

Assessing the Impact of Financial Literacy

Session 1

Today

- **Introductions and ice breakers**
- **Session 1:**
 - Causal inference framework
 - RCT theoretical overview
- **Session 2:**
 - Nuts and Bolts of RCTs
- **Session 3:**
 - Applications of RCTs in Financial Literacy

Introductions

- Lets get to know each other first!
- Everyone please answer the following:
 - Name
 - Background (University, degree program, which year)
 - What's your favorite city to live in and why?
 - If you could pick a superpower, what would it be and why?

Framework for Empirical Methods in Causal Inference

$$Y = T\theta + X\beta + \varepsilon$$

Y: Savings

T: Treatment (e.g., Financial literacy training)

X: Other controls

Ideally

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$$\theta = \underbrace{E(Y^T | T)} - \underbrace{E(Y^C | T)} = E(Y^T - Y^C | T)$$

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Ideally

$$\theta = \underbrace{E(Y^T | T)}_{\text{Outcome for treated individuals if they were treated}} - \underbrace{E(Y^C | T)}_{\text{Outcome for treated individuals had they not been treated}} = E(Y^T - Y^C | T)$$

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$$\theta = \underbrace{E(Y^T | T)}_{\substack{\text{Outcome for treated} \\ \text{individuals if they} \\ \text{were treated}}} - \underbrace{E(Y^C | T)}_{\substack{\text{Outcome for treated} \\ \text{individuals had they} \\ \text{not been treated}}} = E(Y^T - Y^C | T)$$

Unobserved!

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Unobserved!

So we cannot conduct this comparison!

Instead, we estimate

$$\theta: E(Y^T | T) - E(Y^C | C)$$

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Now, add & subtract $E(Y^C | T)$:

$$\theta = \underbrace{E(Y^T | T) - E(Y^C | T)} + \underbrace{E(Y^C | T) - E(Y^C | C)}$$

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Now, add & subtract $E(Y^C | T)$:

$$\theta = \underbrace{E(Y^T | T) - E(Y^C | T)}_{\text{Average Treatment Effect}} + \underbrace{E(Y^C | T) - E(Y^C | C)}_{\text{Selection Bias}}$$

Average Treatment Effect

Selection Bias

If treatment randomly assigned:

Selection bias =

If treatment randomly assigned:

Selection bias = 0

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Outcome Y is independent of assignment to treatment:

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If treatment randomly assigned:

Selection bias = 0

Outcome Y is independent of assignment to treatment:

$\{Y^T, Y^C\} \perp\!\!\!\perp T \quad \longrightarrow \quad \text{Independence property}$

Intuition: This property defines the counterfactual

Had the treatment not existed, then $Y^T = Y^C$

When we don't have random assignment, we can control for things we think explain selection bias.

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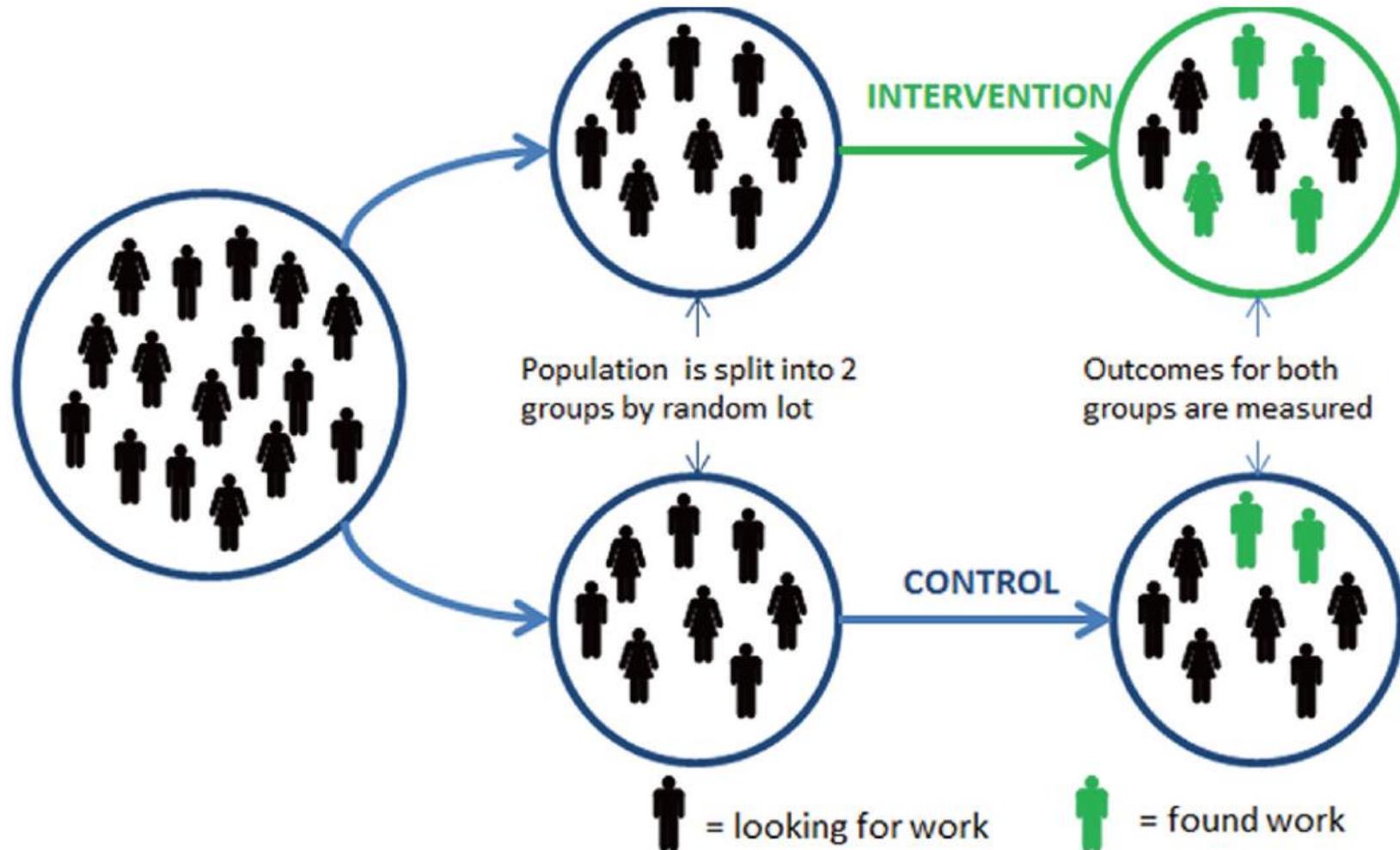
Conditional independence:

$$\{Y^T, Y^C\} \perp\!\!\!\perp T \mid X_k$$

Randomized Control Trials

Concept and Applications

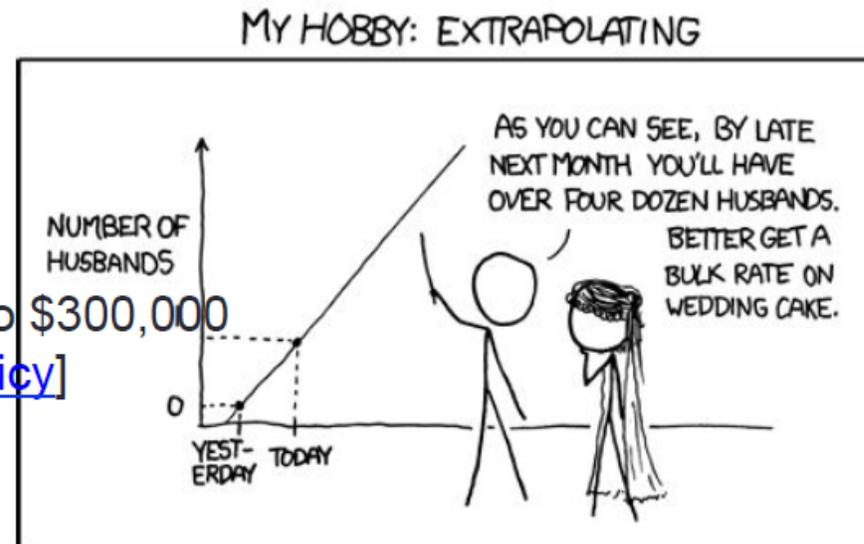
What is an RCT?



Why do we like RCTs?

- Randomly assigning treatment reduces selection bias
- Balances both observable *and unobservable* characteristics between treatment and control groups
- Statistically, this means that post-treatment differences can be interpreted as a *causal effect* of treatment
- **Some concerns**
 - Ethical challenges
 - Practical challenges
 - Evaluation is expensive!
 - Study costs range from \$50,000 to \$300,000
 - External validity challenges

[\[Coalition for Evidence-Based Policy\]](#)



Regression Specification

- RCT regressions are extremely straightforward
- Since Selection/Endogeneity/OVB are, by design, eliminated, we can run a simple OLS:

$$Y_i = \alpha + \beta \cdot Treatment_i + \varepsilon_i$$

Average Treatment Effect: ITT vs TOT/LATE

- We are interested in the Average Treatment Effect of a particular intervention.
- When treatment is randomly assigned, there are two possible reactions within the sample:
 - All assigned to treatment take it up
 - *Some* assigned to treatment take it up

Full Compliance

- Full compliance means:
 - All those assigned the treatment take it up
 - All those assigned to control do not take up the treatment
- In this world, $ATE = ITT$
- We take the average value of outcome of interest in each group (treatment group and control group) and subtract the two to get ATE.

Partial Compliance

- Full compliance is rare. *Partial* compliance can include:
 - Non-takers in the treatment group
 - Spillovers (Always-takers) in the control group
- When there is partial compliance, we no longer calculate an ATE. Instead, we can estimate the ITT and the TOT/LATE

ITT vs TOT/LATE

- ITT is still calculated the same way, using original assignment to calculate differences in means.
- TOT/LATE estimates effect of treatment on those who took it up.
 - Can we estimate this directly? Why or why not?

TOT/LATE

- We estimate the TOT using an IV strategy:
 - Use assignment to treatment as instrument for being treated:
 - Stage 1: Regress Treatment take-up on Treatment Assignment and obtain predicted values.
 - Stage 2: Regress outcome (Y) on predicted values.
- These regression estimate the local average treatment effect or treatment on treated.

ITT or TOT?

- ITT is more relevant for a policy maker who is interested in expanding the policy elsewhere.
- TOT is relevant for understanding if underlying treatment itself is valuable.
- In practice, both estimates are useful.