Capacity Building workshop on Impact Evaluation of Employment Programs

Experimental Design Part 1

Maciej Jakubowski, Gdańsk, February 20, 2017
Impact Evaluation

What is our objective?
Outline

• Objective of Impact Evaluation
• Perfect counterfactuals
• Bad counterfactuals
  • Before and after
  • Enrolled vs not enrolled
Our Objective

Estimate the causal effect (impact) of program (P) on outcome (Y).

Impact = \( Y^T - Y^C \)

P = Program or Treatment
Y = Indicator, Measure of Success
\( Y^T \) = Outcome with the program
\( Y^C \) = Outcome without the program (control)
Example: Progresa
Conditional Cash Transfer

✓ National anti-poverty program in Mexico
✓ Cash Transfers conditional on school and health care attendance.
✓ **Targeting**
  • Eligibility based on a poverty index
✓ **Timing:**
  • Started in 1997
  • Phased Roll-out, 5 million beneficiaries by 2004
Research Question

What is the Impact of....

...a conditional cash transfer... (P)

... on household consumption (Y)
Challenge – No counterfactual

\[ \text{Impact} = Y_T - Y_C \]

We do not observe what would have happened to the pupils if they did not receive any cash transfer (the counterfactual)?

The key to a good impact evaluation is a valid estimate of the counterfactual!
Perfect Counterfactual

CLONE/PARALLEL UNIVERSE
Perfect Experiment

First, identify the target beneficiaries ...
Perfect Experiment - Clones

... and then clone the target beneficiaries
Perfect Experiment - Clones

Give the cash transfer to one set of the clones
Perfect Experiment - Clones
... and compare their consumption some time later

• Because the people who received the cash transfer are exactly the same as those who did not receive the cash transfer, we can truly attribute the difference to the program.
Bad counterfactuals

Case 1: Before & After
**Case 1: Before & After**

(1) Observe only beneficiaries

(2) Two observations in time:
- Consumption in 1997
- Consumption in 1998

**ESTIMATE OF IMPACT =** $A - B = $35
Case 1: Before & After

Problem: we don’t know what would have happened without the program

Economic Boom:
- Real Impact = A - C
- A - B over-estimates impact

Economic Recession:
- Real Impact = A - D
- A - B under-estimates impact

Before & After problem: other things that matter also change over time!

Impact?
α = $35

Impact?
Time

Problem: we don’t know what would have happened without the program
Case 1: Before & After

<table>
<thead>
<tr>
<th>Consumption (Y)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Consumption after program start (treatment)</td>
<td>268.7</td>
</tr>
<tr>
<td>Consumption before program start (control (counterfactual))</td>
<td>233.4</td>
</tr>
<tr>
<td>Estimate of Impact</td>
<td>35.3***</td>
</tr>
</tbody>
</table>

Note: If the effect is statistically significant at the 1% significance level, we label the estimated impact with 2 stars (**).
Case 1: Before & After

Example of Labor Market Program: Youth training program
Probability of being employed after 6 months of training

(1) Observe only participants in the program

(2) Two observations in time
1997/8
1999/9

ESTIMATE OF IMPACT = A - B = -10%
Bad counterfactuals

Case 2: Comparing those enrolled with those who don’t
### Case 2: Some people enroll, others don’t

<table>
<thead>
<tr>
<th>Ineligibles (Non-Poor)</th>
<th>Enrolled</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image" alt="Ineligible" /></td>
<td><img src="image" alt="Enrolled" /></td>
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</table>

<table>
<thead>
<tr>
<th>Eligibles (Poor = Target Population)</th>
<th>Not Enrolled</th>
</tr>
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<tbody>
<tr>
<td><img src="image" alt="Not Enrolled" /></td>
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</table>

- Some people enroll, others don’t.
Case 2: Some people enroll, others don’t
Case 2: Some people enroll, others don’t

Problem of Selection Bias

What if those who choose not to enroll are different?
Case 2: Some people enroll, others don’t

Problem of Selection Bias

And, what if we cannot observe (control for) these differences...
Case 2: Some people enroll, others don’t

Problem of Selection Bias

And, these difference influence outcomes?

Are the factors that determine enrolment correlated with consumption?
Case 2: Some people enroll, others don’t

<table>
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<tr>
<th>Consumption (Y)</th>
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</thead>
<tbody>
<tr>
<td>Consumption with program (enrolled - treatment)</td>
<td>268</td>
</tr>
<tr>
<td>Consumption without program (not enrolled - control)</td>
<td>290</td>
</tr>
<tr>
<td>Estimate of Impact</td>
<td>-22**</td>
</tr>
</tbody>
</table>

Note: If the effect is statistically significant at the 1% significance level, we label the estimated impact with 2 stars (**).
Case 2: Some people enroll, others don’t
Example of Public Works Program (PWP) on first-come first-serve basis

Do you think enrolled jobseekers and those who came to register but were too late are similar?

Jobseekers who arrived early and were enrolled in the program

Jobseekers who arrived later, when no more public works jobs were available

What may be the problems in comparing these two groups?
What can you say about the impact of Progresa?
What would be the policy recommendation using Progresa?

<table>
<thead>
<tr>
<th>Impact on Consumption (Y)</th>
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<td>Case 1: Before &amp; After</td>
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<tr>
<td>Case 2: Enrolled vs Not Enrolled</td>
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Keep in Mind...

Before-After Comparison

**Problem:** other factors that matter also change over time.

Compare those who enroll with those who don’t

**Problem:** Selection bias. The enrolled may be different, and we don’t observe these differences.

Both comparison groups may lead to biased estimates of the program impact.
Example: Effect of Youth Job Guarantee on employment [Denmark]

Program
WHAT? Youth employment program (<30) with intensified activation
WHERE? 2009 to 2010, Denmark
WHY? Increase employment among long-term unemployed youth

Method/Eligibility
Researchers conducted a randomized evaluation (RCT) to test the impact of intensified ALMPs on youth employment and educational attainment. The 32-week program targeted job seekers under 30 who became or were already unemployed in the period from November 2009 to February 2010.
Out of the 3,380 participants, researchers randomly assigned 1,683 job seekers to the treatment group and 1,697 to the comparison group.

Results
The intensified program reduced employment for uneducated youth and had no impact for educated youth. In addition, job seekers in the treatment group spent more time receiving sickness benefits.
The program was not implemented as designed, and in practice, the only difference between the treatment and the comparison group was that job seekers in the treatment group met with a caseworker more frequently.