Discrimination

EC 350: Labor Economics

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Winter 2022

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.

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

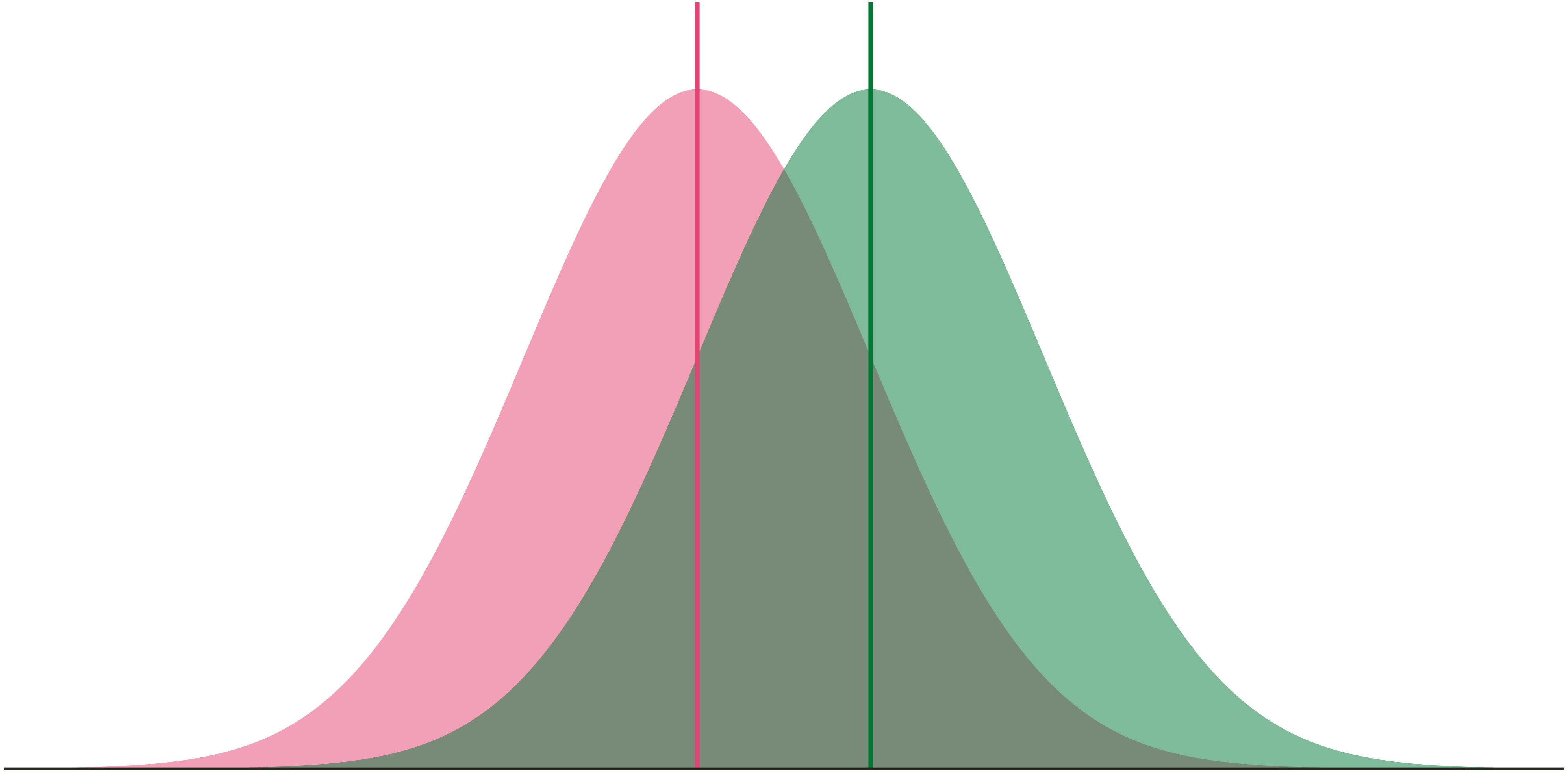
Why should we care?

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**?"



Wage 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 through April (23,556 survey respondents), then incorporate data going back to 2010 (999,313 survey respondents).

The outcome? Hourly wages.

Wage gaps

Approach

Run regressions of the form

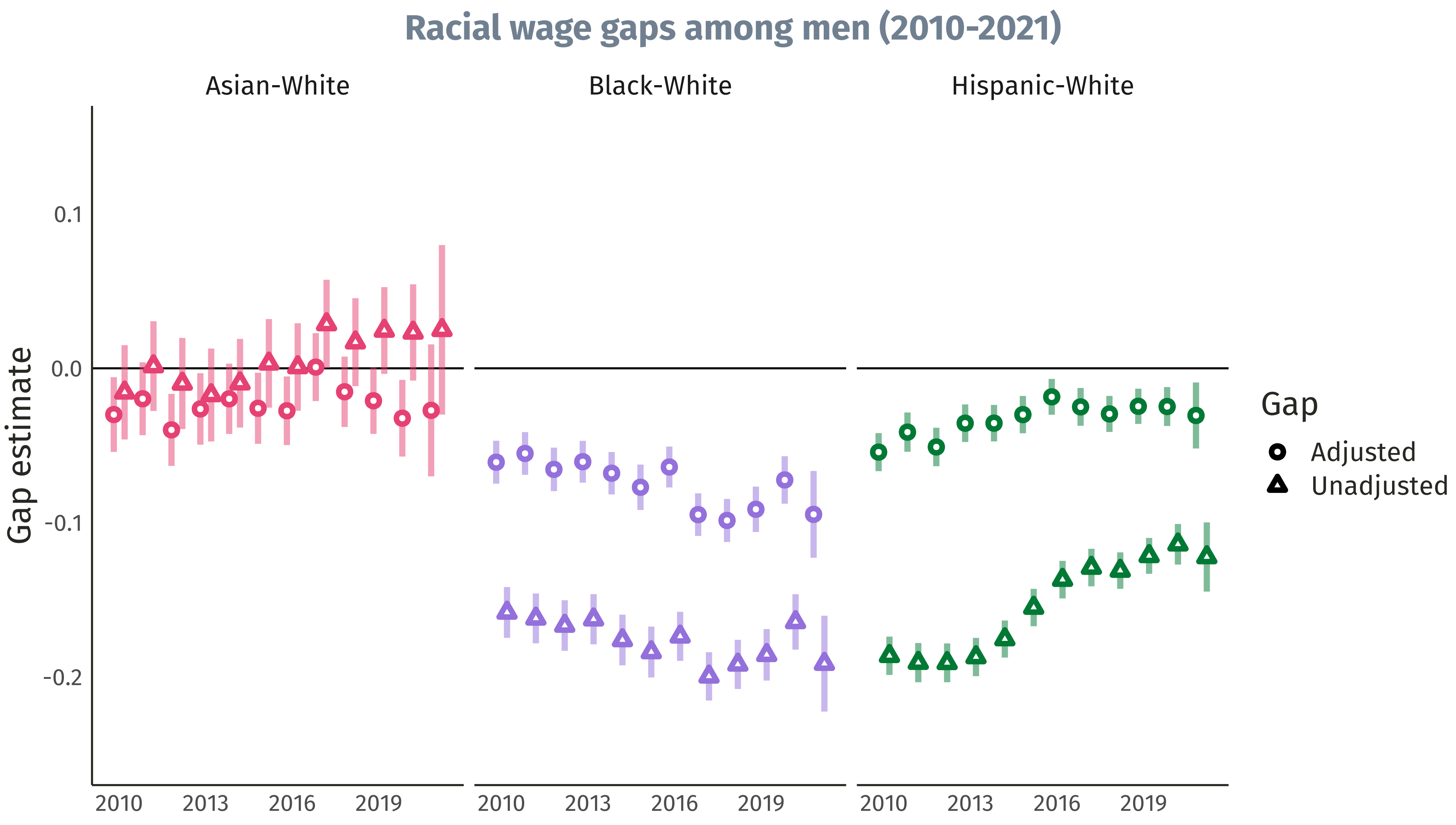
$$\log(\mathbf{Wage}_i) = \alpha + \beta\, \mathbf{Group}_i + X^{'}\Phi + \varepsilon_i$$

- $\mathbf{Group}_i$ is an indicator variable denoting race or gender.
- $\beta \times 100$ is the wage gap, interpreted as a percentage difference.
  - Relative to a "reference group."
- $X^{'}$ is a vector of control variables.

Racial wage gaps among men (2021)

	(1)	(2)	(3)	(4)	(5)	(6)
Asian	0.025	-0.022	-0.022	-0.002	0.004	**-0.027**
	(0.028)	(0.026)	(0.025)	(0.025)	(0.022)	**(0.022)**
Black	-0.191	-0.178	-0.175	-0.145	-0.115	**-0.095**
	(0.016)	(0.015)	(0.014)	(0.014)	(0.014)	**(0.016)**
Hispanic	-0.122	-0.051	-0.034	-0.032	-0.017	**-0.011**
	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	**(0.015)**
Education		✓	✓	✓	✓	✓
Experience			✓	✓	✓	✓
Industry				✓	✓	✓
Occupation					✓	✓
State						✓

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



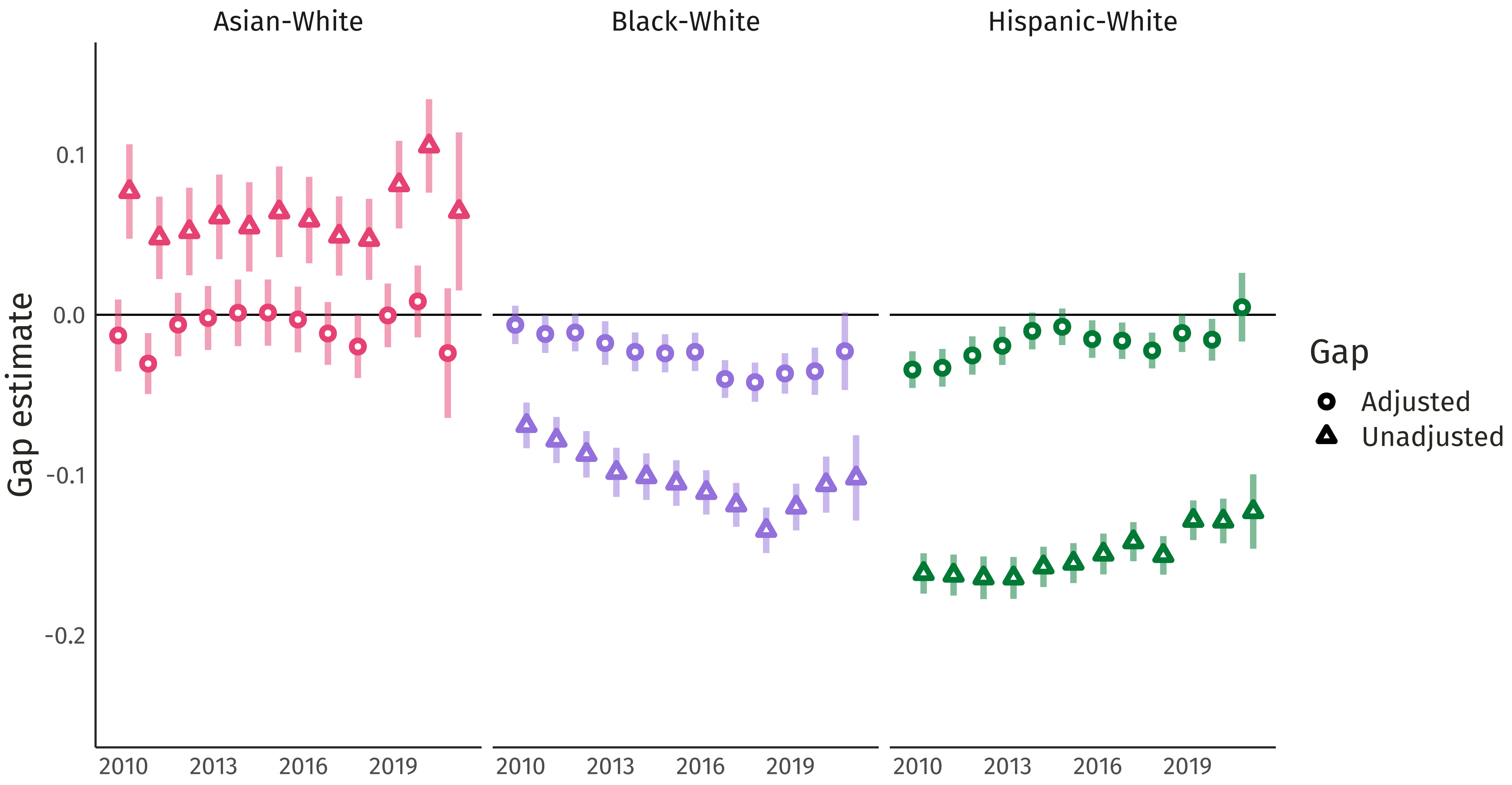
Notes: Outcome variable = log(hourly wage). Vertical bars outline 95% confidence intervals. Reference category = White men.

Racial wage gaps among women (2021)

	(1)	(2)	(3)	(4)	(5)	(6)
Asian	0.065	0.019	0.011	0.019	0.039	**-0.024**
	(0.025)	(0.022)	(0.022)	(0.021)	(0.020)	**(0.021)**
Black	-0.102	-0.063	-0.057	-0.069	-0.04	**-0.023**
	(0.014)	(0.012)	(0.012)	(0.012)	(0.012)	**(0.012)**
Hispanic	-0.123	-0.013	0.004	0.013	0.034	**0.005**
	(0.012)	(0.011)	(0.011)	(0.011)	(0.010)	**(0.011)**
Education		✓	✓	✓	✓	✓
Experience			✓	✓	✓	✓
Industry				✓	✓	✓
Occupation					✓	✓
State						✓

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

Racial wage gaps among women (2010-2021)



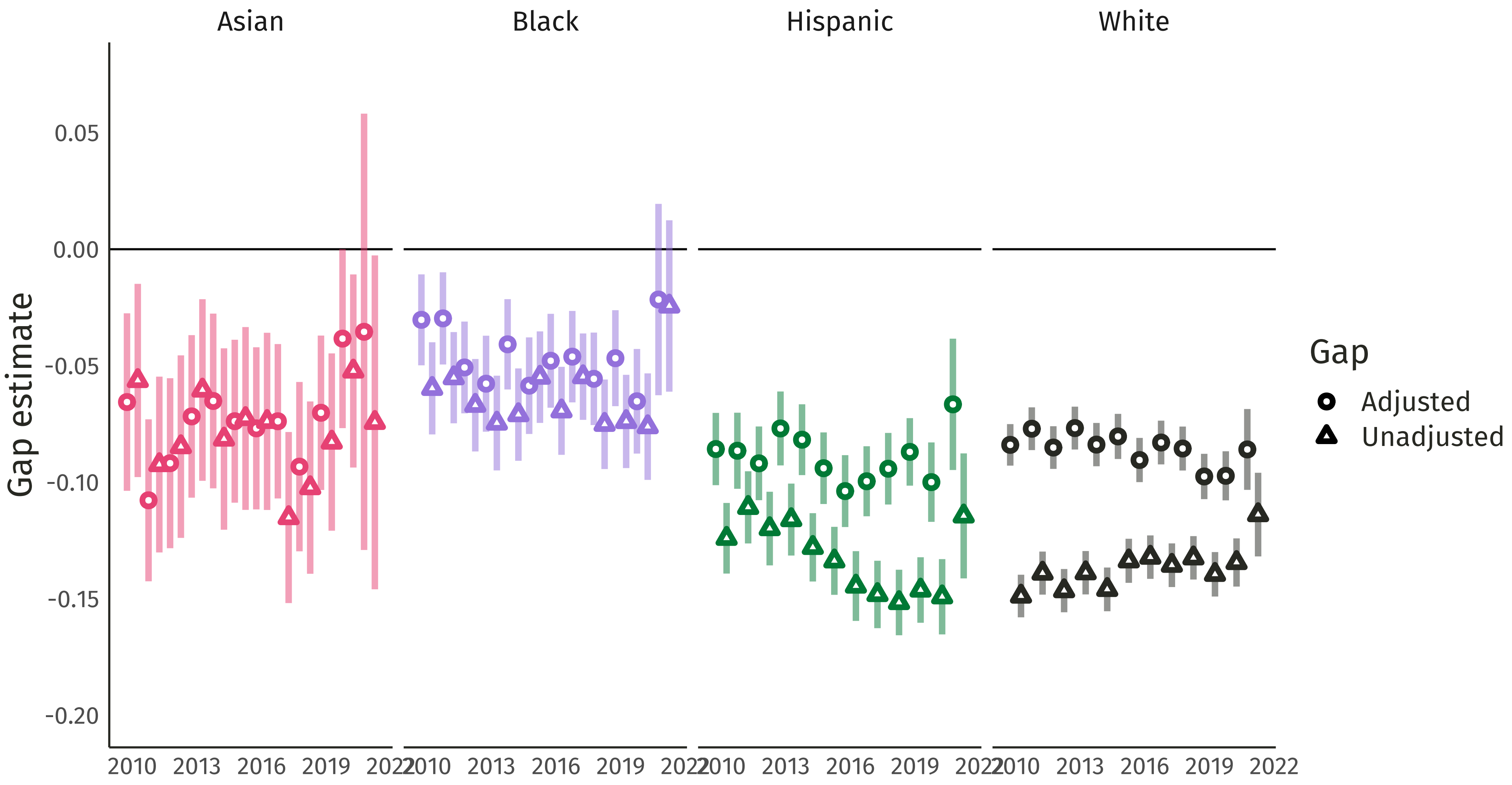
Notes: Outcome variable = log(hourly wage). Vertical bars outline 95% confidence intervals. Reference category = White women.

Gender wage gap among Whites (2021)

	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.114	-0.159	-0.167	-0.121	-0.09	**-0.086**
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	**(0.009)**
Education		✓	✓	✓	✓	✓
Experience			✓	✓	✓	✓
Industry				✓	✓	✓
Occupation					✓	✓
State						✓

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

Gender wage gaps by race (2010-2021)



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

Wage gaps

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

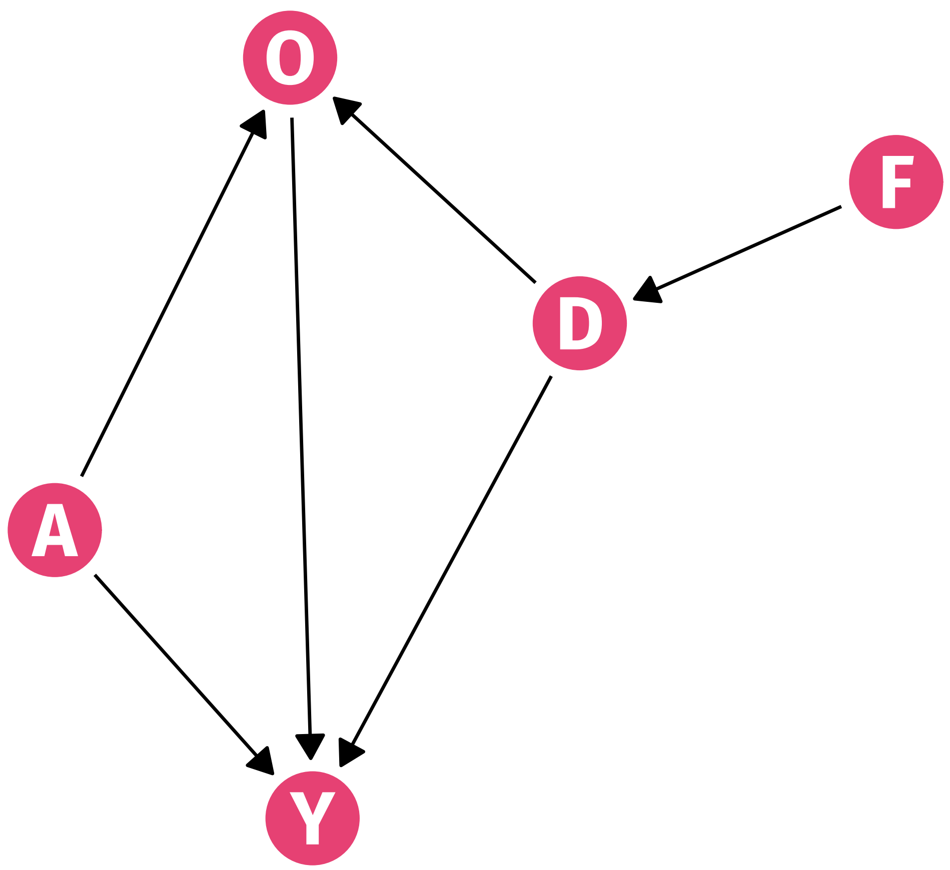
Example: Gender discrimination

Variables

- **F** = Gender
- **D** = Discrimination
- **Y** = Wages
- **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

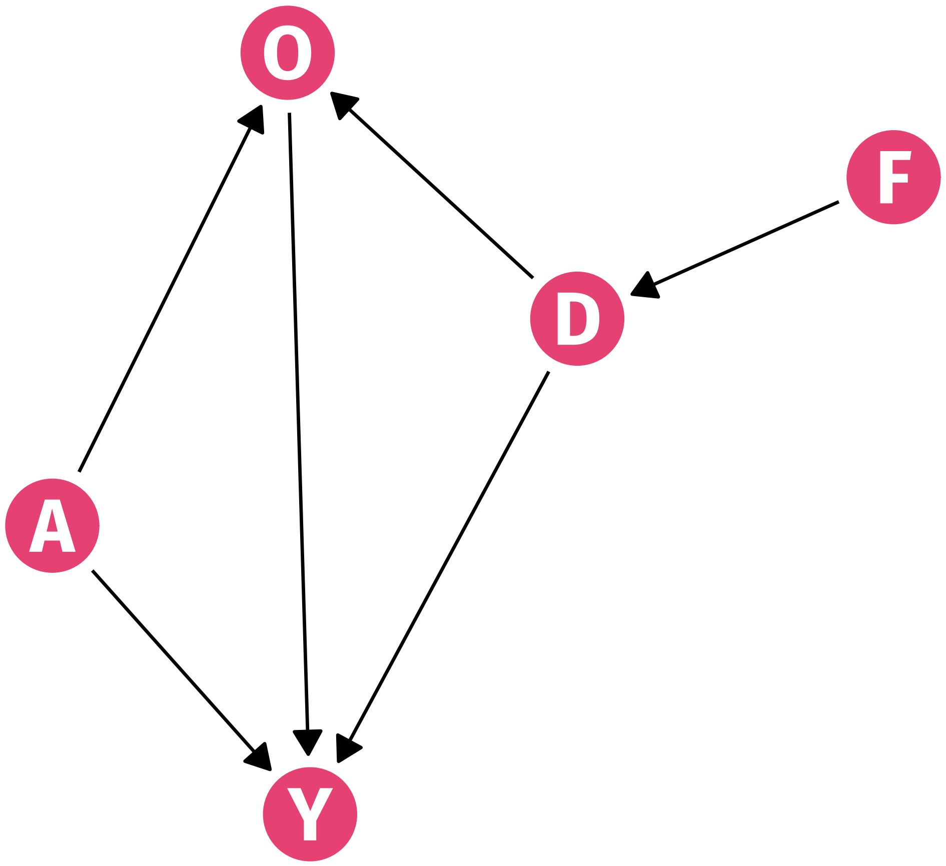
Simulation

```
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

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           data = simulated_data)

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

Results

	(1)	(2)	(3)
Female	-3.05	0.58	**-1.01**
	(0.09)	(0.03)	**(0.03)**
Occupation		1.8	**1**
		(0.01)	**(0.01)**
Ability			**2**
			(0.02)
Intercept	1.95	0.2	**1.01**
	(0.06)	(0.02)	**(0.02)**

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

Bertrand and Mullainathan (2004)

Discussion

Q_1: How does the study measure discrimination in the labor market?

Q_2: What are the advantages of the research design?

Q_3: What are the weaknesses of the study?

Q_4: What are the main findings?

Q_5: What does the study tell us about employers?

Q_6: 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 **Monday, March 7th at 12pm (noon)**.
- The quiz instructions will include a reading guide.