# ECON 251 Discussion

## Instrumental Variables (IV) & Difference-in-Differences (DD)

Elird Haxhiu

Fall 2022


Jack Meyer
@Jackbmeyer
"Just one more episode"
NETFLIX
"Just one more page"
"Just one more control"
$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \varepsilon$
8:50 AM · Nov 6, 2022 · Twitter for iPhone
33 Retweets 6 Quote Tweets 514 Likes

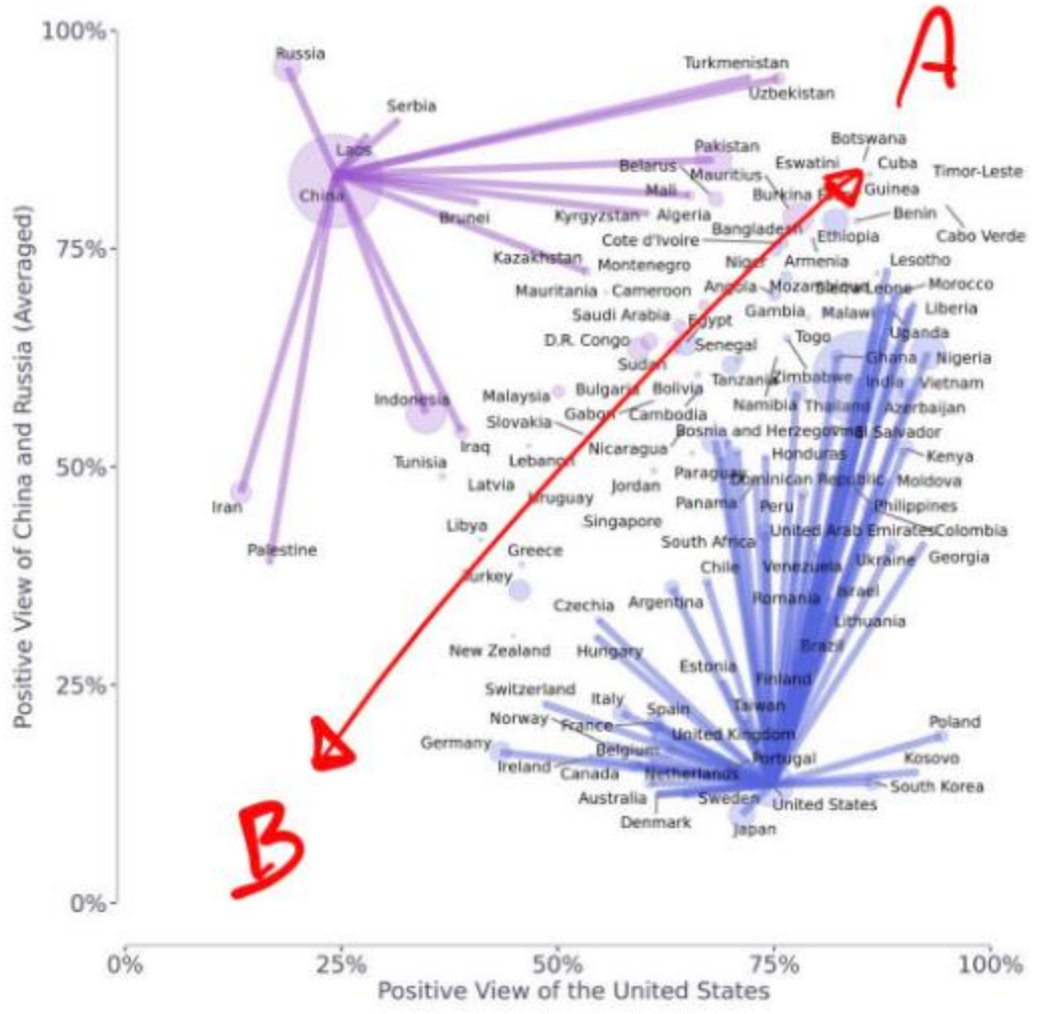
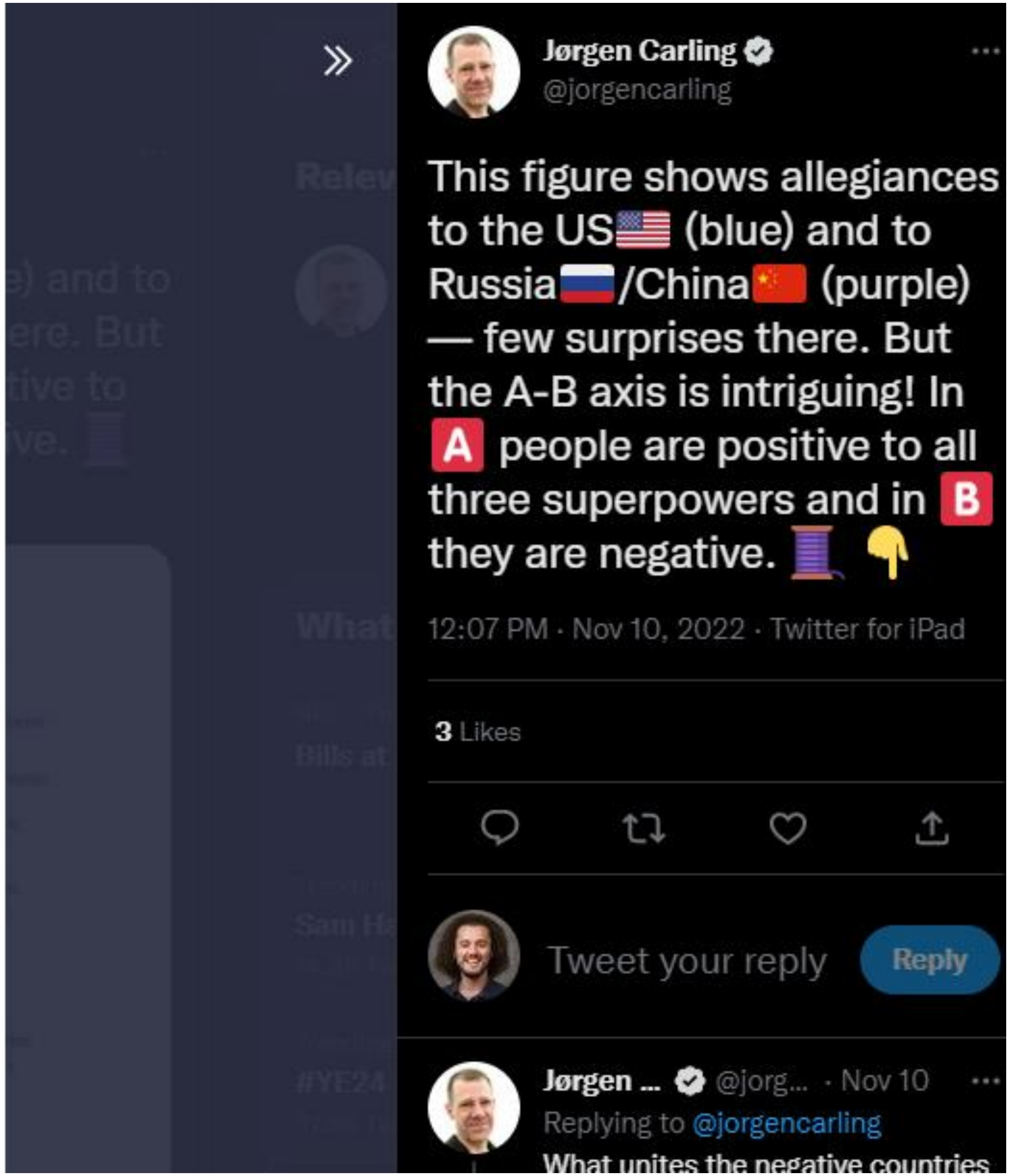



**Figure 5:** *The structure of global allegiances in 2022. Countries with a more than 15 percentage-point lead towards either i) Russia/China or ii) the United States, are indicated by connecting lines. By comparison, the United States enjoys a much larger number of ties to societies that favour America over authoritarian revisionist powers, though, this may in part be due to suppressed favourability towards Russia in the wake of the Ukraine invasion.*



# Announcements

1. HW3 grades coming soon!

2. New office hours/weekly review: Thursdays @ 6 – 8pm, Angell Hall…
   - Why should you attend?
   - More details at the end of discussion

3. Course feedback via teaching evaluations

**Pamela Jakiela**
@PJakiela

Good morning #EconTwitter ! Can you please share links to your favorite papers on student evaluations of teaching (on bias, what they measure, etc)?

Thank you!

6:39 AM · Sep 28, 2021 · Twitter for iPhone

**19** Retweets **49** Likes

Pamela Jakiela
@PJakiela

Good morning #EconTwitter ! Can you please share links to your favorite papers on student evaluations of teaching (on bias, what they measure, etc)?

Thank

6:39 AM

19 Retwe

# GENDER BIAS IN TEACHING EVALUATIONS

**Friederike Mengel**
University of Essex and Lund University

**Jan Sauermann**
Swedish Institute for Social Research (SOFI), Stockholm University

**Ulf Zölitz**
University of Zurich

**Abstract**
This paper provides new evidence on gender bias in teaching evaluations. We exploit a quasi-experimental dataset of 19,952 student evaluations of university faculty in a context where students are randomly allocated to female or male instructors. Despite the fact that neither students' grades nor self-study hours are affected by the instructor's gender, we find that women receive systematically lower teaching evaluations than their male colleagues. This bias is driven by male students' evaluations, is larger for mathematical courses, and particularly pronounced for junior women. The gender bias in teaching evaluations we document may have direct as well as indirect effects on the career progression of women by affecting junior women's confidence and through the reallocation of instructor resources away from research and toward teaching. (JEL: J16, J71, I23, J45)

Pamela Jakiela
@PJakiela

Good morning #EconTwitte
links to your favorite papers
teaching (on bias, what the

Thank

6:39 AM

19 Retwe

# GENDER BIAS IN T


**Friederike Mengel**
University of Essex and Lund Uni

**Ulf Zölitz**
University of Zurich



**Abstract**

This paper provides new evidence on gender bias in teaching evaluations. We exploit a quasi-experimental dataset of 19,952 student evaluations of university faculty in a context where students are randomly allocated to female or male instructors. Despite the fact that neither students' grades nor self-study hours are affected by the instructor's gender, we find that women receive systematically lower teaching evaluations than their male colleagues. This bias is driven by male students' evaluations, is larger for mathematical courses, and particularly pronounced for junior women. The gender bias in teaching evaluations we document may have direct as well as indirect effects on the career progression of women by affecting junior women's confidence and through the reallocation of instructor resources away from research and toward teaching. (JEL: J16, J71, I23, J45)


# Race and gender biases in student evaluations of teachers ☆


Carolyn Chisadza, Nicky Nicholls *, Eleni Yitbarek

*University of Pretoria, Department of Economics, South Africa*


HIGHLIGHTS

- We use an RCT to investigate race and gender bias in student evaluations of teachers.
- We note biases in favor of female lecturers and against black lecturers.
- Of particular concern, black students show bias against black lecturers.

ARTICLE INFO


*Article history:*
Received 5 May 2018
Received in revised form 4 March 2019
Accepted 20 March 2019
Available online 29 March 2019

*JEL classification:*
I23
J15
J16



ABSTRACT

Student ratings of teaching (SETs) are vital for academic career trajectories of higher education lecturers. Although student bias against female lecturers is noted in previous studies, mostly in the developed world, the extent to which race affects such ratings has received limited attention. To better understand the role of race and gender bias in SETs, we conduct an experiment in South Africa, where racial bias is highly prevalent. Students are randomly assigned to follow video lectures with identical narrated slides and script but given by lecturers of different race and gender. We find that black lecturers receive lower ratings than white lecturers, particularly from black students.

Pamela Jakiela
@PJakiela

Good morning #EconTwitte
links to your favorite papers
teaching (on bias, what the

Thank

6:39 AM

19 Retwe

# GENDER BIAS IN T


**Friederike Mengel**
University of Essex and Lund Uni

**Ulf Zölitz**
University of Zurich



**Abstract**
This paper provides new evidence on gender bias in teaching eva experimental dataset of 19,952 student evaluations of university faculty randomly allocated to female or male instructors. Despite the fact that ne study hours are affected by the instructor's gender, we find that wome teaching evaluations than their male colleagues. This bias is driven by larger for mathematical courses, and particularly pronounced for juni teaching evaluations we document may have direct as well as indirect ef of women by affecting junior women's confidence and through the reall away from research and toward teaching. (JEL: J16, J71, I23, J45)


# Race and gender biases in student evaluations of teachers☆


Carolyn Chisadza, Nicky Nicholls*, Eleni Yitbarek
*University of Pretoria, Department of Economics, South Africa*


Check for updates

H I G H L I G H T S

- We use an RCT to investigate race and gender bias in student evaluations of teachers.
- We note biases in favor of female lecturers and against black lecturers.
- Of particular concern, black students show bias against black lecturers.

A R T I C L E  I N F O


*Article history:*
Received 5 May 2018
Received in revised form 4 Ma
Accepted 20 March 2019
Available online 29 March 20

*JEL classification:*
I23
J15
J16




# An evaluation of course evaluations


Student ratings of teaching have been used, studied, and debated for almost a century. This article examines student ratings of teaching from a statistical perspective. The common practice of relying on averages of student teaching evaluation scores as the primary measure of teaching effectiveness for promotion and tenure decisions should be abandoned for substantive and statistical reasons: There is strong evidence that student responses to questions of "effectiveness" do not measure teaching effectiveness. Response rates and response variability matter. And comparing averages of categorical responses, even if the categories are represented by numbers, makes little sense. Student ratings of teaching are valuable when they ask the right questions, report response rates and score distributions, and are balanced by a variety of other sources and methods to evaluate teaching.



Keywords: student course evaluations, teaching evaluations, teaching effectiveness, statistics

**Pamela Jakiela**
@PJakiela

Good morning #EconTwitte
links to your favorite papers
teaching (on bias, what the

Thank

6:39 AM

**GENDER BIAS IN T**

# Race and gender biases in student evaluations of teachers☆

Carolyn Chisadza, Nicky Nicholls *, Eleni Yitbarek

*University of Pretoria, Department of Economics, South Africa*

Check for updates

H I G H L I G H T S

- We use an RCT to investigate race and gender bias in student evaluations of teachers.
- We note biases in favor of female lecturers and against black lecturers.
- Of particular concern, black students show bias against black lecturers.

A R T I C L E I N F O

*P.B. Stark and R. Freishtat* *An Evaluation of Course Evaluations*

**n of course evaluations**

atings of teaching have been used, studied, and debated for almost a
This article examines student ratings of teaching from a statistical
ve. The common practice of relying on averages of student teaching
n scores as the primary measure of teaching effectiveness for promotion
e decisions should be abandoned for substantive and statistical reasons:
trong evidence that student responses to questions of "effectiveness" do
re teaching effectiveness. Response rates and response variability
nd comparing averages of categorical responses, even if the categories
ented by numbers, makes little sense. Student ratings of teaching are
when they ask the right questions, report response rates and score
ns, and are balanced by a variety of other sources and methods to
eaching.

s: student course evaluations, teaching evaluations, teaching
ess, statistics

Followed by some Tweeters you follow

**Alice Evans** @_alice_evans · Sep 28, 2021
Replying to @PJakiela

As far as I am aware, the consensus is that student evaluations don't tightly track learning outcomes, but student satisfaction, and there is bias in favour of white men.

But idk what the 'best' response is, since students may be less biased than peer evaluators.

1 2

**Alice Evans** @_alice_evans · Sep 28, 2021
Replying to @_alice_evans and @PJakiela

And the underlying problem persists: students are graduating with strong gender bias.

2

# Outline

1. Review some key concepts
    - OLS assumptions and main results
    - Omitted variable bias (OVB) formula

2. Review instrumental variables (IV)
    - Examples of instruments + method of moments (MM) estimator consistency proof
    - In practice: when doing IV is worse than just doing OLS

3. Special Panel Data method: Differences-in-differences (DD)
    - Basic intuition and assumptions

# Usual Assumptions

- MLR1 (linear outcome model) $Y_i = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_k X_{ik} + U_i$
- MLR2 (random sampling) $\{Y_i, X_{i1}, \ldots, X_{ik}\}_{i=1}^N$ is random draw
- MLR3 (no collinearity) no $X_{ij}$ linear function of any other $X_{il}$

- MLR4 (independence) $E[U_i | X_{i1}, \ldots, X_{ik}] = 0$

- MLR5 (homoskedasticity) $\mathrm{Var}(U_i | X_{i1}, \ldots, X_{ik}) = \sigma^2$
- MLR6 (normality) $U_i \sim N(0, \sigma^2)$

$$\Rightarrow Y_i \sim N(\beta_0 + \beta_1 X_{i1} + \cdots + \beta_k X_{ik}, \sigma^2)$$

# Ordinary Least Squares (OLS) Estimator + Results

$$Y_i = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_k X_{ik} + U_i$$

$$\min_{\{\beta_0,\beta_1,\ldots,\beta_k\}} \frac{1}{N}\sum_{i=1}^{N}(Y_i - \beta_0 - \beta_1 X_{i1} - \cdots - \beta_k X_{ik})^2 \qquad \Rightarrow \qquad \hat{\beta}_j^{OLS}$$

- T1 (unbiased) MLR1+2+3+4 $\Rightarrow$ $E\left[\widehat{\beta}_j^{\,OLS}\right] = \beta_j \qquad \forall j = \{0,1,\ldots,k\}$
- T2 (efficient) MLR1+2+3+4+5 $\Rightarrow$ $E\left[\widehat{\beta}_j^{\,OLS}\right] = \beta_j \qquad \forall j = \{0,1,\ldots,k\}$

  (Gauss-Markov) $\mathrm{Var}\left[\widehat{\beta}_j^{\,OLS}\right] \leq \mathrm{Var}\left[\widehat{\beta}_j^{\,\text{other linear}}\right]$

# Ordinary Least Squares (OLS) Estimator + Results

$$Y_i = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_k X_{ik} + U_i$$

$$\min_{\{\beta_0,\beta_1,\ldots,\beta_k\}} \frac{1}{N} \sum_{i=1}^{N} (Y_i - \beta_0 - \beta_1 X_{i1} - \cdots - \beta_k X_{ik})^2 \qquad \Rightarrow \qquad \hat{\beta}_j^{OLS}$$

- T3 (efficient) MLR1+2+3+4+5+6 $\Rightarrow$ $\quad \widehat{\beta_j}^{OLS} \sim N\left(\beta_j, \mathrm{Var}\left[\beta_j\right]\right) \quad \forall j = \{0,1,\ldots,k\}$

  (Classical)

$$\frac{\widehat{\beta_j}^{OLS} - \beta_j}{\mathrm{sd}[\beta_j]} \sim N(0,1) \qquad \frac{\widehat{\beta_j}^{OLS} - \beta_j}{\mathrm{se}[\beta_j]} \sim t(N-k-1)$$

# Omitted variable bias (OVB)

"True" model $\log Y_i = \alpha + \beta \cdot S_i + \delta^{X \to Y} \cdot X_i + U_i$ $\quad \mathrm{Cov}(S_i, U_i) = 0$

Our model $\log Y_i = a + b \cdot S_i + E_i$

Auxiliary model $X_i = c + \gamma^{S \to X} \cdot S_i + \eta_i$

In week 5 we proved that naively assuming $\mathrm{Cov}(S_i, E_i) = 0$ in our model implies

$$b = \frac{\mathrm{Cov}(S_i, \log Y_i)}{\mathrm{Var}(S_i)}$$

$$= \beta + \gamma^{S \to X} \cdot \delta^{X \to Y}$$

= causal effect + (var in $S$ related to $X$) $\cdot$ (var in $X$ related to $Y$)

# What if $\text{Cov}(S_i, U_i) = 0$ is also suspect?

1. Despair ⇒ intellectual nihilism, true reality hidden to little humans in the world

2. One answer ⇒ sensitivity analysis + new tools in Cinelli and Hazlett (2020)

3. Traditional approaches ⇒ find an instrumental variable $Z_i$ which generates some exogenous variation in the treatment $S_i$ but does not affect $\log Y_i$ directly (IV)

   find some exogenous policy which affects some units but not others once implemented (DD)

# Outline

1. Review some key concepts
    - OLS assumptions and main results
    - Omitted variable bias (OVB) formula

2. Review instrumental variables (IV)
    - Examples of instruments + method of moments (MM) estimator consistency proof
    - In practice: when doing IV is worse than just doing OLS

3. Special Panel Data method: Differences-in-differences (DD)
    - Basic intuition and assumptions

# Instrumental variable (IV) $Z_i$ decompose $S_i$ into $S_i^{\mathrm{X}}$ and $S_i^{\mathrm{N}}$

- A valid instrument satisfies
  1. Relevance $\quad \mathrm{Cov}(Z_i, S_i) \neq 0$
  2. Exogeneity $\quad \mathrm{Cov}(Z_i, U_i) = 0$
  3. Exclusion $\quad$ no direct effect of $Z_i$ on outcome $Y_i$
     $\Leftrightarrow$ instrument $Z_i$ does not appear in model of $Y_i$

- First stage generates predicted values for the treatment $\hat{S}_i \coloneqq \hat{\pi}_0 + \hat{\pi}_1 Z_i$
- Under IV exogeneity, this is equivalent to exogenous variation $S_i^{\mathrm{X}}$
- We can then estimate returns $\beta$ from model $\log Y_i = \alpha + \beta \cdot \hat{S}_i + U_i$

# Examples of instruments $Z_i$ for $S_i$

1. Distance to college when 16 years old
2. Month of birth interacted with compulsory school attendance laws
3. Natural disasters preventing some people from going to school
4. Number of siblings
5. Opportunities to emigrate (Haxhiu, 2022)

# Can we compare OLS and IV?

- The instrument you choose implicitly defines a “complier” group = the people moved to change the value of their treatment by the IV
- The estimator relies only on these people to construct an estimate of the $\beta$
- Different IVs often lead to different estimates of $\beta$ if the sub-populations they induce into changing their value of $S_i$ are somehow different

- Contrast with OLS, which relies on everyone to construct an estimate of $\beta$
- Therefore, we say OLS (= simple comparison) identifies the ATE
- The estimator under IV identifies a local average treatment effect (LATE)

# Derive MM estimator under IV assumptions

Start w/ IV exogeneity $\mathrm{Cov}(Z_i, U_i) = 0$ + substitute Mincer (1974) earnings model

$$\mathrm{Cov}(Z_i, \log Y_i - \alpha - \beta \cdot S_i) = 0$$
$$\mathrm{Cov}(Z_i, \log Y_i) - \mathrm{Cov}(Z_i, \alpha) - \beta \cdot \mathrm{Cov}(Z_i, S_i) = 0$$
$$\mathrm{Cov}(Z_i, \log Y_i) = \beta \cdot \mathrm{Cov}(Z_i, S_i)$$
$$\beta = \frac{\mathrm{Cov}(Z_i, \log Y_i)}{\mathrm{Cov}(Z_i, S_i)}$$

$$\Rightarrow \hat{\beta}^{MM} = \frac{\widehat{\mathrm{Cov}}(Z_i, \log Y_i)}{\widehat{\mathrm{Cov}}(Z_i, S_i)} := \frac{\sum_{i=1}^{N} \left(Z_i - \overline{Z}\right)\left(\log Y_i - \overline{\log Y}\right)}{\sum_{i=1}^{N} \left(Z_i - \overline{Z}\right)\left(S_i - \overline{S}\right)}$$

# <u>Consistency</u> of MM estimator under IV assumptions

- Start from definition of estimator, and compute the probability limit

$$\hat{\beta}^{MM} = \frac{\widehat{\mathrm{Cov}}(Z_i, \log Y_i)}{\widehat{\mathrm{Cov}}(Z_i, S_i)}$$

$$\operatorname*{plim}_{N\to\infty} \hat{\beta}^{MM} = \operatorname*{plim}_{N\to\infty} \frac{\widehat{\mathrm{Cov}}(Z_i, \log Y_i)}{\widehat{\mathrm{Cov}}(Z_i, S_i)} = \frac{\operatorname*{plim}_{N\to\infty} \widehat{\mathrm{Cov}}(Z_i, \log Y_i)}{\operatorname*{plim}_{N\to\infty} \widehat{\mathrm{Cov}}(Z_i, S_i)}$$

$$= \frac{\mathrm{Cov}(Z_i, \log Y_i)}{\mathrm{Cov}(Z_i, S_i)} = \frac{\mathrm{Cov}(Z_i, \alpha + \beta \cdot S_i + U_i)}{\mathrm{Cov}(Z_i, S_i)}$$

$$= \frac{\mathrm{Cov}(Z_i, \alpha) + \beta \cdot \mathrm{Cov}(Z_i, S_i) + \mathrm{Cov}(Z_i, U_i)}{\mathrm{Cov}(Z_i, S_i)} = \beta + \frac{\mathrm{Cov}(Z_i, U_i)}{\mathrm{Cov}(Z_i, S_i)}$$

# Doing IV can be worse than OLS

- The OVB formula for OLS implies that it converges to

$$\underset{N\to\infty}{\text{plim}}\, \hat{\beta}^{OLS} = \beta + \frac{\text{Cov}(S_i, U_i)}{\text{Var}(S_i)}$$

- We have just shown that the MM estimator converges to

$$\underset{N\to\infty}{\text{plim}}\, \hat{\beta}^{MM} = \beta + \frac{\text{Cov}(Z_i, U_i)}{\text{Cov}(Z_i, S_i)}$$

- What if $\text{Cov}(S_i, U_i) = 0$ or $\text{Cov}(Z_i, U_i) = 0$ are not exactly $= 0$?
- Not clear which is more likely to hold without more context, but...
- If $\text{Cov}(Z_i, S_i) \approx 0$ (weak instrument), then even minor violations of IV exogeneity lead to large asymptotic bias: aka inconsistency!

# Some other practical matters

- We can always write estimator $\hat{\beta}^{MM}$ under IV assumptions as the
    1. ratio of two OLS estimators (reduced form ÷ first stage)
    2. OLS coefficient in regression of outcome on "predicted" treatment

- We can include more than one instrument in the first stage predicting the endogenous variable, and then use any of the estimators above
- Generically called Two-Stage Least Squares (TSLS) estimator
- Potential costs, in addition to benefits, of having more IVs

# Outline

1. Review some key concepts
   - OLS assumptions and main results
   - Omitted variable bias (OVB) formula

2. Review instrumental variables (IV)
   - Examples of instruments + method of moments (MM) estimator consistency proof
   - In practice: when doing IV is worse than just doing OLS

3. Special Panel Data method: Differences-in-differences (DD)
   - Basic intuition and assumptions

# Pooled cross-section + Panel data

- New sample from the population of interest over time means we have a pooled cross-section dataset (when new units are sampled each period) and a panel dataset (when we track the same units)
- Two dimensions (units $i$ and time periods $t$) to consider our research question relating outcome $Y_{it}$ to treatment $X_{it}$

- Random Effects: OLS on $Y_{it} = \theta_t + \beta \cdot X_{it} + U_{it}$ with dummy variables for time periods (interacting with treatment to assess structural change)
- Fixed Effects: OLS on $Y_{it} = \alpha_i + \theta_t + \beta \cdot X_{it} + U_{it}$ with dummy variables for time periods and individual units (if we have a panel) or exogenously defined groups of units (if we have a pooled cross-section)

# Difference-in-differences = compare $Y$ change of units exposed to some policy $T$ with $Y$ change of unexposed

2 periods (before/after) and 2 groups (treated/control)

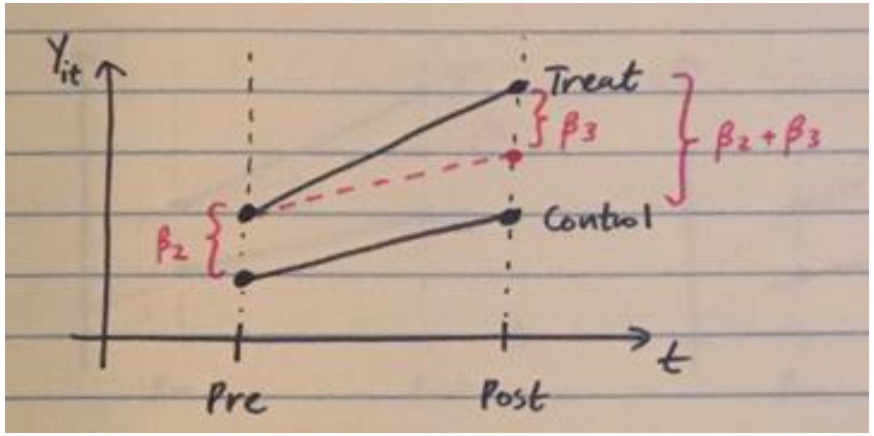
$Y_{it} \coloneqq$ outcome of interest

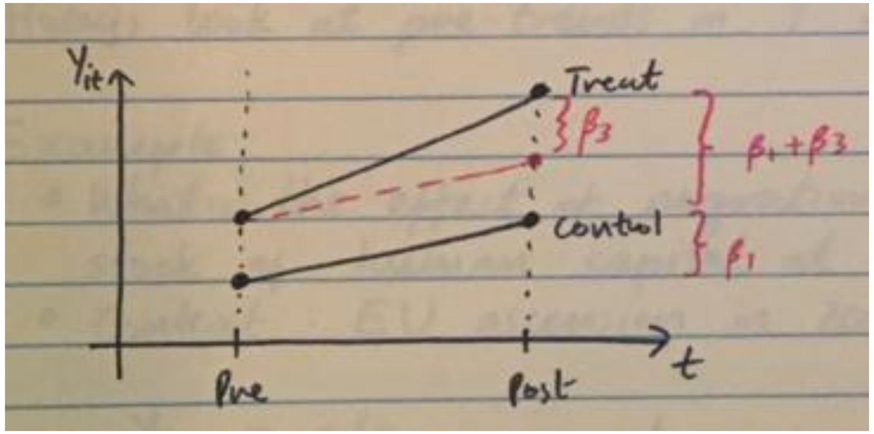
$P_t \coloneqq 1\{t \text{ is after treatment occurs}\}$

$T_i \coloneqq 1\{i \text{ is treated/exposed}\}$

$$Y_{it} = \beta_0 + \beta_1 P_t + \beta_2 T_i + \beta_3 [P_t \cdot T_i] + U_i$$

| | Before | After | After – Before |
|---|---|---|---|
| Control | $\beta_0$ | $\beta_0 + \beta_1$ | $\beta_1$ |
| Treated | $\beta_0 + \beta_2$ | $\beta_0 + \beta_1 + \beta_2 + \beta_3$ | $\beta_1 + \beta_3$ |
| Treat – Control | $\beta_2$ | $\beta_2 + \beta_3$ | $\beta_3$ |



# Parallel Trends Assumption = exposed units $Y$ without policy $T$ would have changed like unexposed units $Y$

- PTA is an untestable assumption, just like OLS exogeneity or IV exogeneity
- However, if we have access to more data before policy, we can assess how likely it is to hold in practice… commonly known as "checking for pre-trends"
- One reason why people seem to like DD… visual check of identifying assumption!