Applied Microeconometrics (L11): Evaluation Methods

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Overview

Treatment Effects

Experimental data

Non-experimental data

Definitions

- Treatment effect: causal effect (e.g. treatment: undergoing a training programme) on an outcome variable of interest (e.g. productivity at work).
- Treatment: binary variable (0/1)
- Potential outcome: For each unit of analysis there is a potential outcome with treatment (y_1), and another potential outcome without treatment (y_0). These outcomes refer to alternative states of the world, and the treatment (causal) effect is the difference $y_1 - y_0$
- However, it is not possible to measure treatment effects at the individual level, since we cannot observe the full set of potential outcomes in alternative states of the world (since an individual cannot be found at the same time in both states). Thus, we focus on average treatment effects (ATE).

Treatment indicator

- Let w a binary treatment indicator

$$\begin{aligned} w = 1 \text{ if treatment} \\ w = 0 \text{ if no treatment} \end{aligned} \tag{1}$$

- We are interested in estimating the effect of treatment on outcomes (i.e. focus on estimating the ATE)
- The average treatment effect (ATE):

$$ATE = E(y_1 - y_0)$$

- The average treatment effect on the treated (ATET):

$$ATET = E(y_1 - y_0 | w = 1)$$

- ATE is the expected effect of treatment for a randomly drawn individual from the population
- ATET is the expected effect of treatment for a randomly drawn individual from those individuals in the population that have undergone treatment.

Observed outcomes

- How can we estimate treatment effects?
- We do have data on actual outcomes
- But we do not have data on potential outcomes
  - for the treated we observe y_1 given $w = 1$
  - for the untreated we observe y_0 given $w = 0$
- Thus, we cannot compute sample averages of the difference $y_1 - y_0$
- In other words, we do not observe the counterfactual (the outcome that did not happen). Thus, we do not observe outcomes
  - without treatment for the treated individuals (i.e. y_0 is unobserved whenever $w = 1$) or
  - outcomes with treatment for the untreated individuals (y_1 is unobserved whenever $w = 0$)
- In the data, the observed outcome y is:

$$y = (1 - w)y_0 + wy_1 = y_0 + w(y_1 - y_0)$$

Randomization: Experimental data

- Randomization: a process in which the outcome of a toss of a coin determines whether an individual get treatment ($w_i = 1$) or not ($w_i = 0$). If treatment is randomized across individuals, then estimation of the ATE is simple.
- Let us to have a sample N observations and we interested in $E(y_1)$ and $E(y_0)$. The problem is that for each individual, either y_{1i} or y_{0i} is unobserved. Is it valid to calculate $E(y_1)$ by taking the average of the observed values of y_1, and vice versa for $E(y_0)$?
- Yes because randomization ensures the potential outcomes (y_1, y_0) are statistically independent of the treatment status.
- Given the independence assumption $ATE = ATET$. Thus, in a randomized framework the difference-in-means estimator is unbiased and consistent. Use OLS to obtain the estimate (β_1): ATE

$$y_i = \beta_0 + \beta_1 w_i + u_i$$

Randomization-Experimental data: Restrictions

- "Social experiments" are rare in economics, and often expensive to implement.
- The external validity of the results of a particular experiment are often questionable.
  - not easy to replicate all components of the program elsewhere
  - the results may be specific to the sample (e.g. small regions, specific sample of firms/workers)
  - results may be specific to the program
- Many practical problems
  - Suppose you start to give free school meals randomly in 50% of the schools in a region where previously school meals were not free. One year later you plan to turn up and compare pupil performance in treated and untreated schools. But how can you be sure parents whose kids are in untreated schools have not reacted to your reform by changing schools? Or could treatment affects the decision as to when someone should leave school?
  - There may be ethical issues: why give some people treatment and not others?

Non-experimental data: Observational data

- When we have non-experimental data, we must assume that individuals at least partly determine whether they receive treatment. This may lead to problems with the simple difference-in-means estimator if the individual's decision to get treatment depends on the benefits of treatment. In such a case, we would say there is self-selection of treatment. Addressing this problem is largely what the literature on treatment effect estimation based on non-experimental data is about. Notice that this is precisely the problem solved - in principle - by randomization.
- Self-selection into treatment breaks down the independence between (y_1, y_0) and w, and so the simple difference-in-means estimator does not estimate the ATE consistently (i.e., omitted variables).

Non-experimental data: Observational data

- Suppose you are interested in evaluating the effect of a job training program on earnings using a random sample of workers, with data on earnings and on whether the individuals have received training (the treatment)
- Some people may self-select (or get self-selected by their boss) into training, depending on certain individual characteristics (e.g. highly educated individuals tend to select training more frequently than low educated individuals). Also, potential outcomes (y_1, y_0) might be positively correlated with education. Thus, (y_1, y_0) and w are both affected by a common factor (education). Therefore, the difference-in-means estimator will provide bias regarding the estimated ATE (upward bias).

Properties

- Ignorability of treatment: Control for the role played by the omitted variables in estimation: estimate the treatment effect consistently (given x).
  - Conditional on x, w and (y_1, y_0) are independent (the conditional independence assumption)
- Conditional mean independence: Comparing two individuals with the same x, the expected outcome under treatment is the same for treated individuals as for untreated individuals (selection on observables)
- Ignorability of treatment implies conditional mean independence: $ATE(x) = ATET(x)$ (need some adjustments for the consistency of the estimator)
- two ways of controlling for observable variables
  - estimation by regression
  - estimation by inexact matching

Estimation by regression

- Consider the two following equations:

$$y_0 = \mu_0 + \upsilon_0$$
$$y_1 = \mu_1 + \upsilon_1$$

- Assume $E(\upsilon_0) = E(\upsilon_1) = 0$
- In the presence of a treatment

$$y = w(\mu_1 + \upsilon_1) + (1 - w)(\mu_0 + \upsilon_0)$$
$$y = \mu_0 + w(\mu_1 - \mu_0) + \upsilon_0 + w(\upsilon_1 - \upsilon_0)$$

- Given that υ_0 and υ_1 are independent of x we get

$$ATE = (\mu_1 - \mu_0)$$

Estimation by regression

- But if υ_0 and υ_1 are a function of x

$$\upsilon_0 = \upsilon_0(x)$$
$$\upsilon_1 = \upsilon_1(x)$$

- using the assumptions that $E(\upsilon_1|x) = E(\upsilon_0|x)$
- and that $E(y_1|x, w) = E(y_1|x)$ and $E(y_0|x, w) = E(y_0|x)$
- We show that

$$ATE = ATET$$
$$E(y|x, w) = \mu_0 + \alpha w + g_0(x)$$

- where $\alpha = (\mu_1 - \mu_0) = ATE$ and $g_0(x) = E(\upsilon_1|x) = E(\upsilon_0|x)$
- using a suitable functional form for $g_0(x)$ we can obtain estimates by OLS

Matching estimators

- Estimation based on the matching involves matching treated and untreated individuals based on their observable characteristics x, and comparing how the outcome differs depending on treatment. As we have seen, exact matching involves comparing individuals for whom the values of x are identical
- In practice very difficult to implement exact matching
- A viable solution is the matching on the propensity score: Suppose we choose a propensity score $p(x)$ at random, and suppose we select two individuals with the same propensity score, where the first individual receives treatment and the second does not.
- In order to estimate the propensity score use probit or logit. The idea of the propensity score estimation is to estimate the counterfactual y_{0i} (i.e. the outcome that individual i who was treated, would have recorded had she not been treated), use one or several observations in the (untreated) control group that are similar to individual i, in terms of the propensity