Exam DXE_EMTR
Econometrics (Fall 2021)

This exam accounts for 40% of your final grade. Time limit is 180min. No books or other materials are allowed.

(6%) TRUE/FALSE

Decide if the following statement is true or false.

(a) Ordinary least squares estimator in a linear regression model is the maximum likelihood estimator under normally distributed homoskedastic errors.

(b) Bootstrap is useful in situations with small sample sizes when asymptotic approximations of distribution of estimators are unreliable.

(c) It is possible to capture Local Average Treatment Effect within the DAG framework in a straightforward manner.

(d) Randomization of treatment removes the selection bias due to a treatment endogeneity, so that average treatment effect can be consistently estimated.

(e) In treatment effects estimation *matching* can help to remove bias due to unobserved confounders (variables that jointly affect the treatment and the outcome).

(f) Parallel trends assumption in the Difference-in-differences research design is sensitive to transformations of the outcome variable.

(6%)

Suppose you have the following linear regression model:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \epsilon_i.$$

You are considering adding another variable x_4 to the model. The new model would look like this:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \epsilon_i.$$

Assume that this new variable x_4 is independent of all the other variables x_1, x_2, x_3. Furthermore, assume that the error ϵ is independent of all the variables x_1, x_2, x_3, x_4.

Answer the following questions and provide a brief explanation:

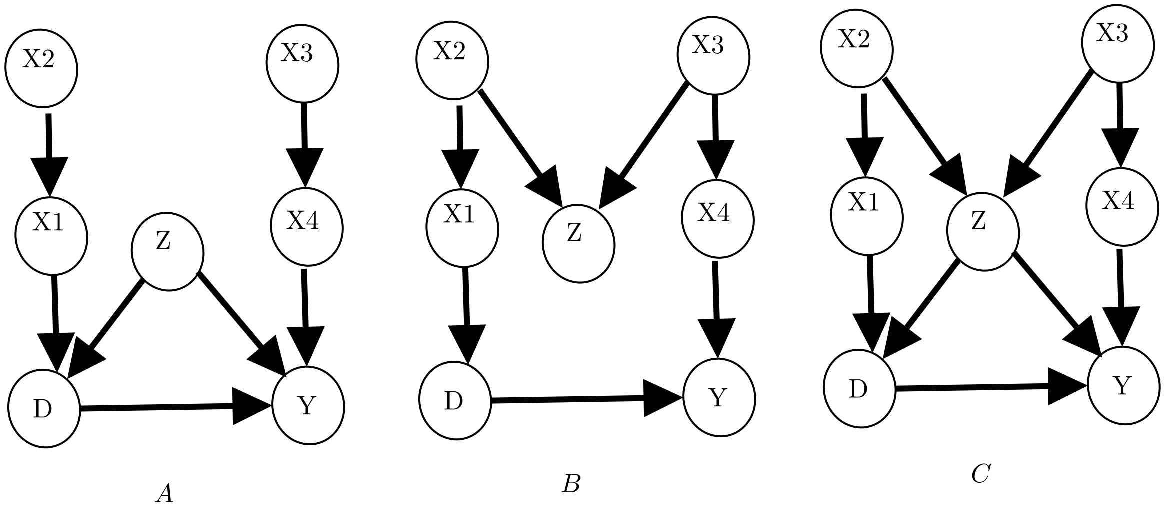
- Will the OLS estimates $\hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3$ change substantially in the new model (the one with x_4) in comparison to the old model (without x_4)?

- Will the standard errors of $\hat{\beta}_1, \hat{\beta}_2, \hat{\beta}_3$ change (In other words, will we get more precise estimates of these quantities)?

- Will the measure of fit R^2 change (In other words, will the new model explain more of the variation in the outcome variable y)?

(6%)

Consider the following three causal graphs, A, B and C.



We are interested in the causal relationship between D and Y. How D affects Y.

(i) Propose any conditioning set that would close all the backdoor paths from D to Y in Graph A.

(ii) Explain why conditioning only on Z does not satisfy the backdoor criterion for identification of the causal relationship between D and Y in Graph B.

(iii) Propose any conditioning set <u>that consists of exactly 2 variables</u> that would close all the backdoor paths from D to Y in Graph C.

(8%)

The notion of Local Average Treatment Effect (LATE) introduced by the recent econ Nobel laureates Angrist and Imbens in the 90's changed the way how researchers think about the instrumental variable estimation.

Explain what LATE is, and list sufficient assumptions for the identification of LATE in a simple setup with a binary instrument and with a binary treatment.

One of the implications of Angrist and Imbens (1994) is that estimates based on different instrumental variables cannot, in general, be compared. Explain why. (Imbens, Guido W., and Joshua D. Angrist. Identification and Estimation of Local Average Treatment Effects. Econometrica 62.2 (1994): 467-475.)

(6%)

Difference-in-differences research design is among the most popular approaches for causal effects estimation.

Provide your favourite real world example of an application of Difference-in-differences and explain the research design in detail on this concrete example.

(8%)

The leading illustrative example in a Synthetic Control Method (SCM) summary paper Abadie (2021) is the one on the economic impact of German reunification. The intervention is 1990 German reunification and the treated unit is the former West Germany, while the donor pool consisted from a set of industrialized countries (this economic problem was initially studied in Abadie, Diamond and Hainmueller 2010).

Use this example to explain the identification strategy in detail: what assumptions does it rely on, what is the motivation behind this approach and what are the potential advantages over competing approaches. Explain how the synthetic weights were constructed.

Below are Figure 1, Table 1 and Table 2 from Abadie (2021), you can make use of them as a support for your arguments.

References:

- Abadie, Alberto. 'Using synthetic controls: Feasibility, data requirements, and methodological aspects.' Journal of Economic Literature 59.2 (2021): 391-425.
- Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. 'Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program.' Journal of the American statistical Association 105.490 (2010): 493-505.)

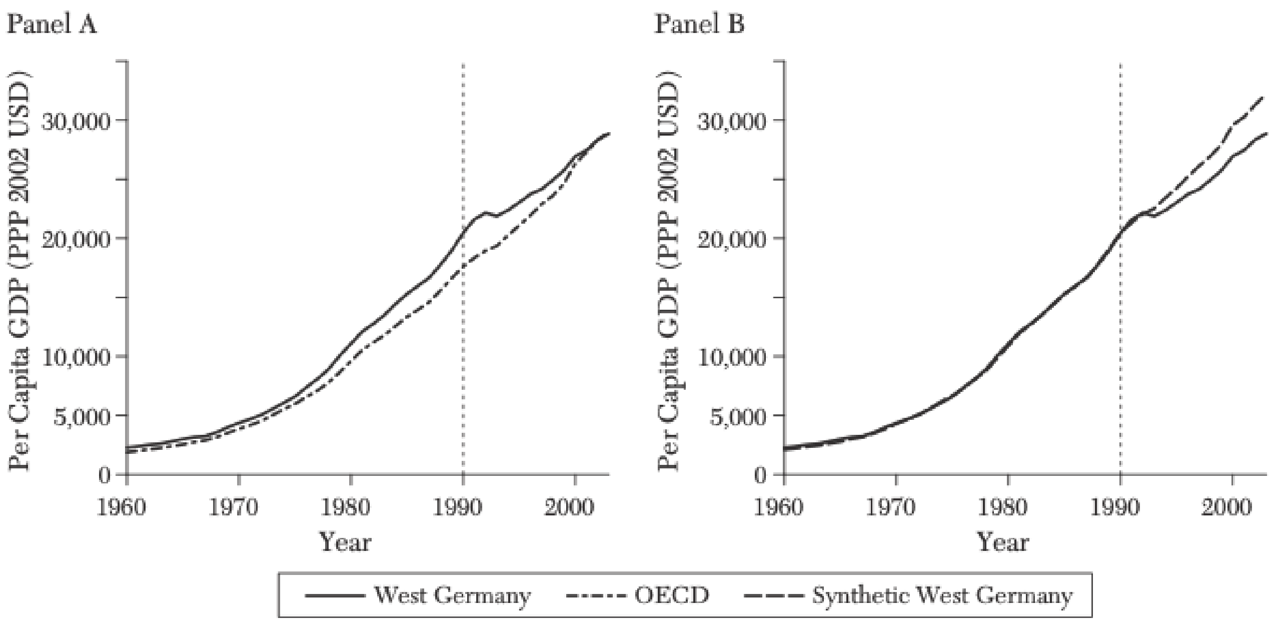


Figure 1. Synthetic Control Estimation in the German Reunification Example

Notes: Panel A compares the evolution of per capita GDP in West Germany to the evolution of per capita GDP for a simple average of OECD countries. In panel B the comparison is with a synthetic control calculated in the manner explained in subsection 3.2. See Abadie, Diamond, and Hainmueller (2015) for details.

TABLE 1
ECONOMIC GROWTH PREDICTOR MEANS BEFORE THE GERMAN REUNIFICATION

	West Germany (1)	Synthetic West Germany (2)	OECD average (3)	Austria (nearest neighbor) (4)
GDP per capita	15,808.9	15,802.2	13,669.4	14,817.0
Trade openness	56.8	56.9	59.8	74.6
Inflation rate	2.6	3.5	7.6	3.5
Industry share	34.5	34.4	33.8	35.5
Schooling	55.5	55.2	38.7	60.9
Investment rate	27.0	27.0	25.9	26.6

Note: The first column reports $\mathbf{X}_1$, the second column reports $\mathbf{X}_0 \mathbf{W}^*$, the third column reports a simple average of $\mathbf{X}_j$ for the 16 OECD countries in the donor pool, and the last column reports the value of $\mathbf{X}_j$ for the nearest neighbor of West Germany in terms of predictors values. GDP per capita, inflation rate, and trade openness are averages for the 1981–90 period. Industry share (of value added) is the average for 1981–89. Schooling is the average for 1980 and 1985. Investment rate is averaged over 1980–84. See Abadie, Diamond, and Hainmueller (2015) for variable definitions and sources. The nearest neighbor in column 4 minimizes the Euclidean norm of the pairwise differences between the values of the predictors for West Germany and for each of the countries in the donor pool, after rescaling the predictors to have unit variance.

TABLE 2
SYNTHETIC CONTROL WEIGHTS FOR WEST GERMANY

Australia	—
Austria	0.42
Belgium	—
Denmark	—
France	—
Greece	—
Italy	—
Japan	0.16
Netherlands	0.09
New Zealand	—
Norway	—
Portugal	—
Spain	—
Switzerland	0.11
United Kingdom	—
United States	0.22

Your answer here:

(BONUS +2%)

Explain what a *collider bias* is and give a concrete example visualized via a Directed Acyclic Graph (DAG).