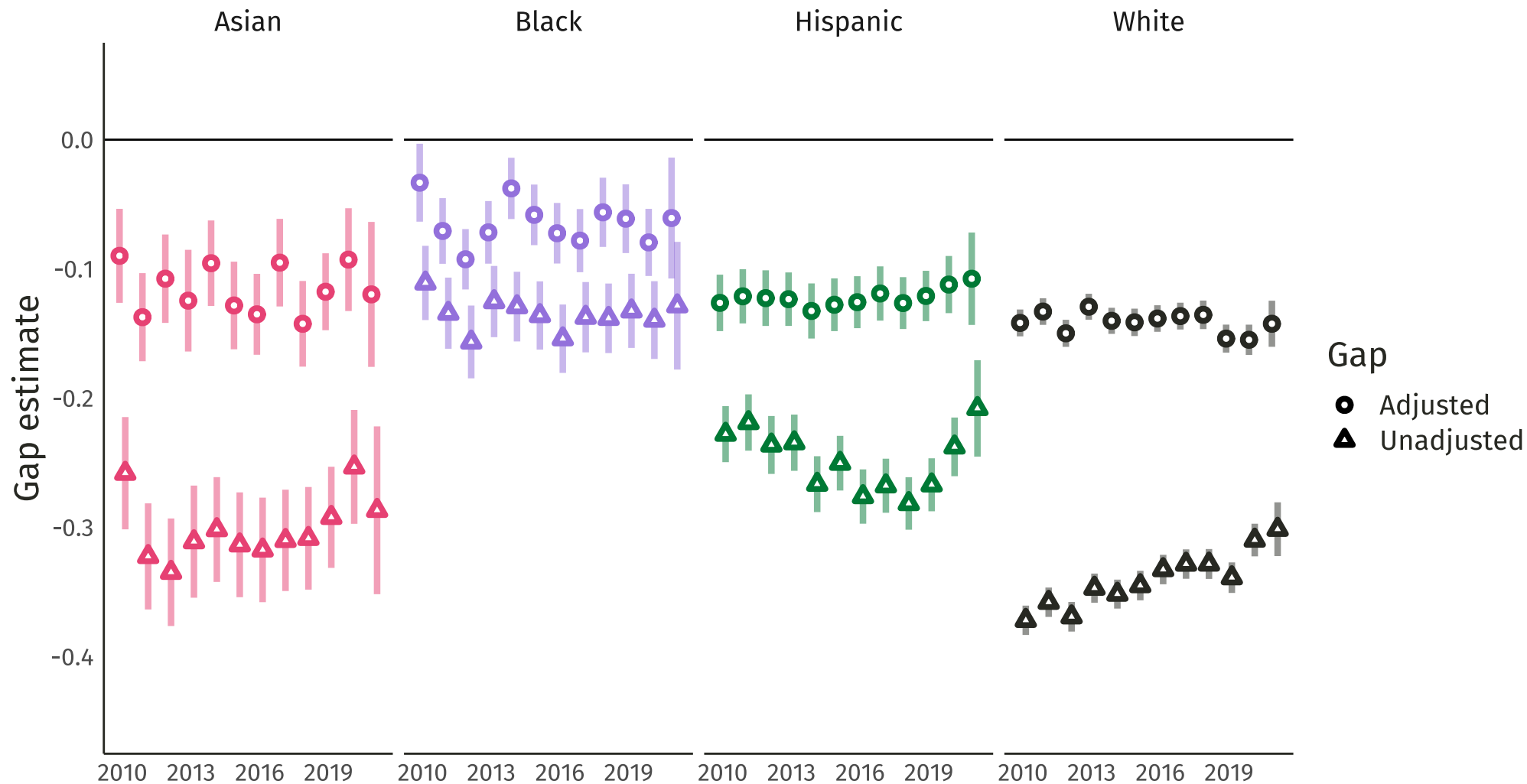
Gender earnings gap among Whites (2021)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---------------------|---------|---------|---------|---------|---------|---------|----------------|
| <i>Female</i> | -0.301 | -0.348 | -0.348 | -0.244 | -0.197 | -0.195 | -0.142 |
| | (0.011) | (0.009) | (0.009) | (0.010) | (0.010) | (0.010) | (0.009) |
| <i>Education</i> | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| <i>Experience</i> | | | ✓ | ✓ | ✓ | ✓ | ✓ |
| <i>Industry</i> | | | | ✓ | ✓ | ✓ | ✓ |
| <i>Occupation</i> | | | | | ✓ | ✓ | ✓ |
| <i>State</i> | | | | | | ✓ | ✓ |
| <i>Hours worked</i> | | | | | | | ✓ |

Notes: Outcome variable = log(weekly earnings). Standard errors in parentheses. Reference category = White men.



Gender earnings gaps by race (2010-2021)



Notes: Outcome variable = log(weekly earnings). Vertical bars outline 95% confidence intervals. Reference category = Men.



Discussion

Q: Do the adjusted gaps provide causal evidence of gender or race discrimination? Why or why not?

- Do the adjusted gaps control for enough factors to make an *all-else-equal* claim?
- Do the adjusted gaps adjust for too much?

Collider bias

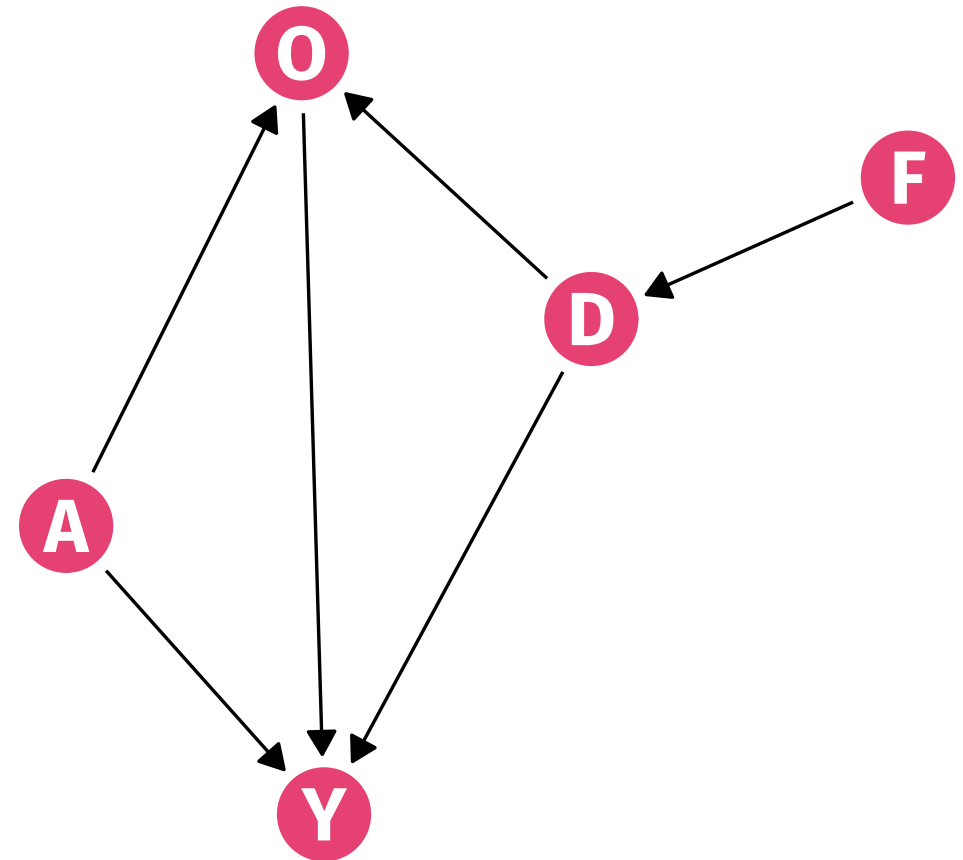
Example: Gender discrimination

Variables

- **F** = Gender
- **D** = Discrimination
- **Y** = Earnings
- **O** = Occupation
- **U** = Unobserved ability

Causal paths

- **D** \longrightarrow **Y** (path of interest)
- **D** \longrightarrow **O** \longrightarrow **Y** (mediated path)
- **D** \longrightarrow **O** \longleftarrow **A** \longrightarrow **Y**

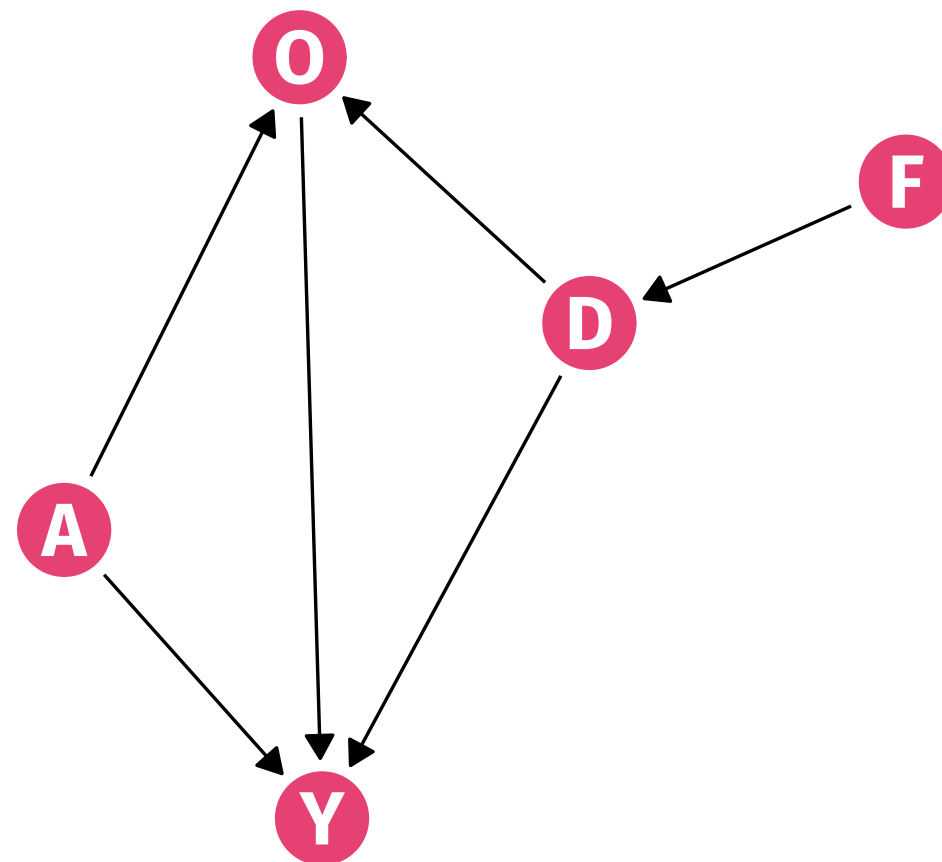


Collider bias

Example: Gender discrimination

Simulation

```
simulated_data <- tibble(  
  female = ifelse(runif(10000) ≥ 0.5, 1, 0),  
  ability = rnorm(10000),  
  discrimination = female,  
  occupation = 1 + 2 * ability + 0 * female - 2 * d,  
  wage = 1 - 1 * discrimination + 1 * occupation + .  
)  
  
lm_1 <- lm(wage ~ female,  
           data = simulated_data)  
  
lm_2 <- lm(wage ~ female + occupation,  
           data = simulated_data)  
  
lm_3 <- lm(wage ~ female + occupation + ability,  
           data = simulated_data)
```



Collider bias



Example: Gender discrimination

Simulation

```
simulated_data <- tibble(  
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           data = simulated_data)  
  
lm_2 <- lm(wage ~ female + occupation,  
           data = simulated_data)  
  
lm_3 <- lm(wage ~ female + occupation + ability,  
           data = simulated_data)
```

Results

| | (1) | (2) | (3) |
|-------------------|--------|--------|---------------|
| <i>Female</i> | -3.05 | 0.58 | -1.01 |
| | (0.09) | (0.03) | (0.03) |
| <i>Occupation</i> | | 1.8 | 1 |
| | | (0.01) | (0.01) |
| <i>Ability</i> | | | 2 |
| | | | (0.02) |
| <i>Intercept</i> | 1.95 | 0.2 | 1.01 |
| | (0.06) | (0.02) | (0.02) |

Notes: Outcome variable = wage. Standard errors in parentheses.
Reference category = Men.



Discussion

Q₁: How does the study measure discrimination in the labor market?

Q₂: What are the advantages of the research design?

Q₃: What are the weaknesses of the study?

Q₄: What are the main findings?

Q₅: What does the study tell us about employers?

Q₆: What did *you* find most interesting and/or depressing?

Housekeeping



Assigned reading for Wednesday: Ban the Box, Criminal Records, and Racial Discrimination: A Field Experiment by Amanda Agan and Sonja Starr (2017).

- Reading Quiz 10 is due by **Wednesday, May 26th at 16:00**.
- The quiz instructions will include a reading guide.

Reading Quiz 9 is also due by Wednesday, May 26th at 16:00.