

The Counterfactual and Treatment Effects: The Conceptual Framework

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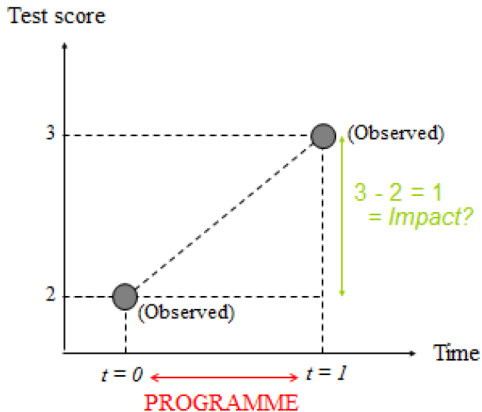
Policy Evaluation and Casual Inferences

How much did people benefit from the policy?

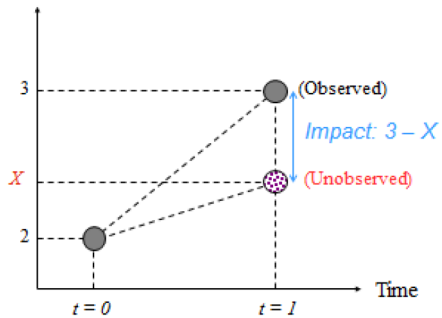
The Counterfactual: Need to know what would have happened in the absence of program

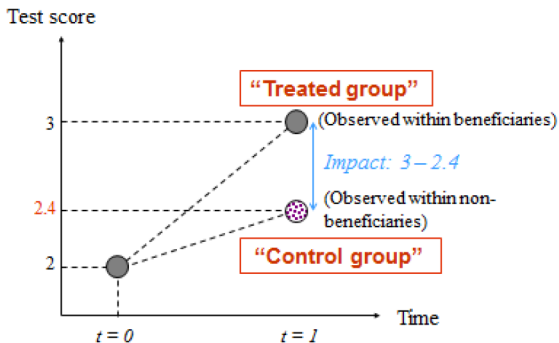
- Ideally, need to observe 2 times in the same world: 1 with the policy, and 1 without the policy
- *Ceteris paribus*

The Counterfactual: Time Series



Test score





The Counterfactual: Cross-section

Statistical association

ID	T	Y
1	0	y_1
2	0	y_2
3	0	y_3
4	1	y_4
5	1	y_5
6	1	y_6

$$\Delta = E(Y_i|T = 1) - E(Y_i|T = 0) = (\sum_{i=4}^6 y_i)/3 - (\sum_{i=1}^3 y_i)/3$$

Potential Outcomes

$$Y_i = Y_{0i} + (Y_{1i} - Y_{0i})T_i$$

ID	T	Y	Y(T=0)	Y(T=1)
1	0	y_{01}	y_{01}	y_{11}
2	0	y_{02}	y_{02}	y_{12}
3	0	y_{03}	y_{03}	y_{13}
4	1	y_{14}	y_{04}	y_{14}
5	1	y_{15}	y_{05}	y_{15}
6	1	y_{16}	y_{06}	y_{16}

Average Treatment Effects (ATE)

$$Y_i = Y_{0i} + (Y_{1i} - Y_{0i})T_i$$

ID	T	Y	Y(T=0)	Y(T=1)
1	0	y ₀₁	y ₀₁	y ₁₁
2	0	y ₀₂	y ₀₂	y ₁₂
3	0	y ₀₃	y ₀₃	y ₁₃
4	1	y ₁₄	y ₀₄	y ₁₄
5	1	y ₁₅	y ₀₅	y ₁₅
6	1	y ₁₆	y ₀₆	y ₁₆

$$ATE = E(Y_{1i} - Y_{0i}) = E(Y_{1i}) - E(Y_{0i}) = (\sum_{i=1}^6 y_{1i})/6 - (\sum_{i=1}^6 y_{0i})/6$$

Average Treatment Effects on the Treated (ATT)

ID	T	Y	Y(T=0)	Y(T=1)
1	0	y ₀₁	y ₀₁	y ₁₁
2	0	y ₀₂	y ₀₂	y ₁₂
3	0	y ₀₃	y ₀₃	y ₁₃
4	1	y ₁₄	y ₀₄	y ₁₄
5	1	y ₁₅	y ₀₅	y ₁₅
6	1	y ₁₆	y ₀₆	y ₁₆

$$\begin{aligned} ATT &= E(Y_{1i} - Y_{0i} | T = 1) \\ &= E(Y_{1i} | T = 1) - E(Y_{0i} | T = 1) \\ &= (\sum_{i=4}^6 y_{1i})/3 - (\sum_{i=4}^6 y_{0i})/3 \end{aligned}$$

Average Treatment Effects on the Un-treated (TUT)

ID	T	Y	Y(T=0)	Y(T=1)
1	0	y ₀₁	y ₀₁	y ₁₁
2	0	y ₀₂	y ₀₂	y ₁₂
3	0	y ₀₃	y ₀₃	y ₁₃
4	1	y ₁₄	y ₀₄	y ₁₄
5	1	y ₁₅	y ₀₅	y ₁₅
6	1	y ₁₆	y ₀₆	y ₁₆

$$\begin{aligned}TUT &= E(Y_{1i} - Y_{0i} | T = 0) \\&= E(Y_{1i} | T = 0) - E(Y_{0i} | T = 0) \\&= (\sum_{i=1}^3 y_{1i})/3 - (\sum_{i=1}^3 y_{0i})/3\end{aligned}$$

The Unobservability of Potential Outcomes

ID	T	Y	Y(T=0)	Y(T=1)
1	0	y_{01}	y_{01}	.
2	0	y_{02}	y_{02}	.
3	0	y_{03}	y_{03}	.
4	1	y_{14}	.	y_{14}
5	1	y_{15}	.	y_{15}
6	1	y_{16}	.	y_{16}

Selection Bias

$$\underbrace{E[Y_i|D_i = 1] - E[Y_i|D_i = 0]}_{\text{Observed difference}} = \underbrace{E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 1]}_{\text{Average treatment effect on the treated}} + \underbrace{E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0]}_{\text{Selection bias}}$$

$$\Delta = ATT + \text{Selection Bias}$$

Key Concepts

- Heterogeneity: ATT vs. TUT
- Selection: Δ vs. ATT
- Heterogeneity + Selection: Δ vs. ATE

Selection Bias: James Heckman (Nobel laureate, 2000)



Indirect (Encouraging) Interventions

ID	Z	T	T(Z=0)	T(Z=1)	Y	Y(T=0)	Y(T=1)
1	0	0	0	1	y_{01}	y_{01}	y_{11}
2	1	1	0	1	y_{12}	y_{02}	y_{12}
3	0	0	0	1	y_{03}	y_{03}	y_{13}
4	1	1	1	1	y_{14}	y_{04}	y_{14}
5	0	1	1	1	y_{15}	y_{05}	y_{15}
6	1	1	1	1	y_{16}	y_{06}	y_{16}

Intention-to-treat (ITT):

$$Z \rightarrow Y$$

ID	Z	T	T(Z=0)	T(Z=1)	Y	Y(T=0)	Y(T=1)
1	0	0	0	1	y ₀₁	y ₀₁	y ₁₁
2	1	1	0	1	y ₁₂	y ₀₂	y ₁₂
3	0	0	0	1	y ₀₃	y ₀₃	y ₁₃
4	1	1	1	1	y ₁₄	y ₀₄	y ₁₄
5	0	1	1	1	y ₁₅	y ₀₅	y ₁₅
6	1	1	1	1	y ₁₆	y ₀₆	y ₁₆

$$ITT = E(Y|Z = 1) - E(Y|Z = 0)$$

Three Players

ID	Z	T	T(Z=0)	T(Z=1)	Y	Y(T=0)	Y(T=1)
1	0	0	0	0	y_{01}	y_{01}	y_{11}
2	1	1	0	1	y_{12}	y_{02}	y_{12}
3	0	0	0	1	y_{03}	y_{03}	y_{13}
4	1	1	1	1	y_{14}	y_{04}	y_{14}
5	0	1	1	1	y_{15}	y_{05}	y_{15}
6	1	1	1	1	y_{16}	y_{06}	y_{16}

1. Compliers: $T_0 = 0, T_1 = 1$
2. Always takers: $T_0 = T_1 = 1$
3. Never takers: $T_0 = T_1 = 0$

Local Average Treatment Effect (LATE): $T \rightarrow Y$

ID	Z	T	T(Z=0)	T(Z=1)	Y	Y(T=0)	Y(T=1)
1	0	0	0	1	y_{01}	y_{01}	y_{11}
2	1	1	0	1	y_{12}	y_{02}	y_{12}
3	0	0	0	1	y_{03}	y_{03}	y_{13}
4	1	1	1	1	y_{14}	y_{04}	y_{14}
5	0	1	1	1	y_{15}	y_{05}	y_{15}
6	1	1	1	1	y_{16}	y_{06}	y_{16}

$$LATE = E(Y_{1i} - Y_{0i} | T_0 = 0, T_1 = 1)$$

$$\text{Wald estimator: } LATE = \frac{ITT}{E(T|Z=1) - E(T|Z=0)} = \frac{E(Y|Z=1) - E(Y|Z=0)}{E(T|Z=1) - E(T|Z=0)}$$

No Never Takers

ID	Z	T	T(Z=0)	T(Z=1)	Y	Y(T=0)	Y(T=1)
1	0	0	0	1	y ₀₁	y ₀₁	y ₁₁
2	1	1	0	1	y ₁₂	y ₀₂	y ₁₂
3	0	0	0	1	y ₀₃	y ₀₃	y ₁₃
4	1	1	1	1	y ₁₄	y ₀₄	y ₁₄
5	0	1	1	1	y ₁₅	y ₀₅	y ₁₅
6	1	1	1	1	y ₁₆	y ₀₆	y ₁₆

$$LATE = TUT$$

No Always Takers

ID	Z	T	T(Z=0)	T(Z=1)	Y	Y(T=0)	Y(T=1)
1	0	0	0	0	y ₀₁	y ₀₁	y ₁₁
2	1	0	0	0	y ₀₂	y ₀₂	y ₁₂
3	0	0	0	0	y ₀₃	y ₀₃	y ₁₃
4	1	1	0	1	y ₁₄	y ₀₄	y ₁₄
5	0	0	0	1	y ₀₅	y ₀₅	y ₁₅
6	1	1	0	1	y ₁₆	y ₀₆	y ₁₆

$$LATE = ATT$$

Neither Never Takers, Nor Always Takers

ID	Z	T	T(Z=0)	T(Z=1)	Y	Y(T=0)	Y(T=1)
1	0	0	0	1	y ₀₁	y ₀₁	y ₁₁
2	1	1	0	1	y ₁₂	y ₀₂	y ₁₂
3	0	0	0	1	y ₀₃	y ₀₃	y ₁₃
4	1	1	0	1	y ₁₄	y ₀₄	y ₁₄
5	0	0	0	1	y ₀₅	y ₀₅	y ₁₅
6	1	1	0	1	y ₁₆	y ₀₆	y ₁₆

$$LATE = ATT = TUT = ATE$$

An Alert: Defiers

ID	Z	T	T(Z=0)	T(Z=1)	Y	Y(T=0)	Y(T=1)
1	0	0	0	0	y ₀₁	y ₀₁	y ₁₁
2	1	1	0	1	y ₁₂	y ₀₂	y ₁₂
3	0	0	0	0	y ₀₃	y ₀₃	y ₁₃
4	1	1	1	1	y ₁₄	y ₀₄	y ₁₄
5	0	1	1	0	y ₁₅	y ₀₅	y ₁₅
6	1	1	1	1	y ₁₆	y ₀₆	y ₁₆

No answer to the question, and need to redesign the experiment.

A Final Remark

Behavioral inferences from the comparisons between Δ , ATE, ATT, TUT, ITT, and LATE are very important!

Need a new framework —Roy Model

Construct Proper Counterfactual

- Experimental approach
- Quasi-experimental approaches
 - Conditional independence, regression, and matching
 - Fixed effects, difference-in-differences, and panel data
 - Excludability and instrumental variable method
 - Jump and regression discontinuity design

Construct proper counterfactual, impact evaluation methods, identification strategies

- The manner in which a researcher uses observational data (i.e., data not generated by a randomized trial) to approximate a real experiment (Angrist and Krueger, 1999)

Policy evaluation, causal inferences

Summary

- Program evaluation
- The counterfactual: The fundamental challenges to program evaluation.
- Treatment effects:
 - ATE
 - ATT
 - TUT
 - ITT
 - LATE