11 – PARALLEL WORLDS: DID

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SECTION 11
PARALLEL WORLDS: DIFFERENCE-IN-DIFFERENCES
THE PLAN

1. The difference-in-differences (DiD) estimator.
2. Checking for pre-trends.
3. A formal derivation of the DiD estimator.
4. A Mississipi experiment
5. Minimum Wages and Employment: The NJ-PA case study
6. Does economics make you selfish?

KEY IDEAS

- *Selection bias*: treated & controls not comparable.

$$E(Y_{0i}|D_i = 1) \neq E(Y_{0i}|D_i = 0)$$

- But suppose that potential outcomes move in synch over time:

$$E(\Delta Y_{0i}|D_i = 1) = E(\Delta Y_{0i}|D_i = 0)$$

- → we can compare observed *changes in outcomes* around treatment to estimate the average causal effect:

$$E(\Delta Y_i|\, D_i = 1) - E(\Delta Y_i|\, D_i = 0) = \mathrm{k}$$

10.1 THE DID ESTIMATOR

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THE DID ESTIMATOR

- 2 groups: treated (T) & control (C).
- 2 periods: post-treatment & pre-treatment.
- *Key idea*: compare pre-post changes (*differences*) in outcomes.
- Difference-in-differences (DiD) estimator:

$$\beta_{DD} = \left(\bar{Y}^T_{post} - \bar{Y}^T_{pre}\right) - \left(\bar{Y}^C_{post} - \bar{Y}^C_{pre}\right)$$

$$= \Delta\bar{Y}^T - \Delta\bar{Y}^C$$

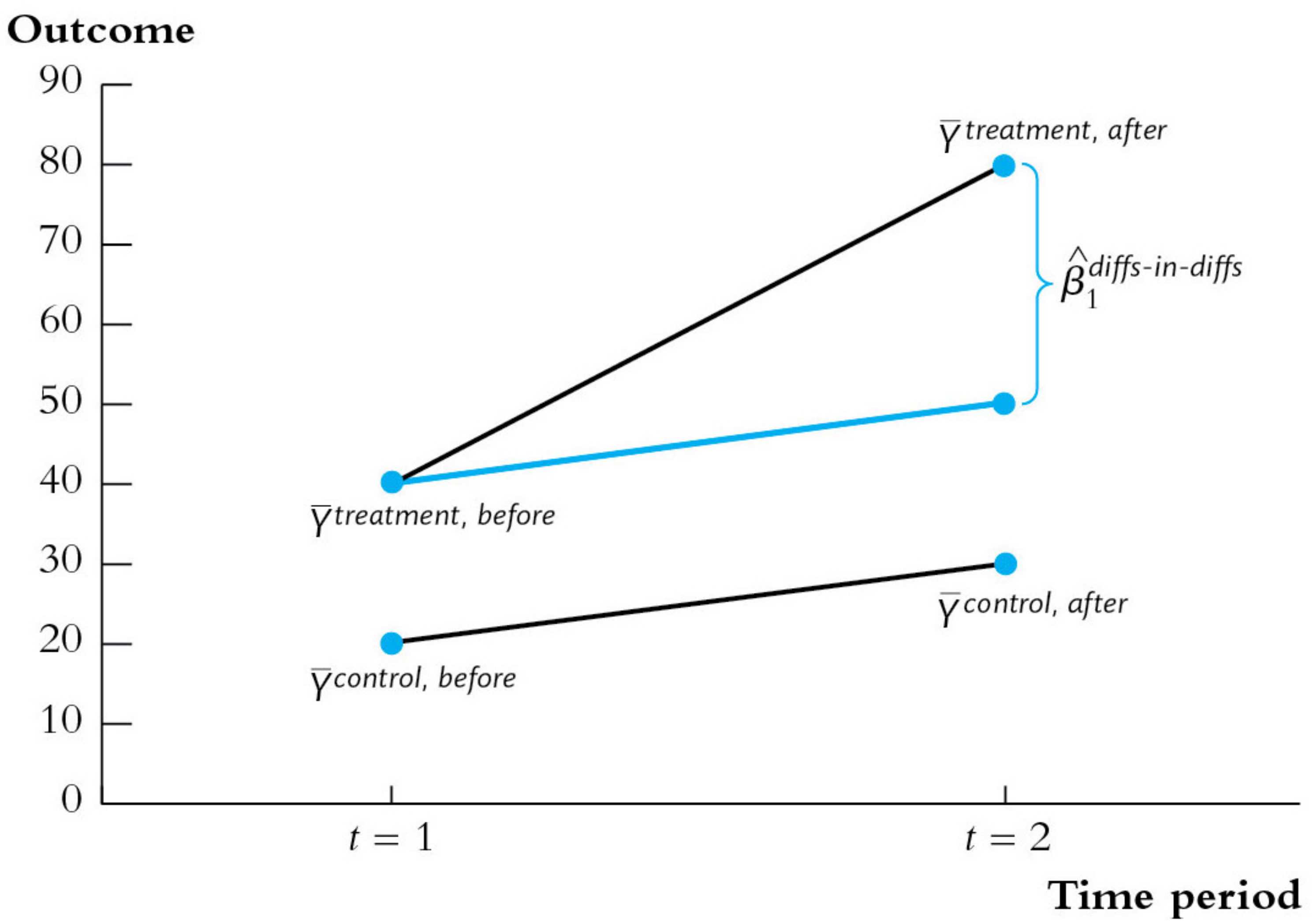
- But also: $\beta_{DD} = \left(\bar{Y}^T_{post} - \bar{Y}^C_{post}\right) - \left(\bar{Y}^T_{pre} - \bar{Y}^C_{pre}\right)$

HYPOTHETICAL EXAMPLE

	t=1 (pre)	t=2 (post)
Treated	10	20
Control	15	18

$$\beta_{DD} = (20 - 10) - (18 - 15)$$
$$= 10 - 3 = 7$$

THE DID ESTIMATOR



Key assumption:
common (or *parallel*) trends

DID REGRESSION

Three ways to obtain β_{DD} through regression:

1. Standard DiD regression

$$Y_{it} = \beta_0 + \beta_1\, Treat_i + \beta_2\, Post_t + \beta_{DD}(Treat_i \times Post_t) + u_{it}$$

- $\hat{\beta}_0 = \bar{Y}^C_{pre}$
- $\hat{\beta}_0 + \hat{\beta}_1 = \bar{Y}^T_{pre}$
- $\hat{\beta}_0 + \hat{\beta}_2 = \bar{Y}^C_{post}$
- $\hat{\beta}_0 + \hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_{DD} = \bar{Y}^T_{post}$

$$\Rightarrow \hat{\beta}_{DD} = (\bar{Y}^T_{post} - \bar{Y}^T_{pre}) - (\bar{Y}^C_{post} - \bar{Y}^C_{pre})$$

DID REGRESSION

Three ways to obtain β_{DD} through regression:

1. Standard DiD regression

$$Y_{it} = \beta_0 + \beta_1\, Treat_i + \beta_2\, Post_t + \beta_{DD}(Treat_i \times Post_t) + u_{it}$$

2. DiD fixed-effects regression

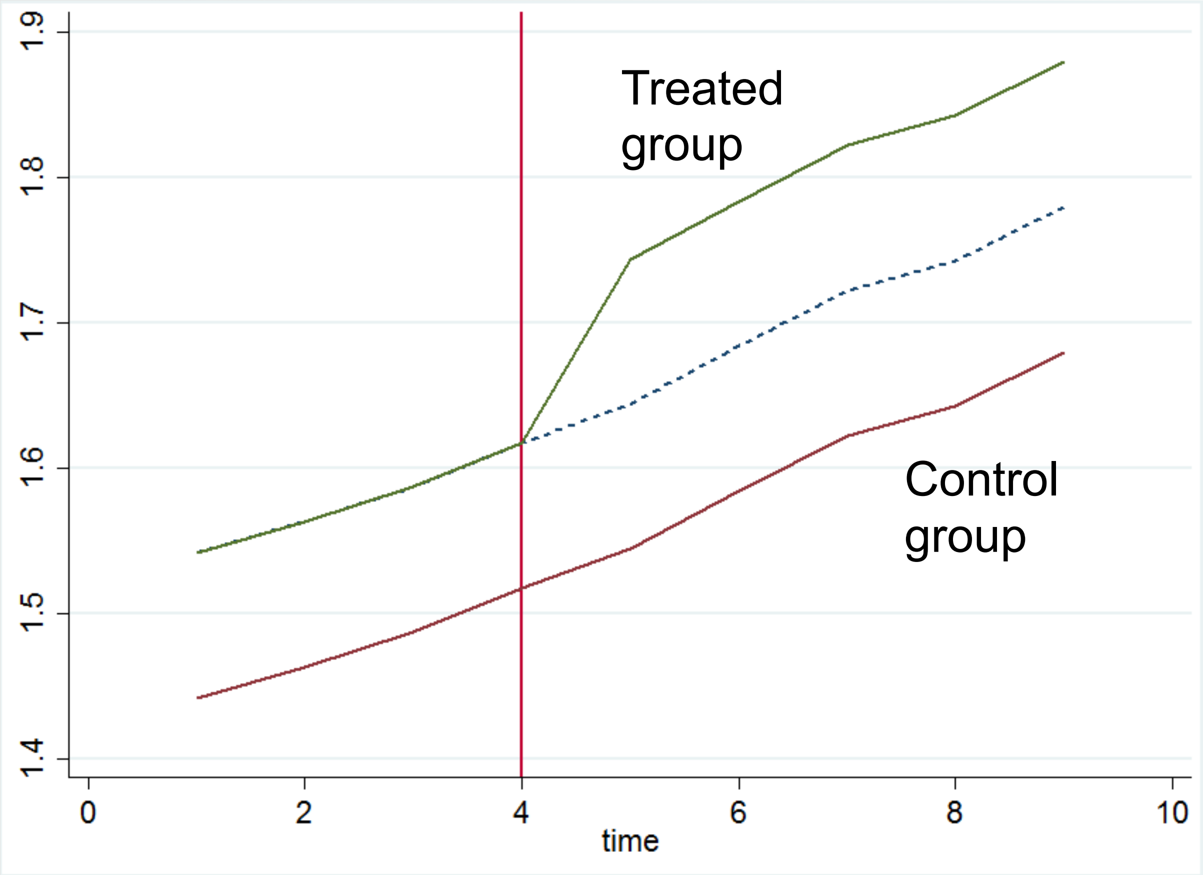
$$Y_{it} = \alpha_i + \beta_2\, Post_t + \beta_{DD}(Treat_i \times Post_t) + u_{it}$$

3. DiD differenced regression

$$\Delta Y_i = \beta_0 + \beta_{DD} Treat_i + u_i$$

10.2 CHECKING FOR PRE-TRENDS

CHECKING FOR PRE-TRENDS



Key idea:
If treated and control follow parallel trends, we would expect them to move in step in pre-treatment periods.

Can check with a graph like this, tracking treated and controls in a wider time-window around the event.

10.3 FORMAL DERIVATION

A FORMAL DERIVATION

- Assume that *potential* outcomes are determined as follows

$$\bar{Y}_{0st} = \gamma_s + \lambda_t$$

  - $\bar{Y}_{0st}$ = average *potential outcome* in group *s* at time *t*
  - *s* = T (treated) or C (control)
  - *t* = pre- or post-treatment.
  - γ_s = group-specific fixed-effect
  - λ_t = time-specific effect.

- Assume constant average causal effect of treatment:

$$\bar{Y}_{1st} - \bar{Y}_{0st} = \kappa$$

$$\bar{Y}_{0st} = \gamma_s + \lambda_t \qquad \bar{Y}_{1st} = \bar{Y}_{0st} + \kappa$$

$$\bar{Y}^{C}_{pre} = \bar{Y}_{0,C,pre} = \gamma_C + \lambda_{pre} \qquad \bar{Y}^{C}_{post} = \bar{Y}_{0,C,post} = \gamma_C + \lambda_{post}$$

$$\bar{Y}^{T}_{pre} = \bar{Y}_{0,T,pre} = \gamma_T + \lambda_{pre} \qquad \bar{Y}^{T}_{post} = \bar{Y}_{1,T,post} = \gamma_T + \lambda_{post} + k$$

$$\beta_{DD} = \left(\bar{Y}^{T}_{post} - \bar{Y}^{T}_{pre}\right) - \left(\bar{Y}^{C}_{post} - \bar{Y}^{C}_{pre}\right)$$

$$= \left[\left(\gamma_T + \lambda_{post} + k\right) - \left(\gamma_T + \lambda_{pre}\right)\right] - \left[\left(\gamma_C + \lambda_{post}\right] - \left(\gamma_C + \lambda_{pre}\right)\right]$$

$$= k$$

$$\beta_{DD} = \left(\bar{Y}^{T}_{post} - \bar{Y}^{T}_{pre}\right) - \left(\bar{Y}^{C}_{post} - \bar{Y}^{C}_{pre}\right)$$

$$= \left[\left(\cancel{\gamma_T} + \lambda_{post} + k\right) - \left(\cancel{\gamma_T} + \lambda_{pre}\right)\right] - \left[\left(\cancel{\gamma_C} + \lambda_{post}\right] - \left(\cancel{\gamma_C} + \lambda_{pre}\right)\right]$$

$$= k$$

Taking changes over time gets rid of the group-specific fixed effects γ_T and γ_C

$$\beta_{DD} = (\bar{Y}^T_{post} - \bar{Y}^T_{pre}) - (\bar{Y}^C_{post} - \bar{Y}^C_{pre})$$

$$= [(\cancel{\gamma_T} + \cancel{\lambda_{post}} + k) - (\cancel{\gamma_T} + \cancel{\lambda_{pre}})] - [(\cancel{\gamma_C} + \cancel{\lambda_{post}}] - (\cancel{\gamma_C} + \cancel{\lambda_{pre}})]$$

$$= k$$

Taking changes over time gets rid of the group-specific fixed effects γ_T and γ_C

Subtracting the control group change from the treated group change gets rid of common time-varying effects λ_{post} and λ_{pre}

TAKEAWAYS

- DiD works if $\bar{Y}_{0st} = \gamma_s + \lambda_t$
  - without treatment, groups differ by a fixed group-specific effect γ_s
  - but any time-specific effects λ_t are common.
  - → common trends: $\Delta\bar{Y}_{0,T,t} = \Delta\bar{Y}_{0,C,t} = \lambda_{post} - \lambda_{pre}$
- DiD would not work if $\bar{Y}_{0st} = \gamma_s + \lambda_{ts}$
  - without treatment, groups follow different time trends.
  - Then $\beta_{DD} = \mathrm{k} + [(\lambda_{post,T} - \lambda_{pre,T}) - (\lambda_{post,C} - \lambda_{pre,C})] = \mathrm{k} + (\Delta\bar{Y}_{0T} - \Delta\bar{Y}_{0C})$
- Treatment & controls can differ in *fixed* characteristics but must be subject to the same time-varying factors.

10.4 A MISSISSIPPI EXPERIMENT

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A MISSISSIPPI EXPERIMENT

- Should the Central Bank support banks during a crisis?
- 1930s Great Depression: Mississippi divided in 2 Fed districts
    1. Atlanta (6^{th}) helped banks (treated).
    2. St. Louis (8^{th}) did nothing (control).

A MISSISSIPPI EXPERIMENT

- Dec 1930: banking crisis hits Mississippi.
  - Banks in Atlanta (6th) get help (treated).
  - Banks in St.Louis (8th) don't (control).
- DiD estimate of the effect of Atlanta Fed policy:

$$\beta_{DD} = \left(Y^{6th}_{1931} - Y^{6th}_{1930}\right) - \left(Y^{8th}_{1931} - Y^{8th}_{1930}\right)$$

  - Y = number of operating banks.

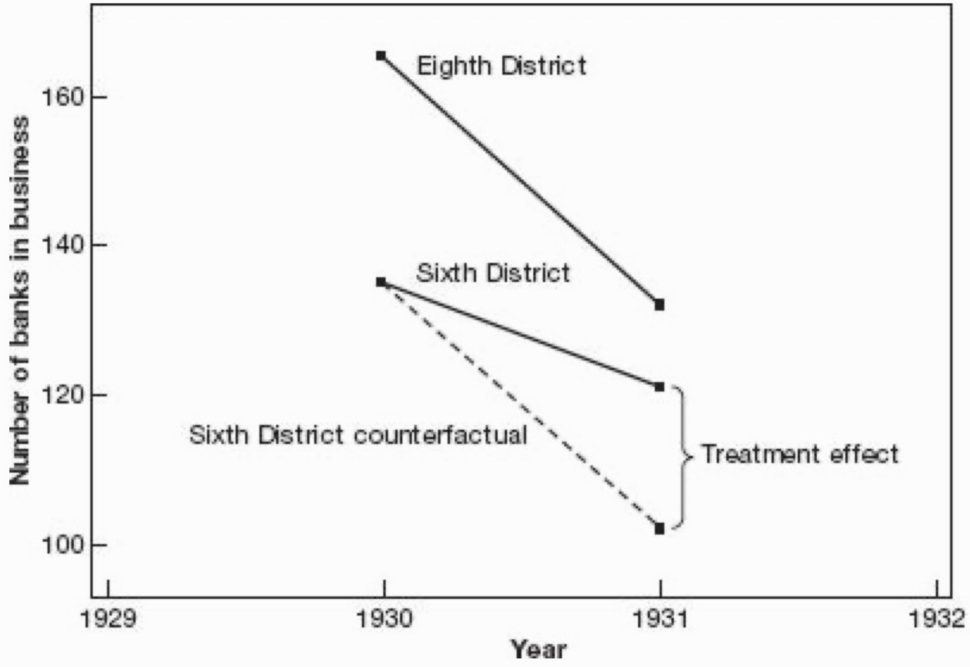
$$\beta_{DD} = \left(Y^{6th}_{1931} - Y^{6th}_{1930}\right) - \left(Y^{8th}_{1931} - Y^{8th}_{1930}\right)$$

$$= (121 - 135) - (132 - 165) =$$

$$= -14 - (-33) = 19$$

"Easy money" policy implemented by the Atlanta Fed saved 19 banks (>10% of existing banks in the district!)

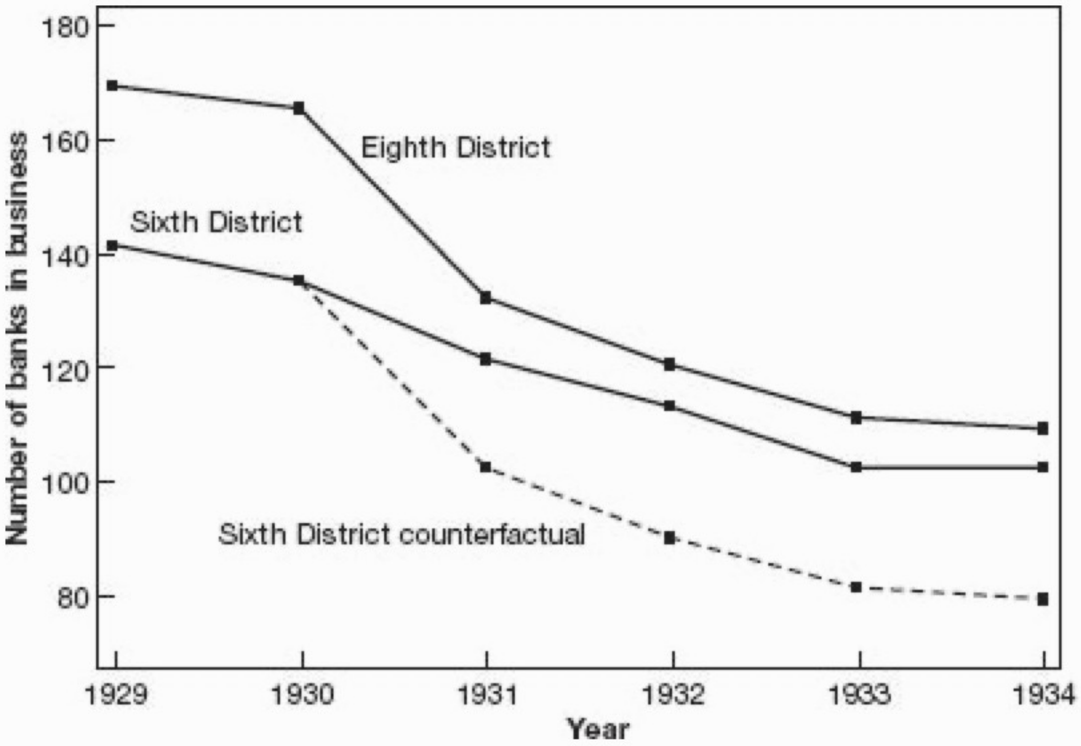
FIGURE 5.1
Bank failures in the Sixth and Eighth Federal Reserve Districts



Notes: This figure shows the number of banks in operation in Mississippi in the Sixth and Eighth Federal Reserve Districts in 1930 and 1931. The dashed line depicts the counterfactual evolution of the number of banks in the Sixth District if the same number of banks had failed in that district in this period as did in the Eighth.

FIGURE 5.3

Trends in bank failures in the Sixth and Eighth Federal Reserve Districts, and the Sixth District's DD counterfactual



Notes: This figure adds DD counterfactual outcomes to the banking data plotted in Figure 5.2. The dashed line depicts the counterfactual evolution of the number of banks in the Sixth District if the same number of banks had failed in that district after 1930 as did in the Eighth.

Further evidence to assess the DiD analysis:

- 6th and 8th moved in parallel before the crisis (similar pre-trends).
- Divergence in outcomes opens up precisely when the crisis hits, and then stabilizes.

10.5 MINIMUM WAGES AND EMPLOYMENT: THE NJ-PA CASE STUDY

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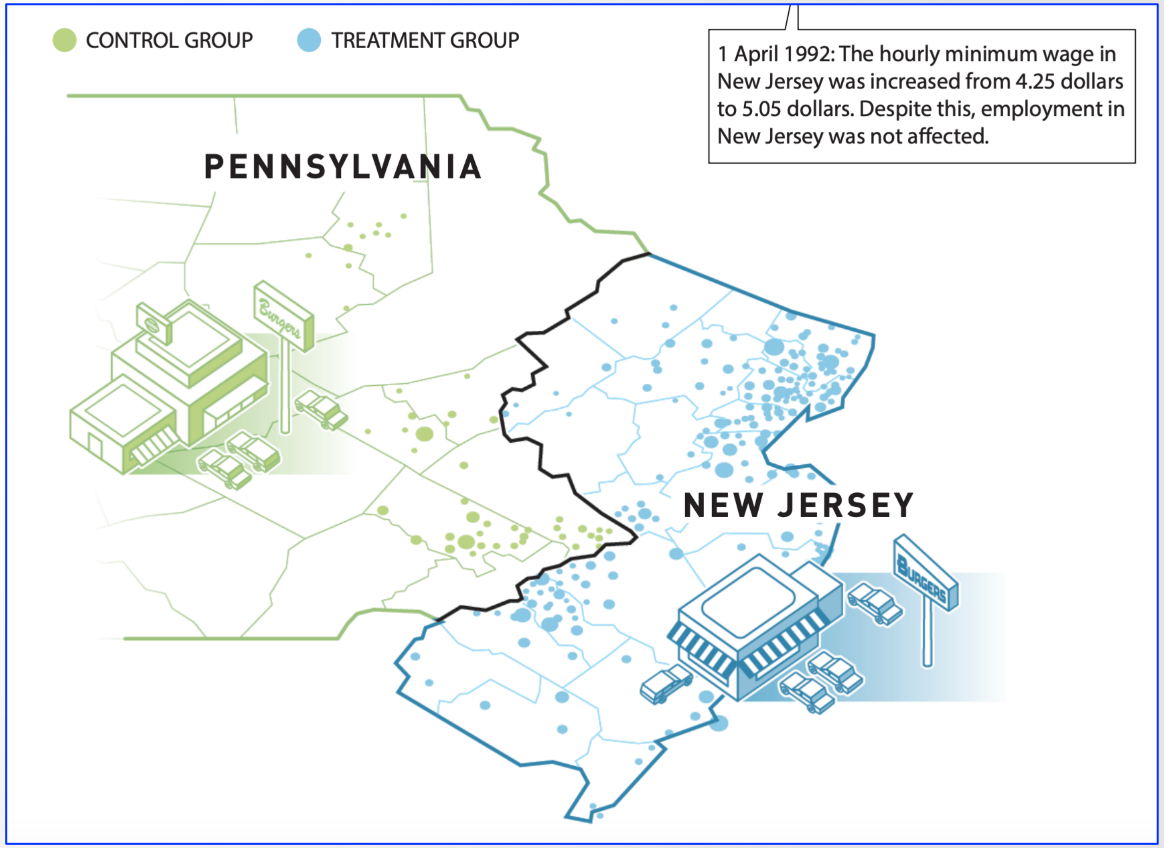
MW & EMPLOYMENT (CARD & KRUEGER, 1994)

- 1 Apr 1992: NJ raises MW (treated)
    - from 4.25 to 5.05$.
- No change in neighboring PA (control).
- Card & Krueger survey fast-food restaurants on both sides of the border.



MW & EMPLOYMENT (CARD & KRUEGER, 1994)

Variable	PA (i)	NJ (ii)	Difference, NJ – PA (iii)
	Stores by state		
1. FTE employment before, all available observations	23.33 (1.35)	20.44 (0.51)	–2.89 (1.44)
2. FTE employment after, all available observations	21.17 (0.94)	21.03 (0.52)	–0.14 (1.07)
3. Change in mean FTE employment	–2.16 (1.25)	0.59 (0.54)	2.76 (1.36)

DiD estimate:

$$(21.03 - 20.44) - (21.17 - 23.33)$$

$$= +2.76$$

MW & EMPLOYMENT (CARD & KRUEGER, 1994)

Variable	Stores in New Jersey[a] Wage = $4.25 (iv)	Wage = $4.26–$4.99 (v)	Wage ≥ $5.00 (vi)
1. FTE employment before, all available observations	19.56 (0.77)	20.08 (0.84)	22.25 (1.14)
2. FTE employment after, all available observations	20.88 (1.01)	20.96 (0.76)	20.21 (1.03)
3. Change in mean FTE employment	1.32 (0.95)	0.87 (0.84)	−2.04 (1.14)

- Within NJ analysis.
- Treated: low-wage stores.
- Controls: high-wage stores.
- Again, no negative effect of MW increase.

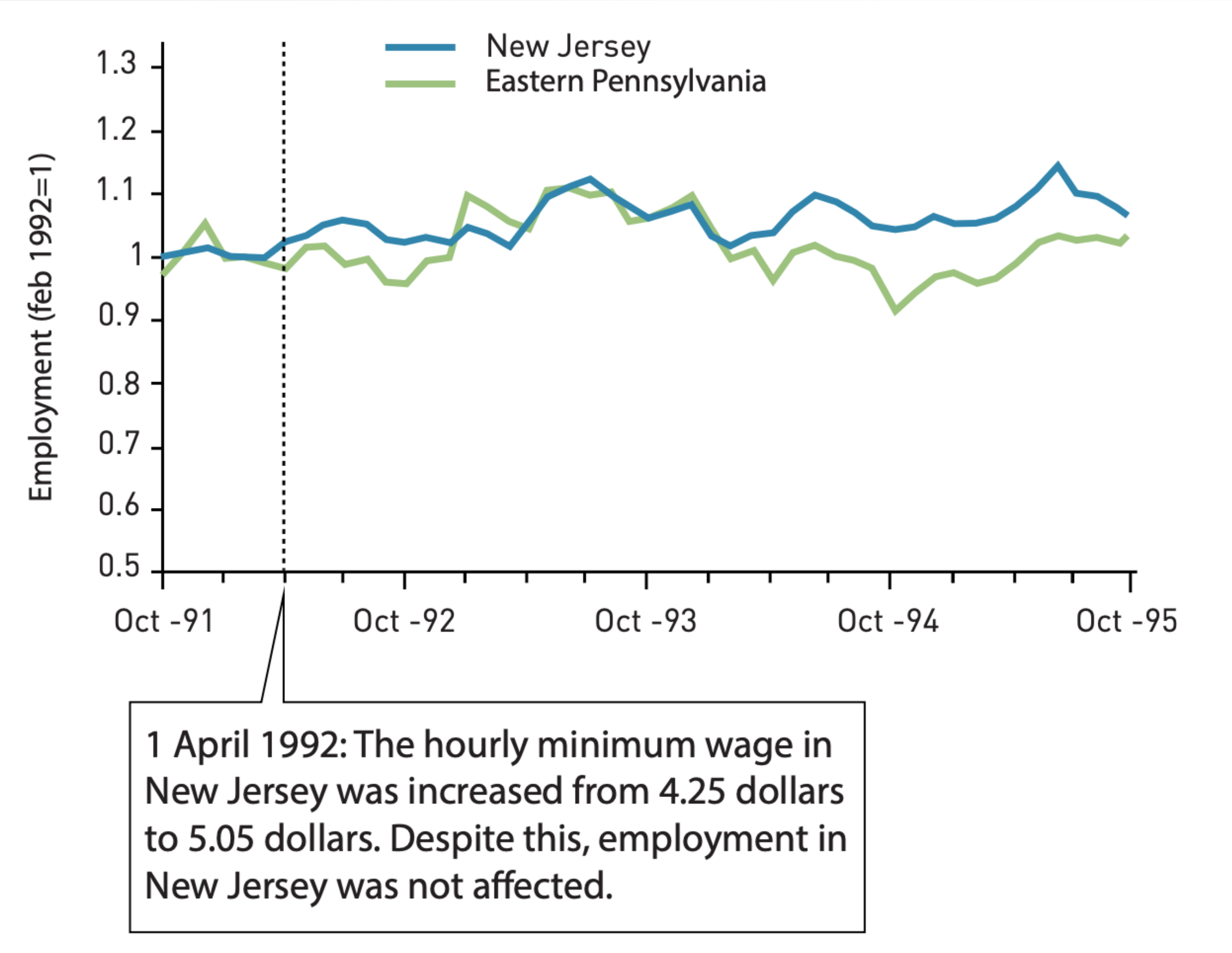
MW & EMPLOYMENT (CARD & KRUEGER, 1994)

DiD differenced regression with control variables:

$$\Delta E_i = \beta_0 + \beta_1 W_{1i} + \cdots + \beta_n W_{ni} + \beta_{DD} NJ_i + u_i$$

- E = employment
- W = control variables
- NJ = treatment indicator, equal to 1 if in NJ, 0 if in PA.

MW & EMPLOYMENT (CARD & KRUEGER, 1994)



Subsequent work using other data sources broadly confirmed the main results.

10.6 DOES ECONOMICS MAKE YOU SELFISH?

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Does economics make you selfish?

Daniele Girardi[*], Sai Madhurika Mamunuru[†], Simon D. Halliday[‡], Samuel Bowles[§]

Abstract

It is widely held that studying economics makes you more selfish and politically conservative. We use a difference-in-differences strategy to disentangle the causal impact of economics education from selection effects. We estimate the effect of four different intermediate microeconomics courses on students' experimentally elicited social preferences and beliefs about others, and policy opinions. We find no discernible effect of studying economics (whatever the course content) on self-interest or beliefs about others' self-interest. Results on policy preferences also point to little effect, except that economics may make students somewhat less opposed to highly restrictive immigration policies.

https://scholarworks.umass.edu/econ_workingpaper/304/

DOES ECONOMICS MAKE YOU SELFISH?

- *Hypothesis*: studying economics might make people more self-interested and influence their political views.
- Some evidence from previous studies that econ students are more self-interested & conservative.
- But is it a causal effect or selection bias?
- DiD strategy to tease out causal effects

DOES ECONOMICS MAKE YOU SELFISH?

Sample:

- 4 Intermediate Microeconomics Classes (treated)
- 1 Large nutrition class (control)
- n = 202 (156 econs)

Online survey:

- Administered pre– and post-treatment (= before & after the courses)
- Incentivized games to measure generosity
- Survey questions to measure political opinions.

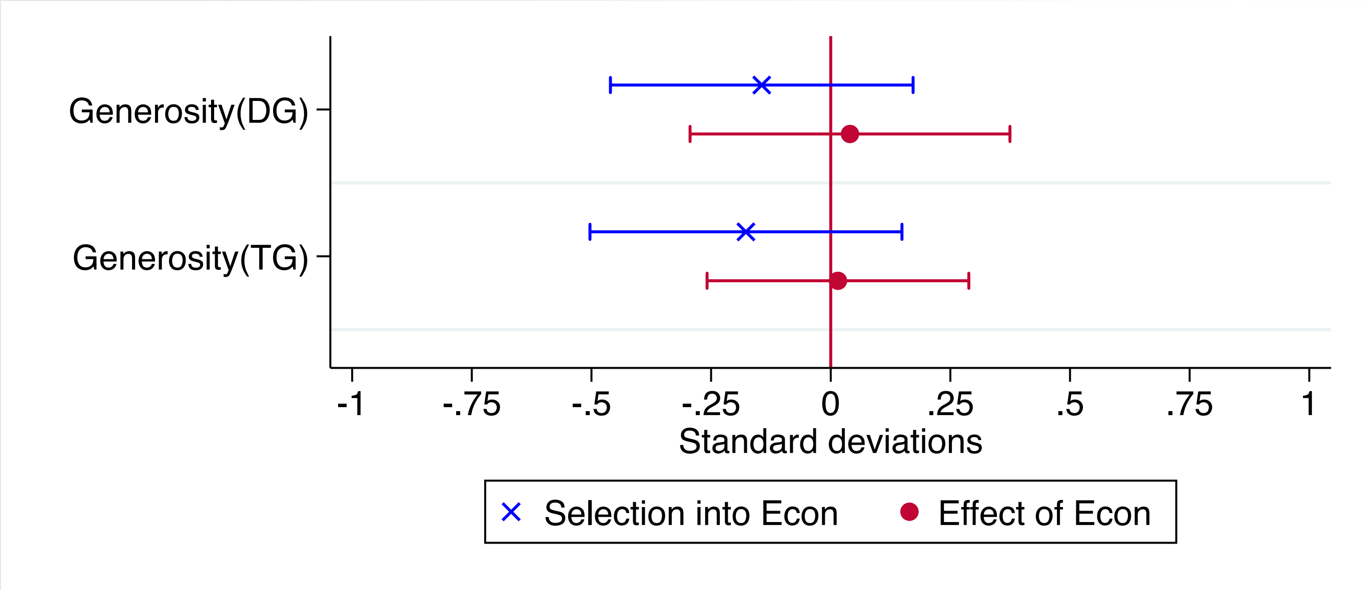
DOES ECONOMICS MAKE YOU SELFISH?

This study uses a DiD fixed-effects regression:

$$y_{it} = \alpha_i + \gamma Post_t + \beta_{DD}(Econ_i \times Post_t) + u_{it}$$

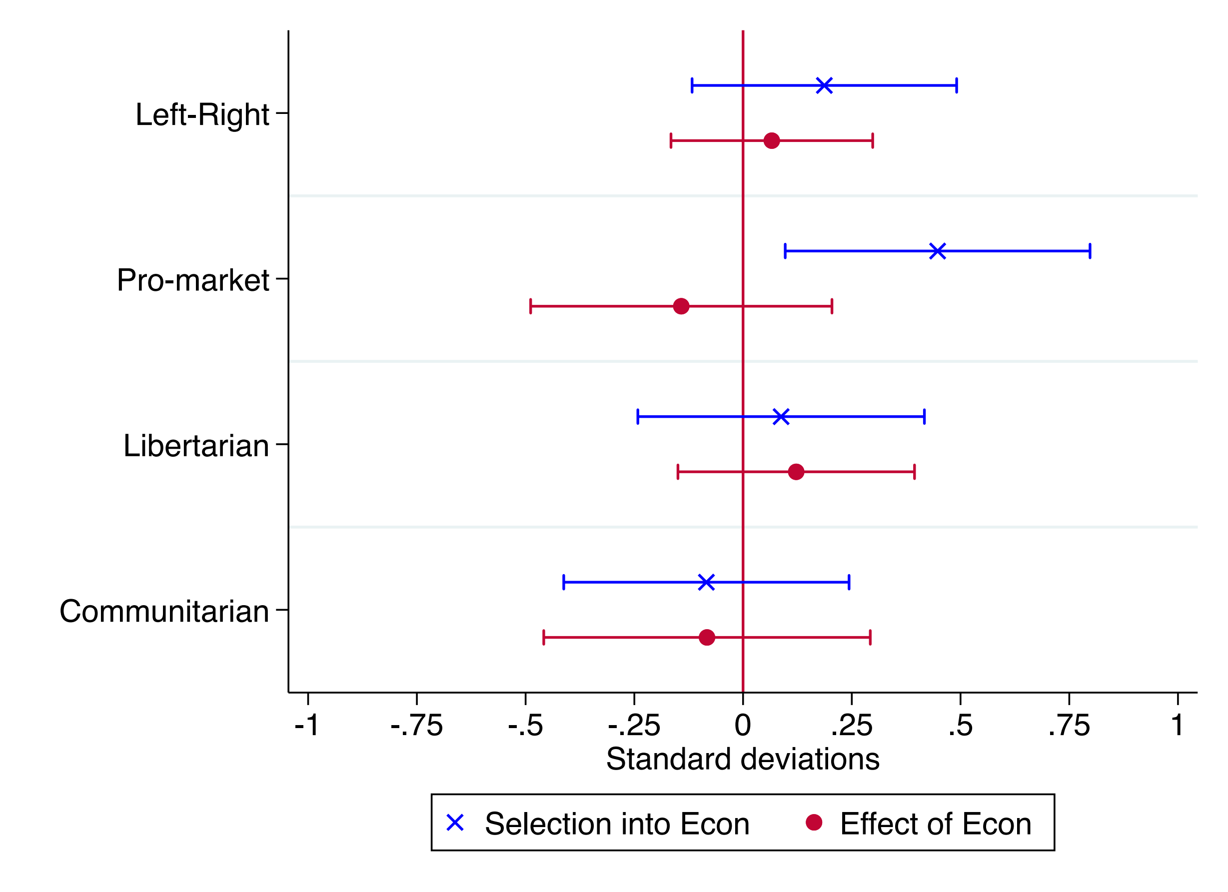
- α_i = individual fixed effects.
- $Post$ = binary variable for survey round (1 if post-semester, 0 if pre-).
- $Econ$= binary variable for taking Intermediate Microeconomics.
- β_{DD} = DiD estimated effect of studying economics on outcome y.

RESULTS: EFFECT ON GENEROSITY



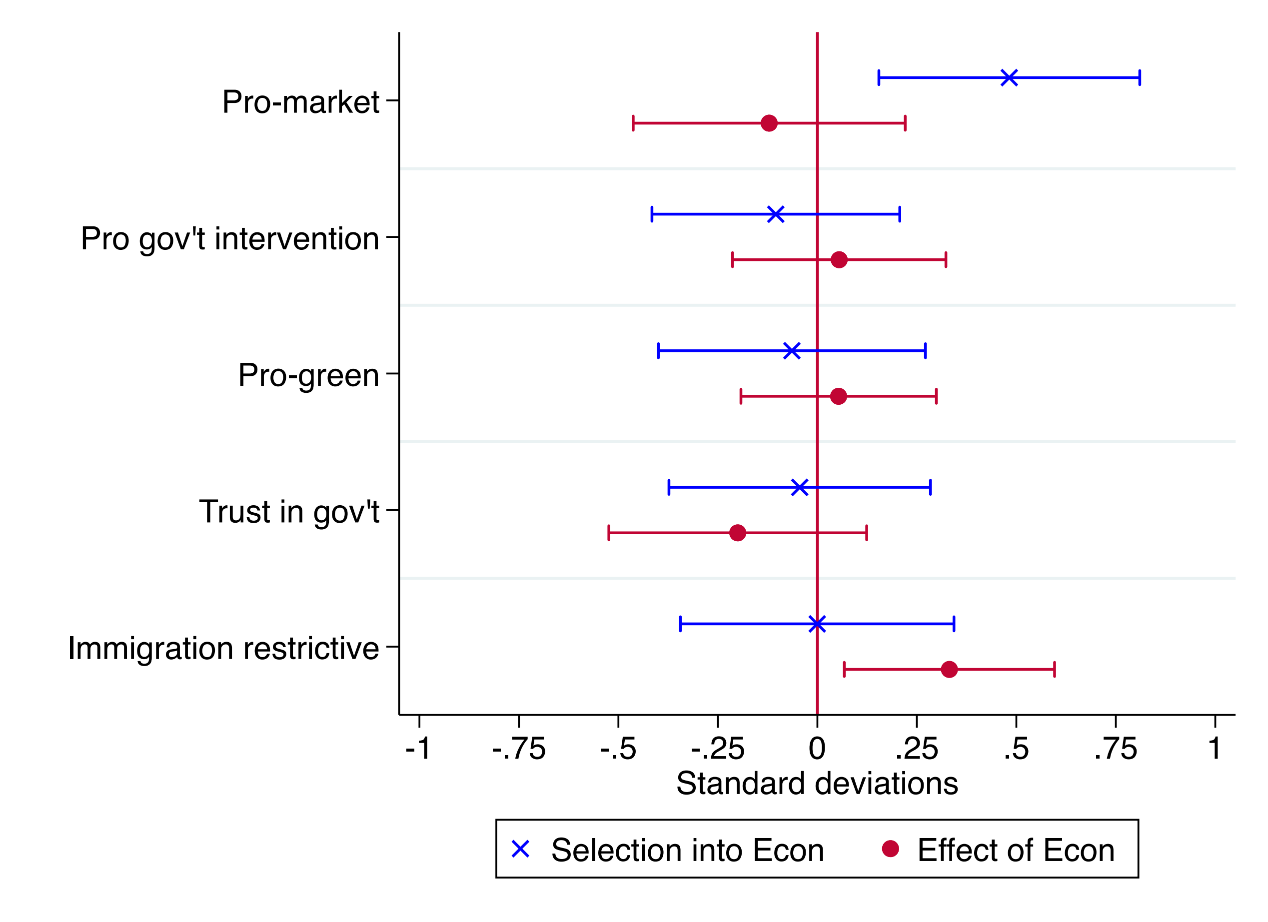
- Blue lines = $\bar{Y}^{T}_{pre} - \bar{Y}^{C}_{pre}$
- Red lines = β_{DD}

RESULTS: EFFECT ON POLITICAL OPINIONS (1)



- Blue lines = $\bar{Y}^{T}_{pre} - \bar{Y}^{C}_{pre}$
- Red lines = β_{DD}

RESULTS: EFFECT ON POLITICAL OPINIONS (2)



- Blue lines = $\bar{Y}^{T}_{pre} - \bar{Y}^{C}_{pre}$
- Red lines = β_{DD}

Studying Microeconomics seems to increase support for the following statement:

'Immigrants from other countries should be prohibited except where it can be shown that they will contribute to the quality of life of the current resident population'