Lecture 11: Policy Evaluation

TIØ4285 Production and Network Economics

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Norwegian University of Science and Technology

Literature

- In fact any textbook on econometrics, usually the introduction and a chapter on experiments/two-period panel data.
  - Prince, Jeff (2019): Predictive Analytics or Business Strategy. McGrawHill.
  - Stock, James H. and Mark W. Watson (2015): Introduction to Econometrics. 3rd edition, Pearson. (Chapter 1 and Chapter 13)
  - Wooldridge, Jeffrey (2009): Introductory Econometrics. 4th edition (4e), Cengage. (Chapter 1.4 and Chapter 13)

- For the problem set:
  - Ritter, Nolan and Sonja Rinne (2016): The causal impact of solar electricity generation on the electricity price. Working paper, presented at EMEE Oviedo, Spain.

Outline

- Economics suggest important relationships, often with policy implications, but virtually never suggest quantitative magnitudes of causal effects

- This lecture is about using methods and data to measure causal effects

Basic concepts

- Causality is linked to a manipulation (treatment, intervention, action, strategy) applied to a unit
- For simplicity, only two possibilities: receiving or not receiving the action or treatment
- Unit is linked to a potential outcome

- Measure outcomes **with** the policy in place and compare to outcomes **without** the policy (the counterfactual)
- Estimating the counterfactual: ‘treatment’ vs. ‘control’ group
- Control group should be on average identical to treatment group with the exception of treatment
- Experimental vs. Quasi-experimental design
- Objective: estimate direct impact of the policy on anyone who is eligible

Potential outcomes

- Only one outcome is realized after the intervention (the other is potential)
- Before the intervention, there are two potential outcomes
- Only one is realized after the action is conducted

- Jargon: economists like to use *a priori, a posteriori, ex ante, ex post*

Definition causal effect

- The causal effect of receiving treatment for unit i is the comparison of potential outcomes

$$Y(training) - Y(no\ training)$$

Or

$$\frac{Y(training)}{Y(no\ training)}$$

- Note that the definition is independent from the measurement of outcome

- Treatment effect is
  a) the comparison of potential outcomes and
  b) does not depend on which action is actually taken

- We do not observe both potential outcomes
- The non-observable or not-realized outcome is the counterfactual

- We only observe one potential outcome for each unit
- Need a way of predicting what would happen to unit i with or without treatment → „predict the counterfactual“

- Use multiple units, some of which will be exposed to intervention, some will not

→ one group serves as counterfactual for the other

NTNU

Econ talk

- The model is endogenous.

  There are unobservable variables not controlled for.

- The model is not identified.

  Whatever model you are estimating does not represent the true model. You cannot learn the ‚true‘ causal value of the parameters from your model.

- Identification strategy

  The method used for finding causal effects, as in ‚my identification strategy is to use XYZ as an instrument for…‘

- Selection on observables

  People (it‘s usually people. or firms.) selected into treatment based on factors that you can measure (and control for).

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- In most statistics books, causal inference is often not discussed

- In econometrics, causal inference is discussed in the context of linear regression

$$Y_i = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki} + \varepsilon_i$$

- Causal inference problems can be expressed in terms of linear regression assumptions (i.e. whether ε_i is correlated with some of the X variables)

Correlation does not imply causation!

Internal and external validity

- Internal validity: the statistical inferences about causal effects are valid for the population and setting being studied.

- External validity: the statistical inferences can be generalized from the population and setting studied to other populations and settings.

Internal vadility in OLS

- $Y_i = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_k X_{ki} + \varepsilon_i$

Two components:

- OLS estimator of β_1 is unbiased and consistent

- Hypothesis tests should have the desired significance level and confidence intervals should have the desired confidence level.

Threats to internal validity

1) $E(\varepsilon_i | X_{1i}) = 0$
2) $(X_{1i}, Y_i), i = 1, \dots, N$ are independently and identically distributed
3) Big outliers are unlikely

- Omitted variables
- Functional form misspecification
- Measurement error
- Sample selection
- Simultaneous causality
- Heteroskedasticity and/or correlated error terms

Experiments

- Can overcome the threats to internal vadility of observational studies (but have their own threats to internal vadility)
- Actual experimetns are rare ($$$) but influential
- Thinking about experiments helps to understand quasi-experiments or „natural experiments“

Terminology

- Experiment: designed and implemented consciously by human researchers
  - Randomly assigns subjects to treatments and control groups

- Quasi-Experiment: has a source of randomization that is „as if“ randomly assigned
  - Variation is not the result of an explicit randomized treatment and control design

- Program Evaluation: field of econometrics aimed at evaluating the effect of a program or policy

Two types of quasi experiments

- Whether a unit receives treatment is „as if“ randomly assigned, possible conditional on certain characteristics
  - New policy measure implemented in one but not in another area, whereby the implementation is „as if“ randomly assigned

- Whether a unit receives treatment is partially determined by another variable that is „as if“ randomly assigned
  - The variable can be used as instrument variable in a 2SLS regression analysis

QE with conditional „as if" randomization

- If the treatment is „as if" randomly assigned, conditional on observed characteristics W…
- … we can estimate the treatment effect by OLS while including W as control variable
- Obtain an unbiased effect of the treatment based on the conditional mean independence assumption…
- … by estimating the following equation by OLS

$Y_i = \beta_0 + \beta_1 X_i + \beta_2 W_i + \varepsilon_i$ with $E[\varepsilon_i | X_i, W_i] = E[\varepsilon_i | W_i]$

Quasi-Experiments and DID

- What if the treatment in a quasi-experiment is „as if“ randomly assigned, conditional on unobserved characteristics?

- If these differences in unobserved characteristics are time-invariant…

- …and we observe outcomes for the treatments & control group before & after the treatment…

- … we can use a method called difference-in-difference

DID: two groups & two time periods

- Treatment group $(g = TR)$ and control group $(g = C)$
- Before $(t = 0)$ and after $(\mathrm{t} = 1)$

Potential outcomes

$Y_{igt}(1)$ outcome for entity i in group g in period t in case of treatment

$Y_{igt}(0)$ outcome for entity i in group g in period t in case of no treatment

Assume additive structure for mean potential outcome in case of no treatment (the heart of d-i-d setup)

$$E\left[Y_{igt}(0)\right] = \alpha_g + \lambda_t$$

α_g= time-invariant group effect / λ_t=time effect which is constant across groups

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- Treatment takes place in treatment group but not in control group
- Suppose we observe outcomes before and after the treatment (panel data)
- Let the treatment indicator X_{gt}

  = 1 for treatment group $(g = TR)$ in the second period ($t = 1$)

  = 0 otherwise
- Write observed outcome as a function of the potential outcomes

$$Y_{igt} = Y_{igt}(1)\, X_{gt} + Y_{igt}(0)\left(1 - X_{gt}\right)$$

Taking expectations and rewriting gives

$$E\ [Y_{igt}] = E[Y_{igt}(1) + Y_{igt}(0)]X_{gt} + E\left[Y_{igt}(0)\right]$$

$$= \beta X_{gt} + \alpha_g + t$$

With the average causal effect of the treatment:

$$E[Y_{igt}\ (1) - Y_{igt}(0)] = \beta$$

$$E[Y_{igt}] = \beta \cdot X_{gt} + \alpha_g + \lambda_t$$

	Before ($t = 0$)	**After ($t = 1$)**
Treatment group ($g = Tr$)	$E[Y_{i\,Tr\,0}] = \alpha_{Tr} + \lambda_0$	$E[Y_{i\,Tr\,1}] = \beta + \alpha_{Tr} + \lambda_1$
control group ($g = C$)	$E[Y_{i\,C\,0}] = \alpha_C + \lambda_0$	$E[Y_{i\,C\,1}] = \alpha_C + \lambda_1$

- Comparing outcomes for treated and controls after intervention:

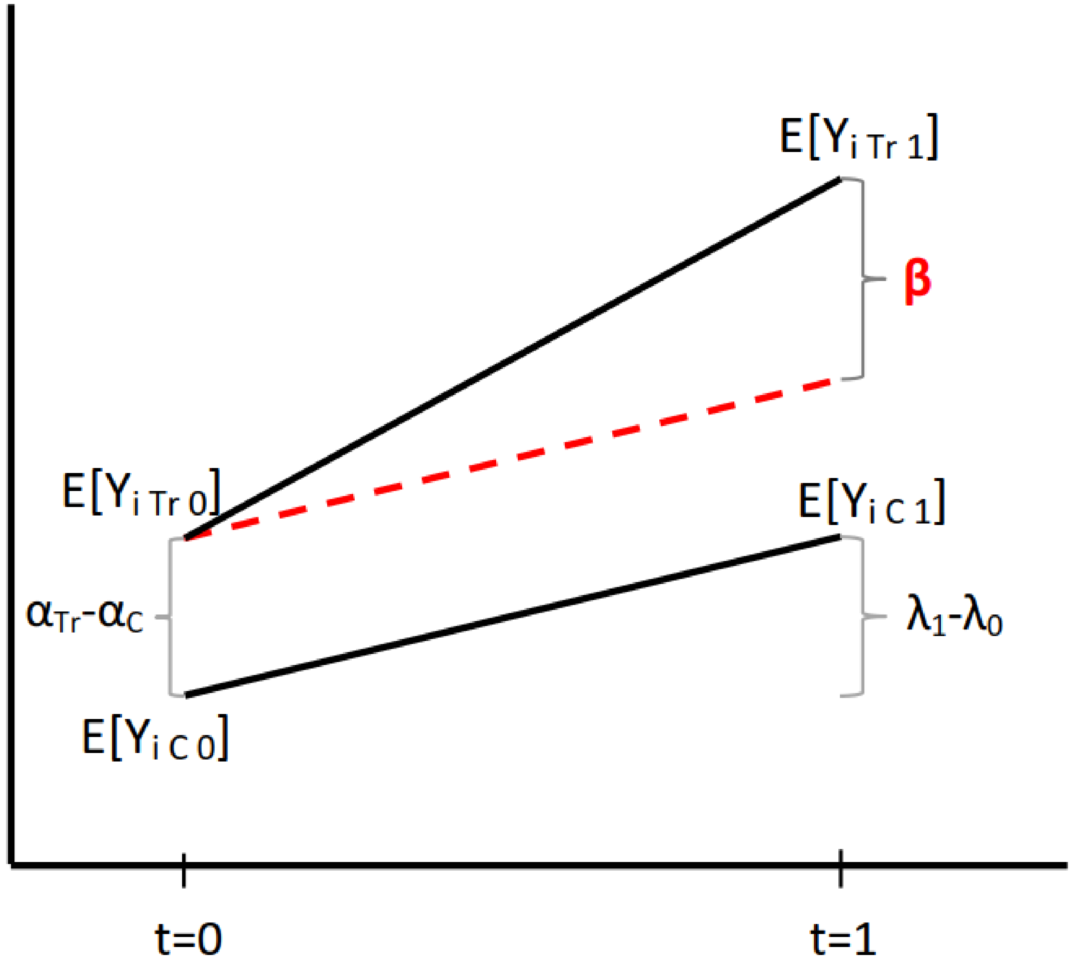
$$E[Y_{i\,Tr\,1}] - E[Y_{i\,C\,1}] = \beta + (\alpha_{Tr} - \alpha_C)$$

- Comparing outcomes for treated before and after treatment:

$$E[Y_{i\,Tr\,1}] - E[Y_{i\,Tr\,0}] = \beta + (\lambda_1 - \lambda_2)$$

- Instead subtract change for controls from change for treated:

$$\begin{aligned}
DID &= (E[Y_{i\,Tr\,1}] - E[Y_{i\,Tr\,0}]) - (E[Y_{i\,C\,1}] - E[Y_{i\,C\,0}]) \\
&= ((\beta + \alpha_{Tr} + \lambda_1) - (\alpha_{Tr} + \lambda_0)) - ((\alpha_C + \lambda_1) - (\alpha_C + \lambda_0)) \\
&= (\beta + \lambda_1 - \lambda_0) - (\lambda_1 - \lambda_0) \\
&= \beta
\end{aligned}$$



Common trend assumption: In absence of intervention, the treatment group would have had the same trend in Y as the control group.