Econometrics 1

Lecture 14: Experiments and Quasi-Experiments

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Potential outcomes, causal effect, and idealized experiments

Potential outcome

- Receiving *treatment* — e.g. taking a drug for medical condition, enrolling a job training program, or doing an optimal econometric problem set.

- Two hypothetical situations
    1. receive the treatment
    2. not receive the treatment

- A *potential outcome* is the outcome for an individual under a potential treatment. The *causal effect* for the individual is the difference in the potential outcomes if the treatment is received and if it is not.

Average causal effect

- The causal effect cannot be measured for a single individual, since the individual either receives the treatment or does not. Only one potential outcome can be observed.

- In many applications it suffices to know the mean causal effect in a population. This is called the *average causal effect*, or the *average treatment effect* (ATE).

- The ATE for a given population can be estimated using an ideal randomized controlled experiment.

Ideal randomized controlled experiment

1. Select the subjects at random from the population of interest.

2. Randomly assign the subjects to the treatment or the control group.

- The average causal effect is then

$$\underbrace{\mathrm{E}(Y_i \mid X_i = 1)}_{\text{treatment group}} - \underbrace{\mathrm{E}(Y_i \mid X_i = 0)}_{\text{control group}}$$

Econometric methods for analyzing experimental data

- The differences estimator

$$\overline{Y}^{\text{treatment}} - \overline{Y}^{\text{control}}$$

- Let X be a binary treatment indicator variable, then the differences estimator can be estimated by the following regression model

$$Y_i = \beta_0 + \beta_1 X_i + u_i$$

- $\mathrm{E}(Y_i \mid X_i = 1) = \beta_0 + \beta_1, \quad \mathrm{E}(Y_i \mid X_i = 0) = \beta_0$

The differences estimator with additional regressors

- Additional control variables can be added to the above regression model to improve efficiency

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 W_{1i} + \cdots + \beta_{1+r} W_{ri} + u_i$$

- Including W reduces the standard error of the regression and, typically, that of $\hat{\beta}_1$.

- It must be satisfied that $\mathrm{E}(u_i \mid X_i, W_i) = \mathrm{E}(u_i \mid W_i)$. Here W_i should be a pretreatment individual characteristics, but not an experimental outcome.

Threats to validity of experiments

- Threats to internal validity
  - Failure to randomize
  - Failure to follow the treatment protocol
  - Attrition
  - Experimental effects (Hawthorne effect)
  - Small samples
- Threats to external validity
  - Nonrepresentative sample
  - Nonrepresentative program or policy
  - General equilibrium effects

The Tennessee STAR experimental design

- Three different class arrangement:
  - A regular class (22-25 students), with a single teacher, no aides
  - A small class (13-17 students), with a single teacher, no aides
  - A regular class, with a single teacher and a teacher’s aide.
- From kindergarten through third grade (4 years)
- Both students and teachers are randomly assigned.
- Deviations from the experimental design:
  Switch classes (approximately 10% of the students)
  Class sizes change

The STAR_SW data set

- 40 variables, 11598 observations (obs = student).
  Many missing values.

- Test score = total score of math and reading.

- Two treatment groups:
  small class (sc), regular class with aide (ra)

- Four grades:
  kindergarten (k), 1st grade (1), 2nd grade (2),
  3rd grade (3)

Differences estimates in Table 13.1

- Regression model

$$\text{TestScore}_i = \beta_0 + \beta_1 \text{SmallClass}_i + \beta_2 \text{RegAide}_i + u_i$$

- Differences estimators

$$\beta_1 = \text{E}(\text{TestScore}_i \mid i \text{ in SmallClass}) - \text{E}(\text{TestScore}_i \mid i \text{ in RegClass})$$
$$\beta_2 = \text{E}(\text{TestScore}_i \mid i \text{ in RegAide}) - \text{E}(\text{TestScore}_i \mid i \text{ in RegClass})$$

Example: reproduce Table 13.1

```
open "@workdir/data/SW3/star_sw.xlsx"

# Table 13.1
list ylist = tscorek tscore1 tscore2 tscore3
list x1list = sck sc1 sc2 sc3
list x2list = rak ra1 ra2 ra3

matrix T131 = zeros(7,4)

loop i = 1..4
    ols ylist[i] const x1list[i] x2list[i] --robust --quiet
    T131[1,i] = $coeff[2]
    T131[3,i] = $coeff[3]
    T131[5,i] = $coeff[1]
    T131[2,i] = $stderr[2]
    T131[4,i] = $stderr[3]
    T131[6,i] = $stderr[1]
    T131[7,i] = $T
endloop
eval T131
```

Regression with additional control variables

- Several control variables may be considered: teacher's experience, school fixed effects, race, family income, etc.

- Table 13.2 summarizes models with additional control variables for kindergarten students.

- Reproduce Table 13.2.
  Hints:
  1. School indicator variables are dummies, so you need to generate them from `schidkn` in the data set.
  2. Use `modeltab` command.

Quasi-experiments

Quasi-experiments

- Quasi-experiment (natural experiment) — randomness is introduced by variations in individual circumstances that make it appear *as if* the treatment is randomly assigned.

- Sources of variations:
  vagaries in legal institution
  location
  timing of policy or program implementation
  birth dates
  rainfall
  etc.

Two types of quasi-experiments

- 1st type — the as if random variation totally determines the treatment.

  OLS using the treatment as indep. var. is useful.

- 2nd type — the as if random variation partially determines the treatment.

  IV regression is useful (the as if random source of variation provides the IV).

ExamplesLabor market effects of immigration

- Labor market effects of immigration (1st type)
- Effects on civilian earnings of military service (2nd type)
- The effect of cardiac catheterization (2nd type)

The differences-in-differences estimator

- There might be differences between the treatment and control group even after including control variables in the difference regression.

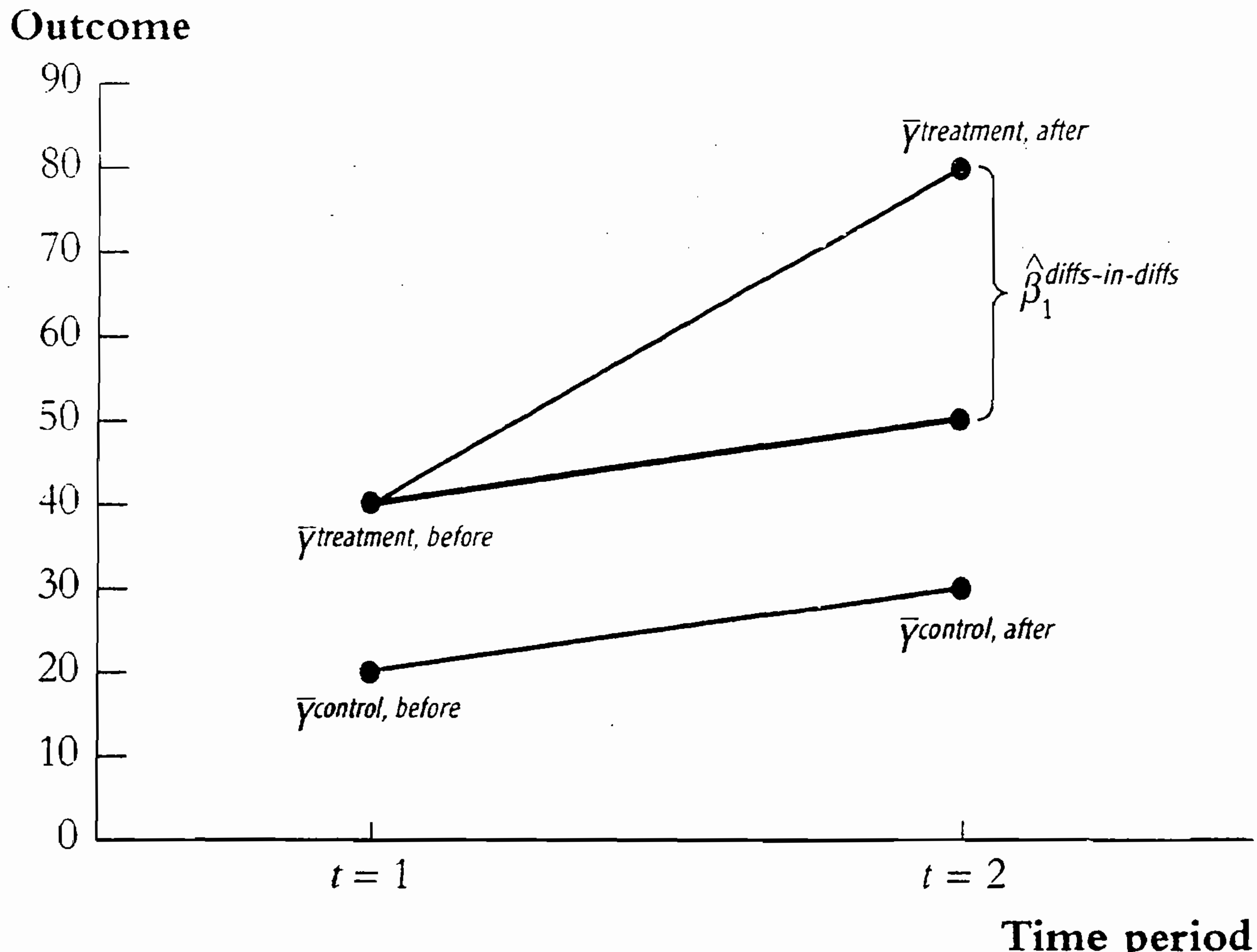
- In order to adjust those differences, we can take the changes before and after the treatment in the two groups. This leads to the *differences-in-differences* (DID, or DD) estimator.

$$\hat{\beta}_1^{\text{DID}} = \left(\overline{Y}^{\text{treat, after}} - \overline{Y}^{\text{treat, before}}\right) - \left(\overline{Y}^{\text{ctrl, after}} - \overline{Y}^{\text{ctrl, before}}\right)$$
$$= \boxed{\Delta\overline{Y}^{\text{treat}}} - \boxed{\Delta\overline{Y}^{\text{ctrl}}}$$

average change in Y in the treatment group

average change in Y in the control group

If the treatment is randomly assigned, then $\hat{\beta}_1^{\text{DID}}$ is an unbiased and consistent estimator of the causal effect.


Outcome
90
80
70
60
50
40
30
20
10
0
$\bar{y}$treatment, after
$\hat{\beta}_1^{diffs\text{-}in\text{-}diffs}$
$\bar{y}$treatment, before
$\bar{y}$control, after
$\bar{y}$control, before
$t = 1$
$t = 2$
Time period

DID in regression

- The DID estimator is the OLS estimator of β_1 in the regression

$$\Delta Y_i = \beta_0 + \beta_1 X_i + u_i$$

where X_i is the binary treatment variable, and ΔY_i is the post experiment value of Y for the *i*th individual minus the pre experiment value.

$$\mathrm{E}(Y_i^{\text{after}} - Y_i^{\text{before}} \mid X_i = 1) = \beta_0 + \beta_1$$
$$\mathrm{E}(Y_i^{\text{after}} - Y_i^{\text{before}} \mid X_i = 0) = \beta_0$$

DID in regression

- DID estimator with additional regressors

$$\Delta Y_i = \beta_0 + \beta_1 X_i + \beta_2 W_{1i} + \cdots + \beta_{1+r} W_{ri} + u_i$$

- DID estimator using repeated cross-sectional data (two periods)

$$Y_{it} = \beta_0 + \beta_1 \overset{\text{actual treatment}}{\boxed{X_{it}}} + \beta_2 \overset{\text{treatment group indicator}}{\boxed{G_i}} + \beta_3 \overset{\text{second period indicator}}{\boxed{D_t}}$$
$$+ \beta_4 W_{1it} + \cdots + \beta_{3+r} W_{rit} + u_i t$$

X is as if randomly assigned conditional on W's.

- Why β_1 in the second regression is the DID estimator?

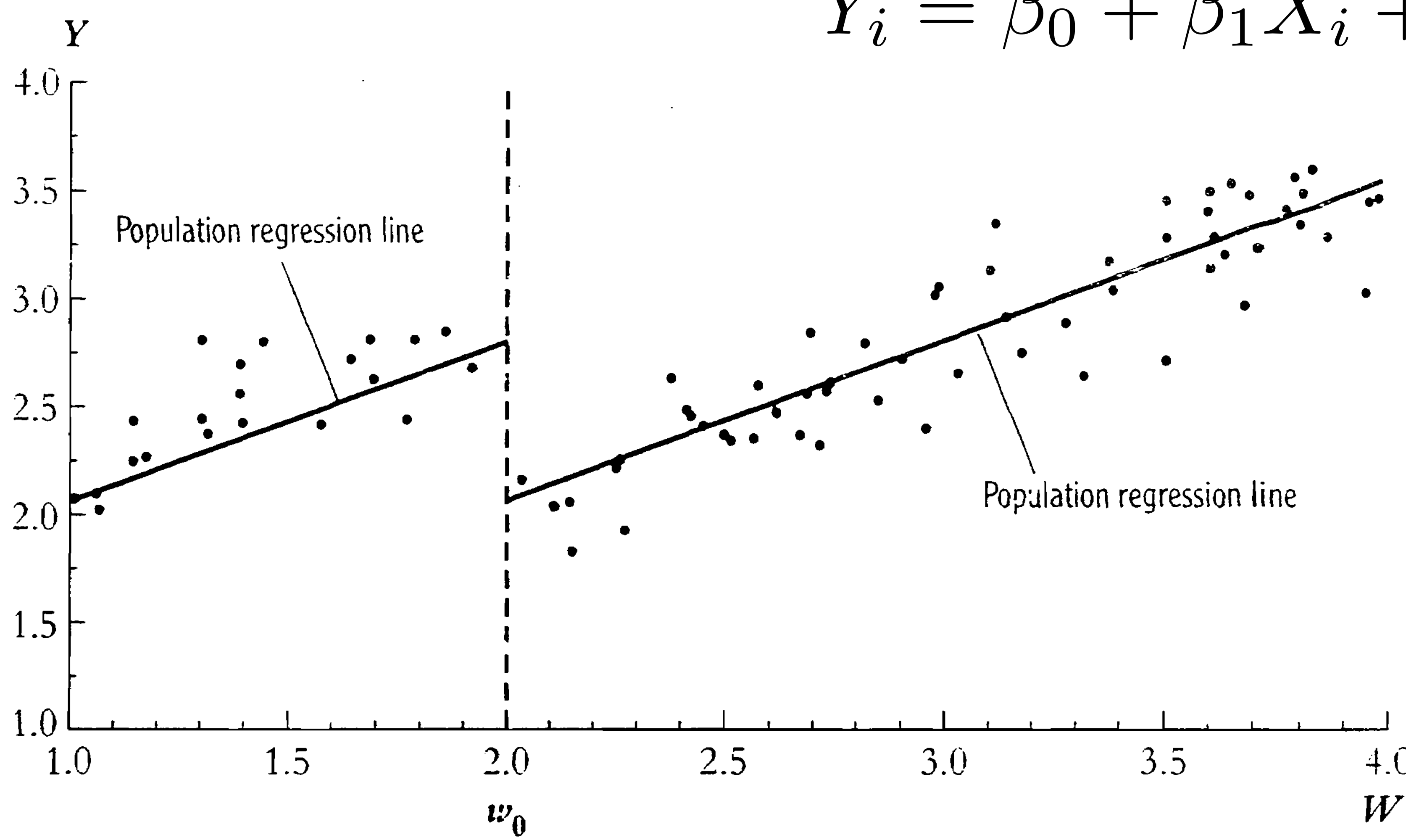
IV estimators

- The IV estimator can be used in the following situation:
  - the quasi-experiment yields a variable Z_i that influences receipt of treatment,
  - data are available both on Z_i and on the treatment actually received X_i ,
  - Z_i is as if randomly assigned (perhaps after controlling for some additional variables).
- Z_i is a valid instrument for X_i.

Regression discontinuity estimators

- Treatment can depend in whole or in part on whether an observable variable W crosses a threshold value. E.g., GPA determines whether a student is required to attend a summer school.

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 W_i + u_i$$



$$X_i = \begin{cases} 1 & \text{if } W_i < w_0 \\ 0 & \text{if } W_i \geq w_0 \end{cases}$$

Potential problems

- Threats to internal validity
  - Failure to randomize
  - Failure to follow the treatment protocol
  - Attrition
  - Instrumental validity
- Threats to external validity
  - Nonrepresentative sample
  - Nonrepresentative program or policy
  - General equilibrium effects
  - Difficult to generalize

Further readings

- Angrist, J. D. and Pischke, J.-S.
  Mastering 'Metrics: The Path from Cause to Effect.
  Princeton University Press, 2015.

- Angrist, J. D. and Pischke, J.-S.
  Mostly Harmless Econometrics: An Empiricist's Companion.
  Princeton University Press, 2008.

References

1. Stock, J. H. and Watson, M. M., *Introduction to Econometrics*, 3rd Edition, Pearson, 2012.