UNIVERSITY OF ILLINOIS

AT URBANA-CHAMPAIGN

Measuring Treatment Effects

illinois.edu

Outline for the Session

1. Types of treatment effects
2. Calculating the Average Treatment Effect
3. Calculating the Average Treatment Effect on the Treated and Untreated
4. Calculating the Local Average Treatment Effect
5. Calculating the Marginal Treatment Effect
6. Issues in establishing the validity of your treatment effect

Types of Treatment Effects

Which Treatment Effect to Measure?

- There are a number of different ways to measure the effect of treatment
  - ATE: Average Treatment Effect
  - ATT: Average Treatment Effect on the Treated
  - ATUT: Average Treatment Effect on the Untreated
  - ITT: Intent to Treat Estimate
  - LATE: Local Average Treatment Effect
  - MTE: Marginal Treatment Effect

Which Treatment Effect to Measure?

- Different treatment effects are an average over parts of the distribution of impacts
  - The ATE averages over the entire distribution
  - The ATT averages over the distribution of impacts for those allocated to the treatment
  - The LATE averages over the distribution of impacts for those who switch into the treatment as the result of a change in an some instrument

Which Treatment Effect to Measure?

- These all represent an aggregation over different margins
  - As such, they are not comparable to each other
- As a unifying measurement Heckman and Vytlacil (2005) defined the MTE
  - The MTE is the effect of the treatment on the marginal individual entering treatment

Basic Requirements

- What is needed to measuring the treatment effect?
  - Assumptions
    - *SUTVA*
    - *Ignorability/Unconfoundedness*
  - Data
    - *Observations on outcomes for those who were treated*
    - *Observations on outcomes for some constructed control group*
- Without observations from treated individuals and from some sort of control group we cannot measure the effect of the treatment!

What We Can Never Measure

- Notice that all our measurements of treatment effects are averages
  - The Fundamental Problem of Causal Inference
  - We do not observe subject in simultaneous treated and untreated states
- So, we can never determine the effect of the treatment on an individual
  - We can only ever determine the average effect of the treatment or the effect of the treatment on an average individual

Calculating the Average Treatment Effect (ATE)

Average Treatment Effect

$$ATE = E[Y_i^T - Y_i^C]$$

- In words: the average effect on outcome of treatment for a random draw from the population

Average Treatment Effect Regression

- If we had perfect randomization then we could run the following regression

$$Y_i = \alpha + \beta T_i + \epsilon_i$$

- Then $\hat{\beta} = ATE$

Average Treatment Effect with Covariates

- Typically we only have partial randomization conditional on a set of covariates

$$ATE = E[ATE(X)]$$
$$= E[Y_i^T - Y_i^C | X = x,] = E[Y_i^T - Y_i^C]$$

- In words: the average effect on outcome of treatment for a random draw conditional on X

Average Treatment Effect Regression

- To get the ATE we just include the covariates and run the following regression

$$Y_i = \alpha X_i + \beta T_i + \epsilon_i$$

- Then $\hat{\beta} = ATE$

Calculating the Average Treatment Effect on the Treated (ATT) and Untreated (ATUT)

Average Treatment Effect on the Treated

$$ATT = E[ATT(X)]$$
$$= E[Y_i^T - Y_i^C | X = x, T = 1] = E[Y_i^T - Y_i^C | T = 1]$$

- In words: the average effect on outcome of treatment for a random draw from the subpopulation selecting (or assigned) treatment

Average Treatment Effect on the Untreated

$$ATUT = E[ATUT(X)]$$
$$= E[Y_i^T - Y_i^C | X = x, T = 0] = E[Y_i^T - Y_i^C | T = 0]$$

- In words: the average effect on outcome of treatment for a random draw from the subpopulation selecting (or assigned) no treatment

How Are All these Different?

- When we have random assignment

$$E\left[Y_i^T \middle| T = 1 - E[Y_i^C | T = 1\right] = ATT = E\left[Y_i^T\right] - E\left[Y_i^C\right] = \text{ATE}$$

- When assignment is not random and we have heterogeneous effects the ATE and ATT can be very different
  - ATE averages across gains from units that might never be subject to treatment

Calculating the Local Average Treatment Effect (LATE)

Intent to Treat (ITT)

- In some RCTs, actual treatment (T) is distinct from the variable that is randomized (Z)
- Alternatively, in a non-experimental case we can think of an instrument that we observe that affects treatment assignment but not outcome
  - Propensity Score
  - Instrumental Variable

Intent to Treat (ITT)

- In these cases our standard methods calculate the Intent to Treat estimate (ITT) instead of the ATE

$$ITT = E[Y_i|Z = 1] - E[Y_i|Z = 0]$$

From ITT to LATE

- Without going into too much detail about IVs
  - Lets assume Z is random and therefore can, in principle, be a valid instrument for T
  - Lets also assume that $Cov(Z_i, \epsilon_i) = 0$

From ITT to LATE

- We can write the effect of the randomized variable (Z) on the outcome as

$$Cov(Y_i, Z_i) = Cov(\beta T_i + \epsilon_i, Z_i) = \beta Cov(T_i, Z_i)$$

- So then $\beta = \frac{Cov(Y_i, Z_i)}{Cov(T_i, Z_i)}$

Estimating the LATE

- Our estimate of the treatment effect is then

$$\widehat{\beta_{LATE}} = \beta + \frac{Cov(Y_i, Z_i)}{Cov(T_i, Z_i)}$$

- This is known as the Local Average Treatment Effect (LATE)
  - It is only a local effect because it's the effect of T_i on Y_i for the subpopulation of compliers, and not the whole

Discussion: Deaton (2009)

- In terms of our irrigation example, suppose rainfall is our random variable (Z) that induces treatment
  - What exactly does the LATE measure?
  - What is the population over which we are averaging?
  - In our example is the LATE a parameter of interest?

Discussion: Deaton (2009)

- In terms of our irrigation example, suppose rainfall is our random variable (Z) that induces treatment
  - What exactly does the LATE measure?
  - What is the population over which we are averaging?
  - In our example is the LATE a parameter of interest?
- The LATE will typically *not* be the average effect over the treatment nor will it be the average effect over all participants
  - If treatment effects are heterogeneous, what will the LATE measure?

Calculating the Marginal Treatment Effect (MTE)

Marginal Treatment Effect

- Consider a treatment allocation rule

$$T = 1(v_i \leq \gamma Z_i)$$

  - This rule allocation could be random assignment or a propensity score or some instrument
- For a particular value of γZ_i the marginal individual is the one with

$$v_i = \gamma Z_i$$

Marginal Treatment Effect

$$MTE = E[MTE(\gamma Z_i)]$$
$$= E[Y_i^T - Y_i^C | X = x, v_i = \gamma Z_i] = E[Y_i^T - Y_i^C | v_i = \gamma Z_i]$$

- In words: the average impact for the marginal individual receiving treatment among those with value of the index equal to γZ_i
- It turns out that all the treatment effects we have looked at can be written as weighted averages of the MTE

MTE and Other Treatment Effects

- Assume
  - All individuals fall within the region of common support $U_i \in (0,1)$
  - We can measure the probability of assignment to treatment as $P(Z)$
- Then the ATE is

$$ATE = \int_{u=0}^{u=1} \Delta^{MTE}(p)dp$$

MTE and Other Treatment Effects

- Then the ATT is

$$ATT = \int_{u=0}^{u=P(z)} \Delta^{MTE}(p)dp$$

- Then the LATE is

$$\mathrm{L}ATE = \int_{u=P(z')}^{u=P(z)} \Delta^{MTE}(p)dp$$

Estimating the MTE

- We can then estimate the MTE as:

$$\beta_{MTE} = \lim_{P(z')\to P(z)} \frac{E[Y|P(Z) = P(z)] - E[Y|P(Z) = P(z')]}{P(z) - P(z')}$$

- This looks messy but it is just a slight variation on the LATE estimator which is also the IV estimator
  - We will discuss in more detail tomorrow

Estimating the MTE

- Use two stage estimation procedure
  - First, estimate participation as a function of the instrument Z to obtain the propensity score $\hat{P}(Z)$
  - Second, estimate the nonparametric local linear regression of the outcome on $\hat{P}(Z)$

$$Y_i = [T_i * Y_i^T + (1 - T_i) * Y_i^C]$$

  - Evaluating this function at different values of $\hat{P}(Z)$ yields the MTE function

Issues in Establishing the Validity of Your Treatment Effect

Replication

- Social science research is often a solitary activity.
- Researchers make decisions about coding, which groups to compare, time periods to consider, etc.
- Publication bias--significant results get published, insignificant ones remain in the file drawer
- How can we know whether a finding is correct?
- Provide incentives to replicate important papers in development economics

Registries

- Issues with RCTs--running analyses on different groups until you find something that is statistically significant.
- But even if there is no true causal effect, statistical analyses would find a significant effect 5 percent of the time
- Movement towards registries
  - Before the experiment, register what outcomes will be examined and by which groups

Is Deworming Really “All That"?

- Miguel and Kremer (2004) did an RCT in Kenya with deworming medicine
- MK found large effects on school attendance in treated groups and also spillover effects
- 3ie commissioned a replication by Davey et al.
- They did some new analyses--media picked up that MK was debunked
- Issues--looking year by year, measurement of the radius of spillover effects

Resources

- International Initiative for Impact Evaluation (3ie)
  - Provides grants and commissions studies
  - Leader in replication
  - http://www.3ieimpact.org
- Abdul Latif Jameel Poverty Action Lab
  - Advocates of RCTs
  - povertyactionlab.org
- World Bank Development Impacts blog
  - http://blogs.worldbank.org/impactevaluations/

Research Grants

- We are now just over half way through the workshop
- We wanted to end early and provide an opportunity for us to discuss with each of you
  - Our thoughts on your grant proposal
  - Ways to improve and prepare for the Phase 2 proposal