
Causal Inference for Frontline Research: *Concept, Frameworks, and Applications*

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Roadmap

Topics and Exercises

What is Causal Inference?

Growth, Examples, and Definitions

Cross-Sectional Methods

Assumptions (Unconfounded Assignment and Positivity)

Methods

Example: Random Assignment and Meta-Learner (t-learner)

SUTVA

Assumptions (Stable Treatment, No Contamination)

Example: Regional Distributed Treatment (No Interference Violation)

Panel Methods

Assumptions (Parallel Trends, No Anticipation, No Spillover)

Methods

Example: Counterfactual Imputation Estimator

Concluding Remarks

Causal Inference Flowchart

Growth in Causal Inference

Why now? What's changed?



“Credibility Revolution”



**Data Access and Method
Development**



Policy Evaluation Importance

What IF?

(What is the Effect of Bluey on Maddie's Mood?)

Individual



Treatment



Observed Outcome



Counterfactual Outcome



Treatment Effect

What are we estimating?

Potential Outcomes Notation

Treatment Assignment

$$D_i = \begin{cases} 1 & \text{if individual } i \text{ is given treatment} \\ 0 & \text{if individual } i \text{ is not given treatment} \end{cases}$$



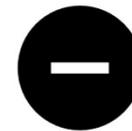
Outcome

$$Y_i = \begin{cases} Y_1 & \text{the outcome if } i \text{ is given treatment} \\ Y_0 & \text{the outcome if } i \text{ is not given treatment} \end{cases}$$



Individual Treatment Effect

$$\tau_i = Y_i(1) - Y_i(0)$$



What are we estimating?

Potential Outcomes – Aggregate Measures

ATE – Average Treatment Effect

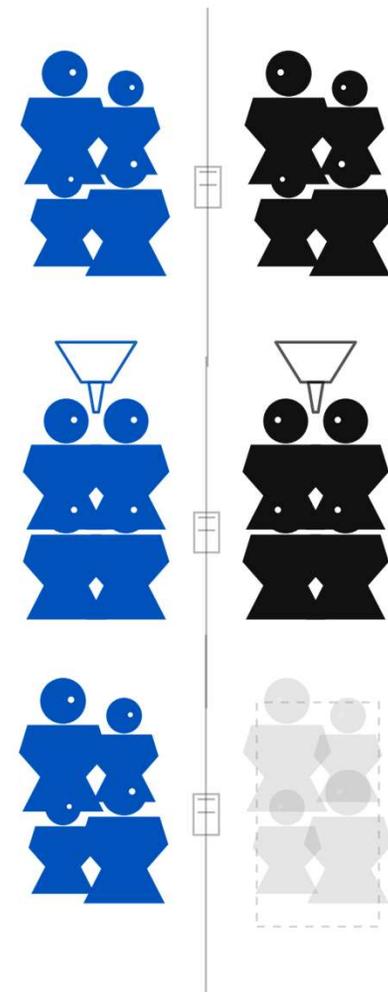
$$ATE_t = E[Y_t(1) - Y_t(0)]$$

CATE – Conditional Average Treatment Effect

$$CATE_t = E[Y_t(1) - Y_t(0)|X]$$

ATT – Average Treatment Effect on the Treated

$$ATT_t = E[Y_t(1) - Y_t(0)|D_t = 1]$$



Cross-Sectional Approaches

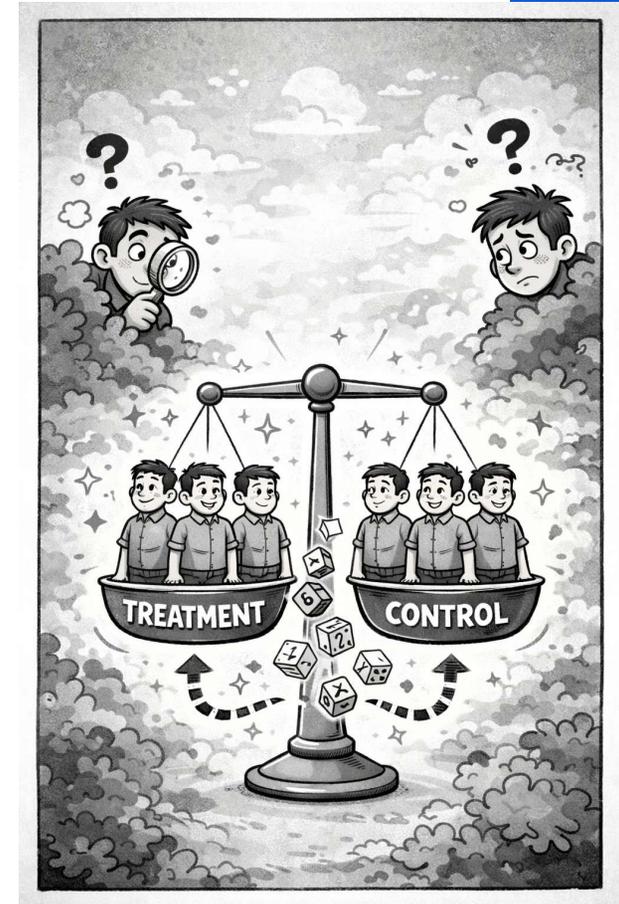
Underlying Assumptions – Unconfounded Assignment

Once you account for the information that drove treatment decision, treatment (D) is independent of outcome (Y)

$$(Y(1), Y(0)) \perp D \mid X$$

Why: avoids selection bias from X (the drivers of D)

Evidence: Untestable – justify with assignment story and substantive knowledge



Cross-Sectional Approaches

Underlying Assumptions – Overlap/Positivity

For each covariate profile in the target population, there is positive probability of being treated and untreated

$$0 < e(X) = \Pr(D = 1 | X = x) < 1 \text{ for all } x$$

Why: Ensure that counterfactual values are constructed by interpolation (nearby observations)

Overlap (positivity): propensity score overlap; weights not extreme; effective sample size not collapsing

Balance (after design): standardized mean differences or PSB scores (McCaffery 2013).

Cross-Sectional Approaches

What if you only have 1 outcome after treatment per individual?

**Regression
Adjustment**

**Inverse Propensity
Weighing**

AIPW

**Double Machine
Learning
(Regression)**

ATE
(Average Effects)

Causal Forest

**Meta-learners
(s-, t-, x-learners)**

**Bayesian Adaptive
Regression Trees**

**Double Machine
Learning
(Influence Function)**

CATE
(Heterogeneity)

Matching

Balancing Weights

Design-Based Balancing

Cross-Sectional Approaches

Random Assignment and t-learner in Excel

We want to study how a particular training program affects the performance of our frontline workers.

We consider three designs of treatment

- 1) Random Assignment
- 2) Non-random assignment, but with overlap
- 3) Non-random assignment, but without overlap

Goal: Lack of overlap -> Extrapolation not Interpolation

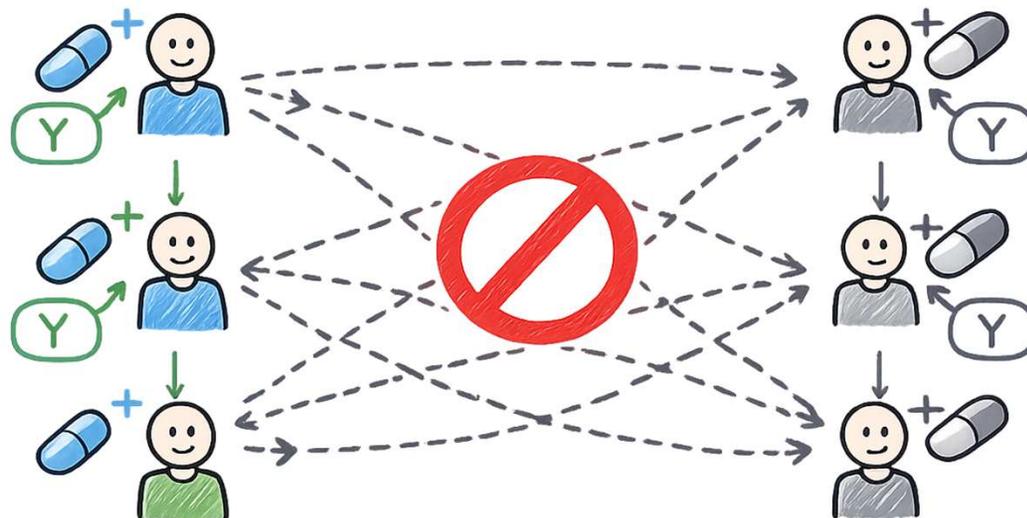


SUTVA

What is it? What are the Assumptions?

Ensures no bias in the estimation of treatment effects

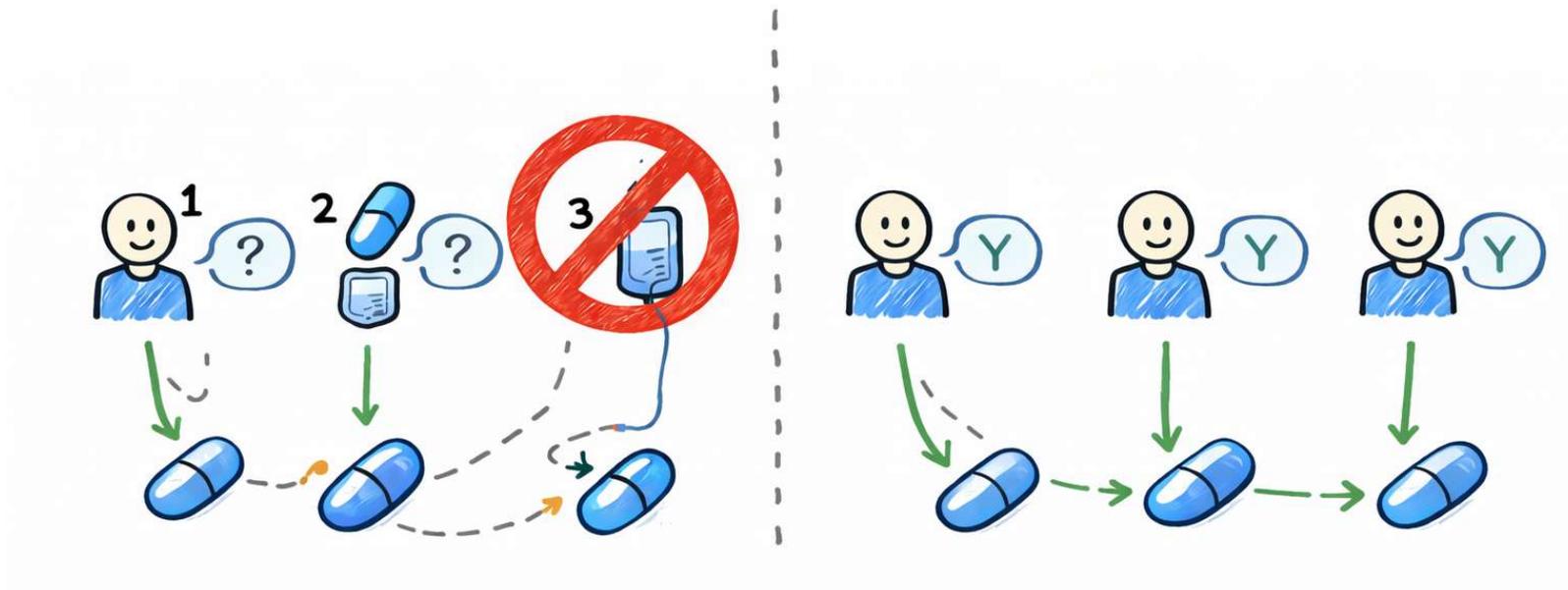
No Interference – my treatment today does not affect your ability to be treated nor your outcomes



SUTVA

What is it? What are the Assumptions?

No hidden treatment levels – everyone gets the exact same treatment



SUTVA

Exercise – Importance of no interference

We want to compute the value of giving a new AI training tool to reps.

Partial random assignment of new AI training tool at different locations and it is the same tool.

What if those reps using the tool end up helping out other reps?

Goal: No interference violation -> Bias Results



Panel Approaches

Underlying Assumptions

1. No anticipation

People did not change their behavior prior to treatment if they knew they would be treated

Test: Pre-trend plots



2. No carryover

If treatment turns “off” you go back to prior behavior

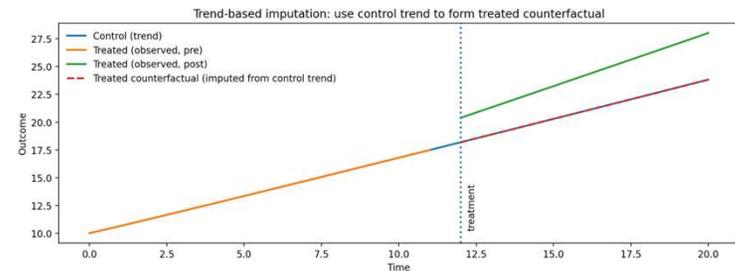
Test: Post-treatment plot or time regression coefficients



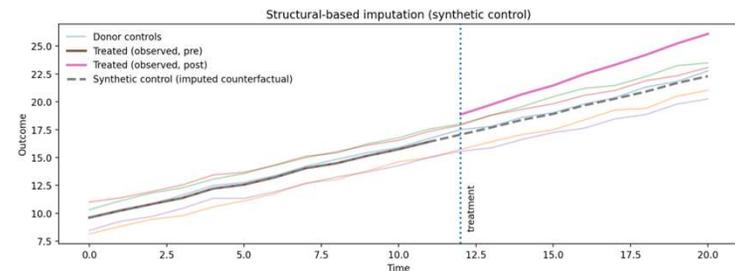
Panel Approaches

Underlying Assumptions

Trend-Based Imputation: Treated units would behave as untreated units absent treatment and follow same path (Parallel Trends)



Structure-Based Imputation: Untreated outcomes have stable structure (convex combination, factor model, low rank) so you can predict the missing trajectory.

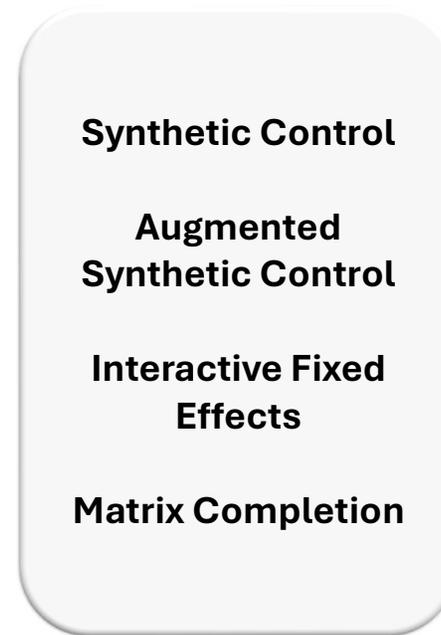


Panel Data Approaches

What if you care about effects over time?



*Trend-Based Imputation
(Parallel Trends Required)*



*Structure-Based Imputation
(“Reconstructability” Required)*

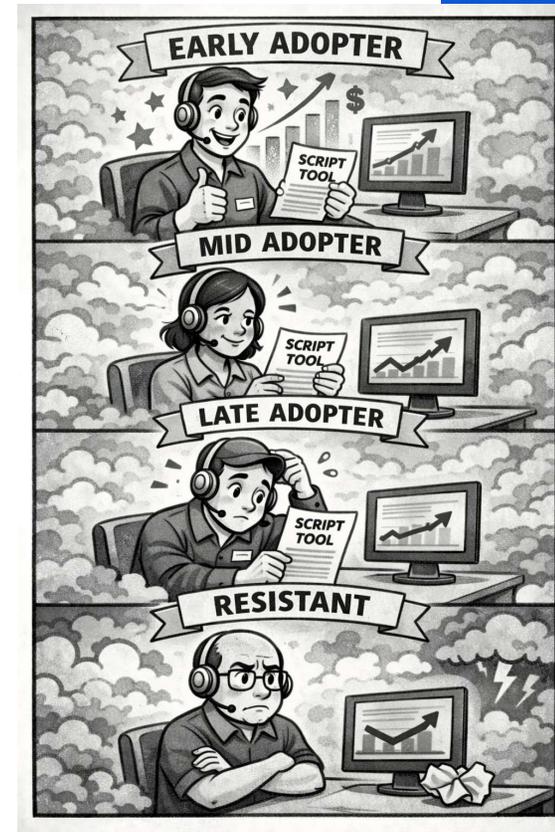
Panel Approaches

Excel Exercise – Counterfactual Imputation

Assume agents at a call center are given access to a script tool where different agents adopt its use at different times.

We observe the weeks when the rep has access to it and we calculate the average Handle Time of the calls by the reps.

Goal: Heterogeneity and Differential Timing Biases Results -> Counterfactual Imputation (Liu et al 2023)



Common Failure Models

Summary of Major Road Blocks

Post-treatment adjustment (bad controls)

Risk: conditioning on variables affected by treatment can induce bias

Limited overlap / weak common support

Risk: estimated effects rely on functional-form assumptions (extrapolation).

Selection into treatment (unobserved confounding)

Risk: unconfounded assignment may fail if important drivers of both D and Y are unmeasured.

Treatment mismeasurement / multiple versions of treatment

Risk: the estimand becomes ill-defined if “treatment” varies in content or intensity across units.

Interference / spillovers (SUTVA violations)

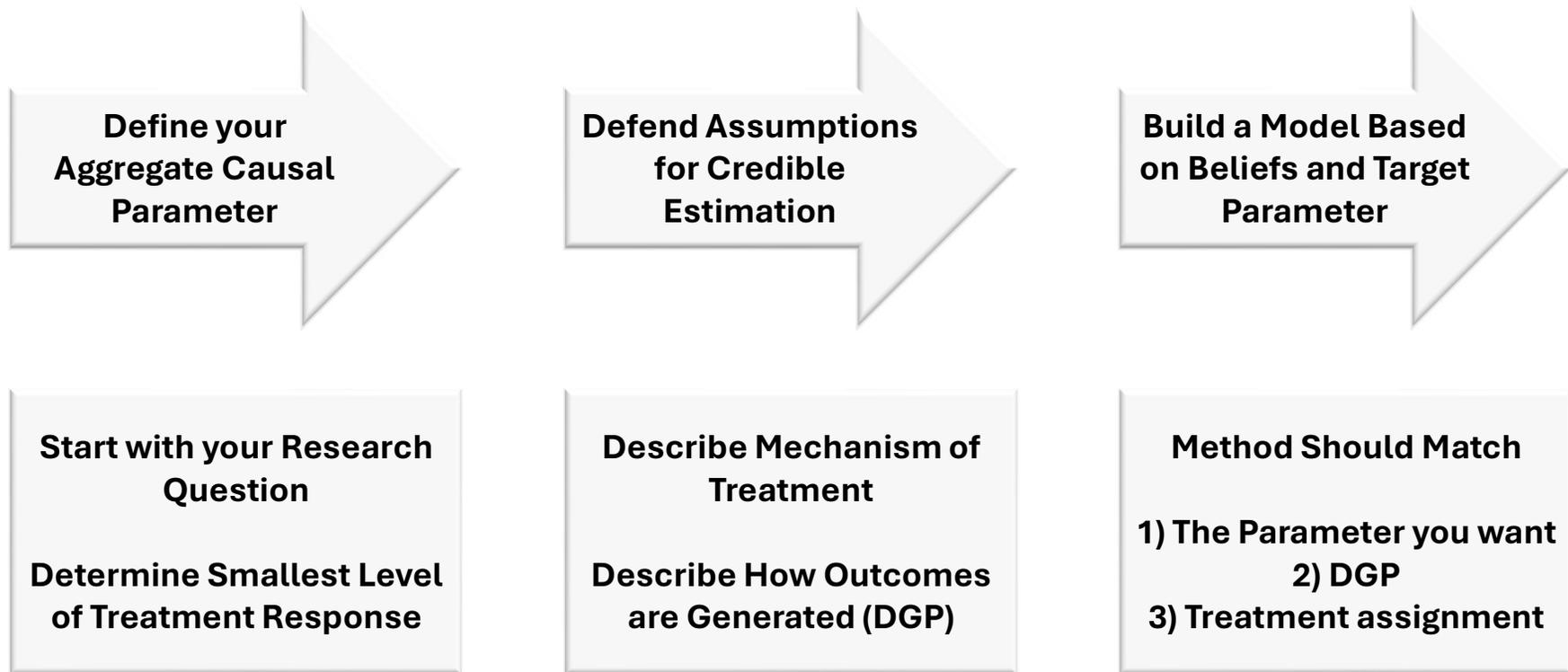
Risk: one unit’s treatment affects another unit’s outcome, so unit-level potential outcomes are not well-defined.

Panel designs: differential timing + heterogeneous effects

Risk: two-way fixed effects can mix comparisons across cohorts and periods in unintuitive ways.

Causal Analysis Building Blocks

Modeling Is Not the First Step



Scott Cunningham "Causal Inference: The Mixtape"

Causal Analysis As Missing Data Workflow

Different Methods, Same Logic

Core Problem: Each observation has at least one potential outcome missing (counterfactual)

Identification: Assumptions determine the credibility of imputation

Estimation: Regression is a baseline imputer, ML can enhance imputation with complex response surfaces

Practice: Cleanly state assumptions (treatment) assignment and provide diagnostics to support claims

Thank You!



Research Website



LinkedIn Profile