Causal Inference - Mini Course

session 1 — intro: identification, estimation, and inference

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August 23

Intro

About this course

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   - a fallback if other methods are unavailable?

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Problem sets with data for self-study will be shared after classes

Learning goals

1. Understanding of the concept of causality
2. Basic knowledgie of 3 canonical research designs (RCT, RD, DD)
3. Ability to apply these designs to own work
4. Ability to critically assess other work using these strategies

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I assume familiarity with linear regression and conditional expectations

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The problem

Terminology: Treatment effects, Counterfactual

Ex.: Job training program

A training for low-wage workers to improve their skills.

- What is a treatment effect?
  - The difference in outcomes between what happened and what would have happened without the program.

What is a counterfactual?

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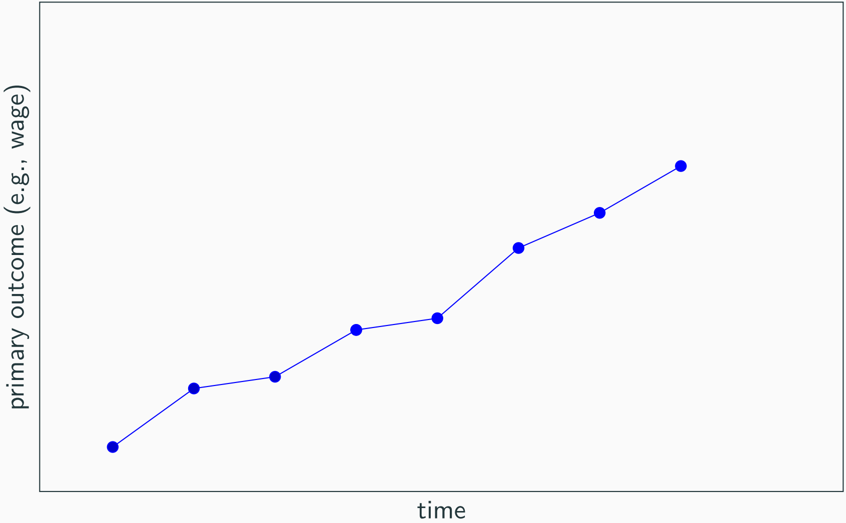
All causal inference is about finding credible answers to **"what if?"-questions**

Measuring effects



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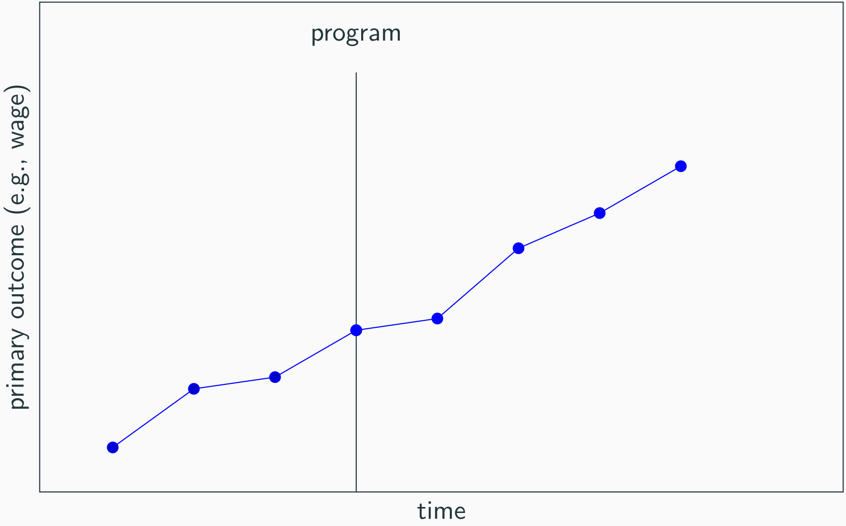

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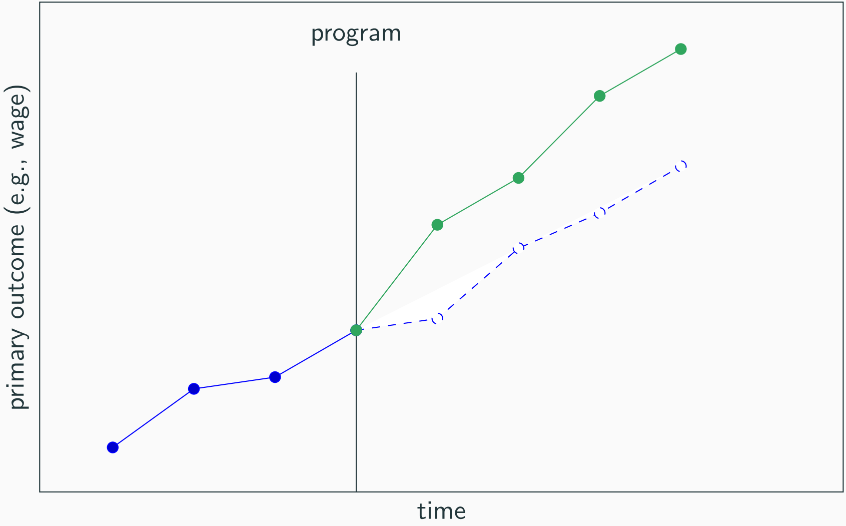

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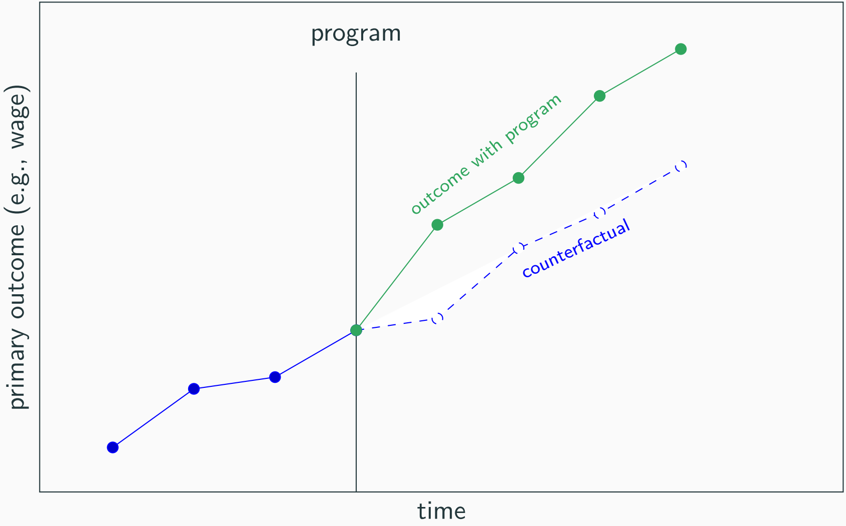

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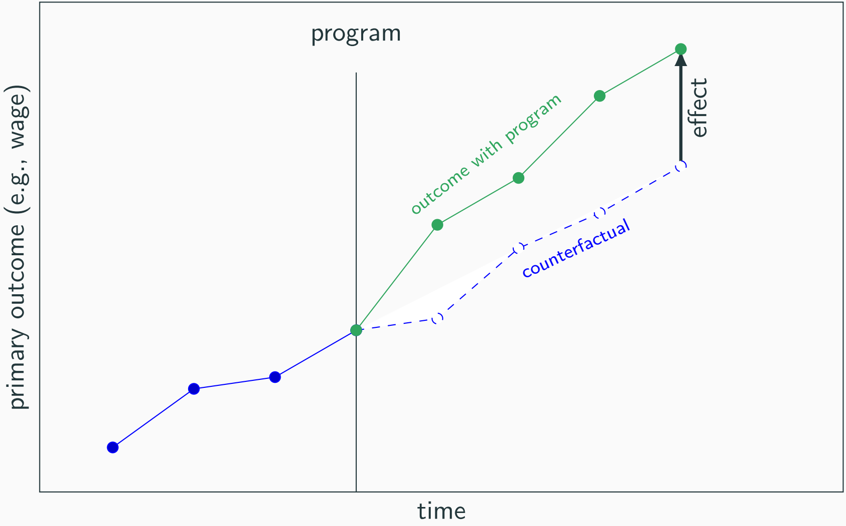

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1. Do participants prior to the program make a good counterfactual?
   - **Generally no!**

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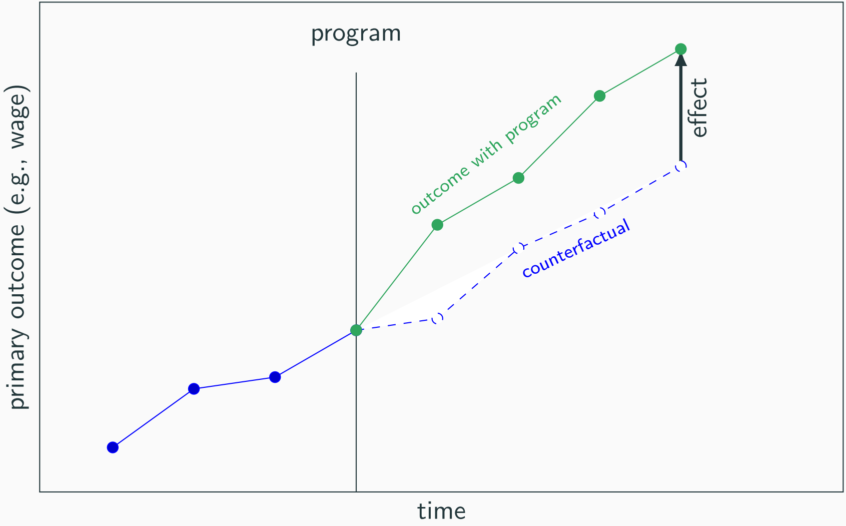
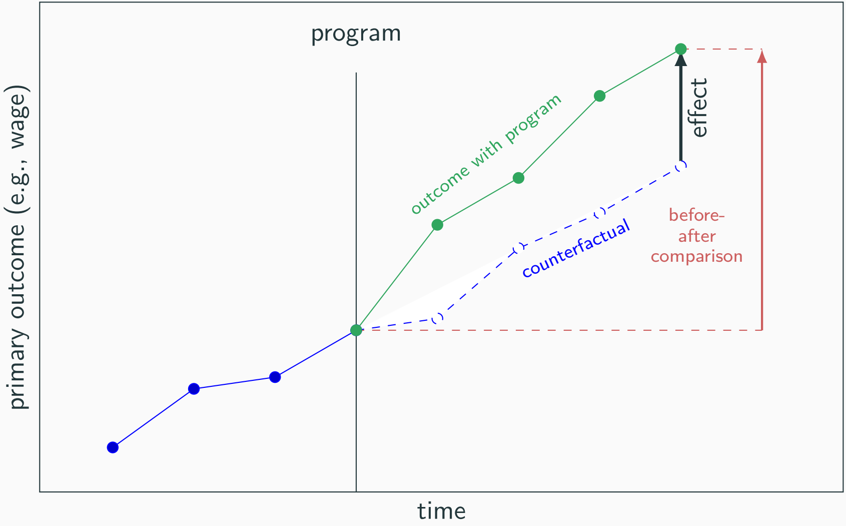


Measuring effects: Why not compare before and after? Trends



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1. Do participants prior to the program make a good counterfactual?
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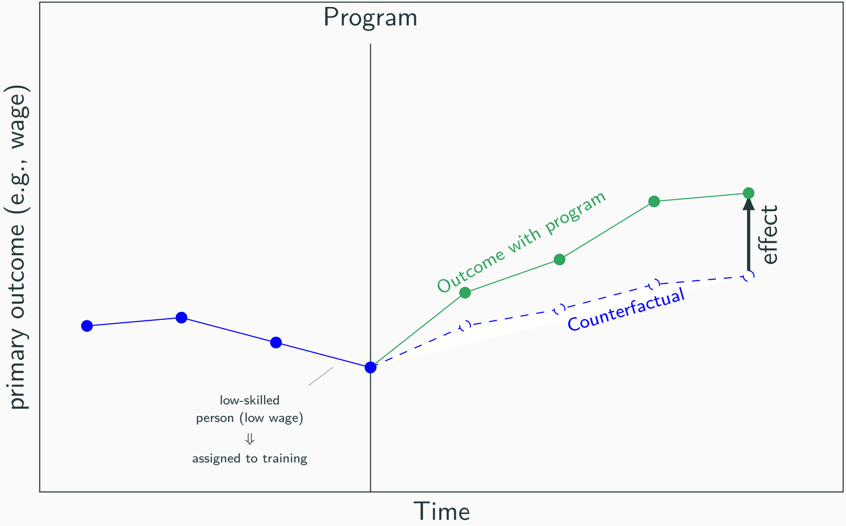
2. Do people who choose not to participate (are not assigned to participation) make a good counterfactual?
    - **Generally no!**

Why not compare participants and non-participants?



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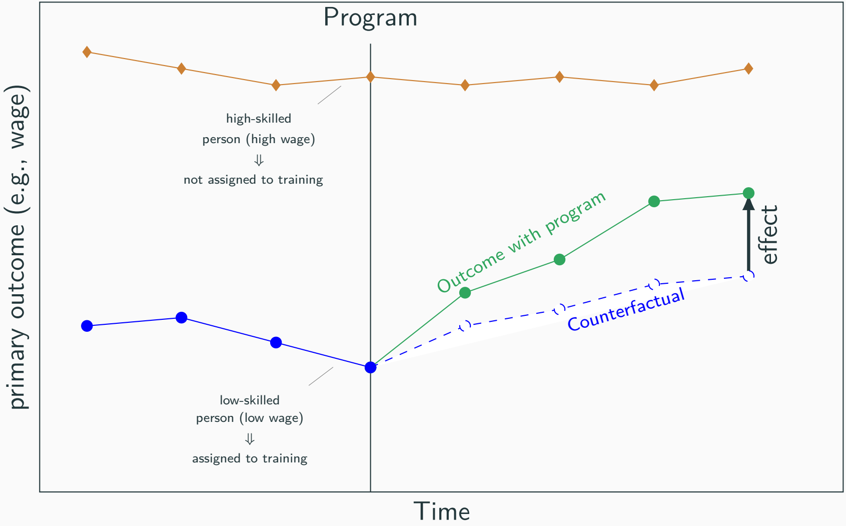

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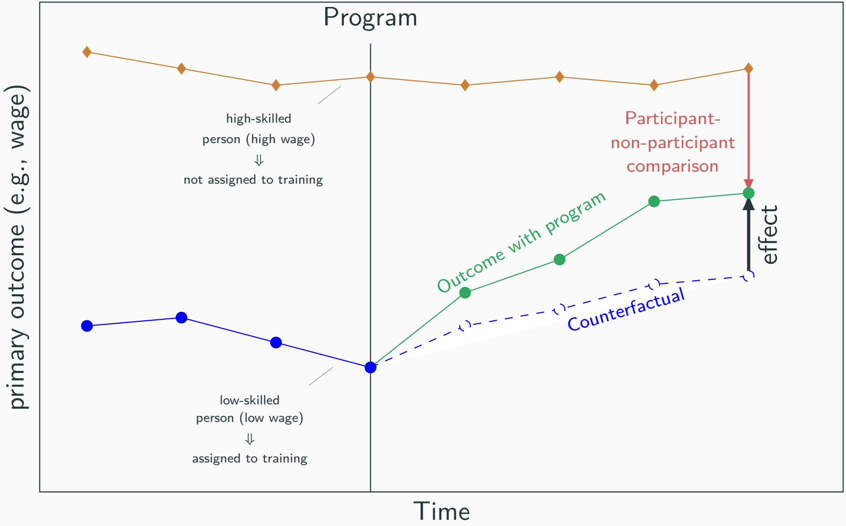

Recap

- to estimate effects, need to estimate the counterfactual ("what if"-scenario)
- observable outcomes (pre-intervention baseline outcomes, or non-participants) provide poor counterfactuals

Why care about causality

many interesting econometric questions are causal questions

Q: do people send their kids to school if they have a more stable income?

questions are about the underlying structure of the observable world

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Identification, estimation, inference

sample/data

population

underlying structure

Identification, estimation, inference

sample/data — observed

population — observable

underlying structure — unobservable

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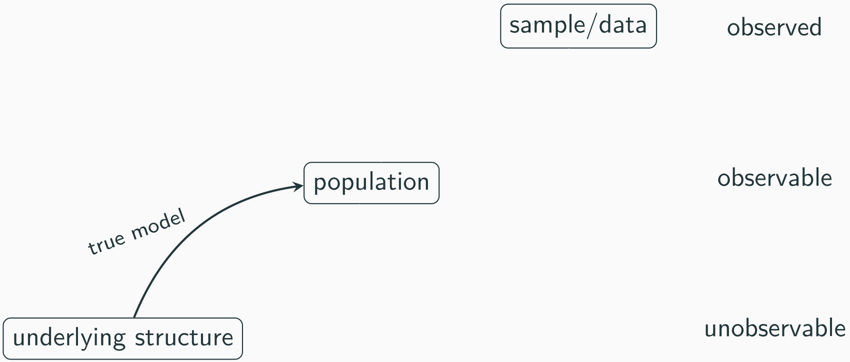

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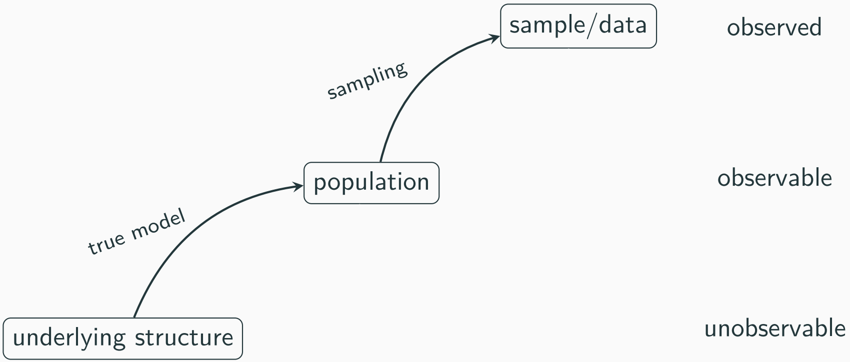

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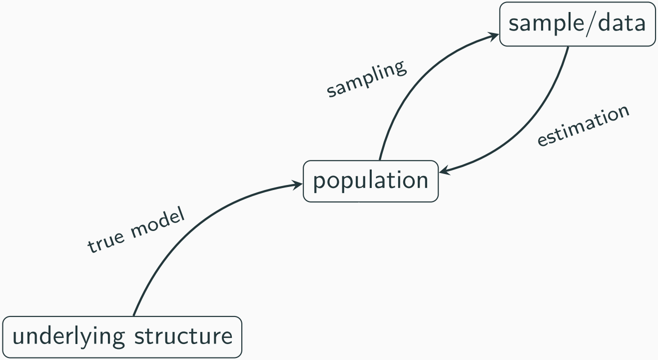

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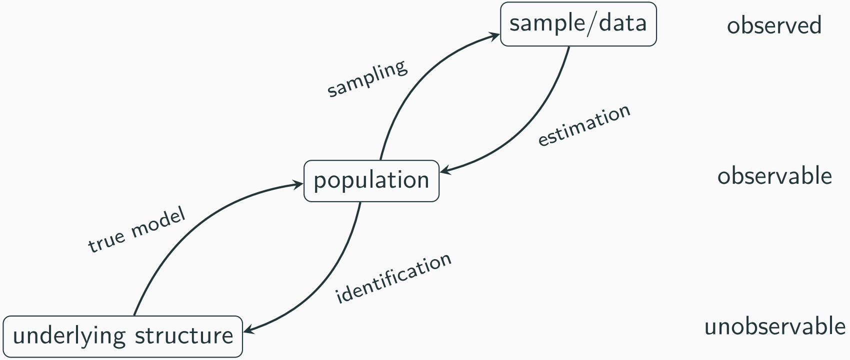

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Ex.: identification

if we have a randomized experiment, the causal effect is identified by a difference in population means of the treated and untreated population (more on this later.)

Estimation (and inference)

- learning about a population distribution
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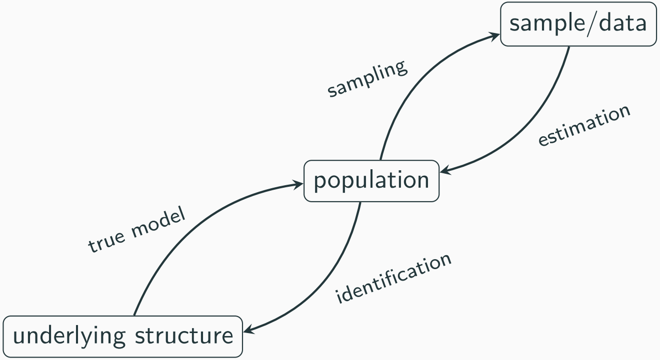
Note:

- "inference" sometimes refers to the last step (e.g., conducting a test) and sometimes to the whole process (as in the title of this class)

Identification, estimation, inference



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Recap

- examples of causal questions
- identification: linking population characteristics to causal mechanisms
- estimation: learning about population characteristics from a sample

Next:

- identification
  - potential outcome framework
  - selection bias
  - a tour through **identification strategies**
- some words on estimation

Potential outcomes

Counterfactuals

Causal analysis tries to answer 'what if'-questions

Cal took a job training and later on earned US$40k.

- Did the training improve Cal's wage?
- What would Cal earn in the *counterfactual* world where Cal did not take the training?

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- Let's formalize the problem to see if we can solve it.
  - I.e., if we can learn something about the counterfactual.

The potential outcome framework ...

... conceptualizes the idea of counterfactuals

- binary treatment: $D_i = 1$ if treated, $D_i = 0$ if not
- every unit i has two potential outcomes: y_i^0 and y_i^1

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$$\Delta_i = y_i^1 - y_i^0.$$

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- this is never observable. but summary measures of its distribution can be identified, e.g.:
  - the average treatment effect (ATE): $\mathbb{E}[\Delta_i]$

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$$\text{ATE} = \mathbb{E}[\Delta_i] = \mathbb{E}[y_i^1 - y_i^0]$$

or the conditional version:

$$= \mathbb{E}[y_i^1 - y_i^0 | x_i].$$

where x_i is a vector of observed characteristics (e.g., age, gender, etc.).

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ATE measures average effects of treatment on a unit in the population

- average effect of job training on wages among all unemployed
- average effect of smoking on the probability of developing cancer

A note on heterogeneity

- ATE looks at *average effects*
- treatment effects can be heterogeneous:
  - a development intervention may help some but leave others worse off
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- ATE might be positive even if the majority has a negative Δ_i
- studying heterogeneous treatment effects is a large field of research
  - looking at heterogeneity may help understand **how** a treatment works (mechanism)

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=&\underbrace{\mathbb{E}[y_i^1 - y_i^0|D_i = 1]}_{\text{ATE among all with } D_i = 1} + \underbrace{\mathbb{E}[y_i^0|D_i = 1] - \mathbb{E}[y_i^0|D_i = 0])}_{\text{selection bias}}
\end{aligned}
$$

- first term is the treatment effect
- second term is a confounding selection bias
  - zero if potential outcomes are independent from treatment ($\mathbb{E}[y_i^0|D_i = 1] = \mathbb{E}[y_i^0|D_i = 0]$)

Selection bias (2)

Ex.: selection bias in job training

People who enroll in job training differ in terms of unobservable characteristics (motivation, mindset, etc.) from people who do not.

Iff D_i is assigned independently from potential outcomes (e.g., by coin toss) **then** comparing means between groups identifies the causal effect

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Recap

- Potential outcomes conceptualize the idea of counterfactuals.
- An ATE is a summary of “underlying structure” that is useful in identification arguments and to describe causal effects.
- Selection bias implies that simple comparisons between treated and untreated observations do not identify the ATE.

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- An ATE is a summary of "underlying structure" that is useful in identification arguments and to describe causal effects.
- Selection bias implies that simple comparisons between treated and untreated observations do not identify the ATE.

Next:

- Identification strategies that overcome selection bias.

RCTs

Independence of treatment and potential outcomes: RCTs

- no selection bias if D_i and potential outcomes are independent
- easiest way to ensure independence is to flip a coin for each person to decide if they get treatment:
  - a randomized control trial (RCT)

100 village; 50 are randomly selected to open a microfinance bank

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- shorter but successful track record in social sciences (Econ Nobel Prize 2019 for Banerjee, Duflo, Kremer)

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Causal identification strategies as generalizations of RCTs

Generalizing from D_i random ...

(RD) ... to D_i random conditional on $x_i \in (\bar{x} - c, \bar{x} + c)$ for $c \to 0$.

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(DD) ... to D_i random relative to $y^0_{i,t} - y^0_{i,t-1}$.

RD

Regression discontinuity designs – Two identifying assumptions

1.

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1. Discontinuous assignment of treatment: Treatment is determined based on whether an observable continuous running variable x exceeds some threshold $\bar{x}$.

$$D_i = \begin{cases} 1 \text{ if } x \geq \bar{x} \\ 0 \text{ if } x < \bar{x} \end{cases}$$

- e.g., students scoring $> 95\%$ get a stipend ...

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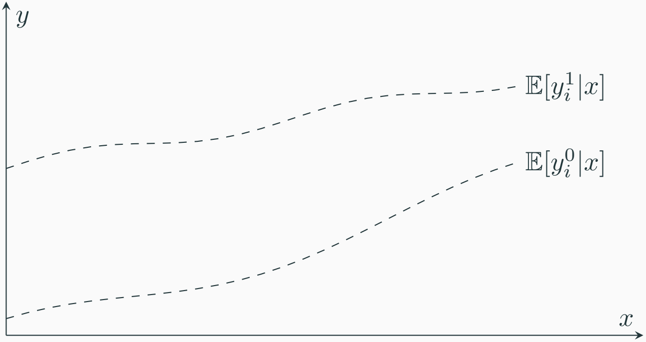
   - e.g., students scoring $> 95\%$ get a stipend ...

2. Continuous mean of potential outcomes:
   - $\mathbb{E}[y_i^1|x]$ and $\mathbb{E}[y_i^0|x]$ are continuous in x.

Then, the conditional ATE at $x = \bar{x}$, $\mathbb{E}[y^1 - y^0|x = \bar{x}]$, can be identified.

Regression discontinuity designs – graphical illustration



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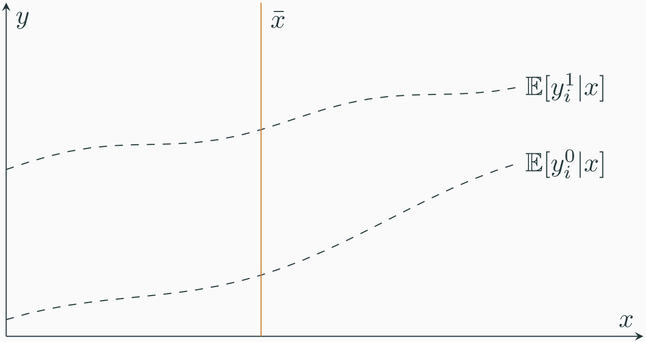

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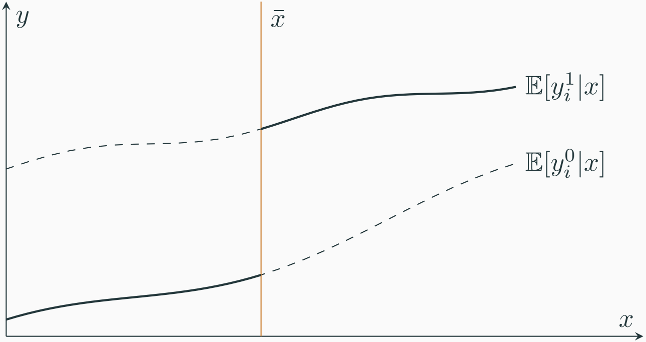

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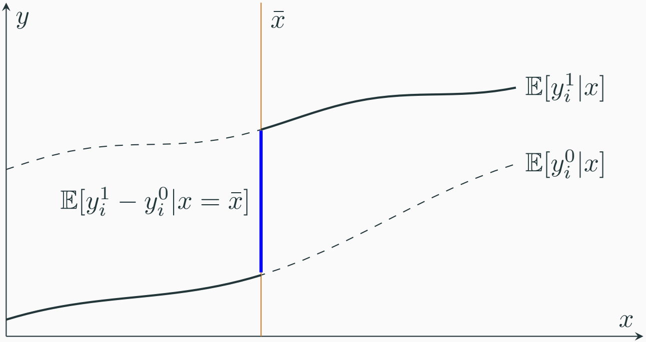

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Difference-in-differences – Setup

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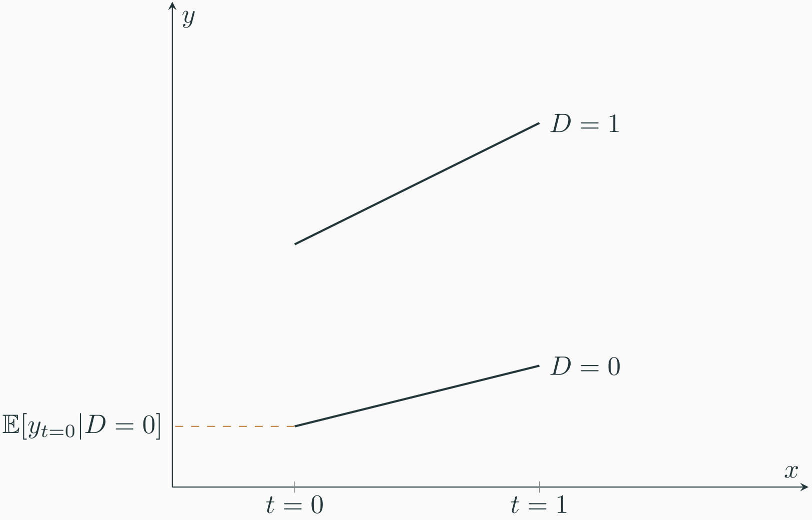
  (i.e, without treatment, treated and untreated exhibit same trend)
- then, the treatment effect is identified by the difference of two differences:

$$\underbrace{(\mathbb{E}[y_{t=1}|D = 1] - \mathbb{E}[y_{t=1}|D = 0])}_{\text{post difference}} - \underbrace{(\mathbb{E}[y_{t=0}|D = 1] - \mathbb{E}[y_{t=0}|D = 0])}_{\text{pre difference}}$$

Difference-in-differences – Graphical representation



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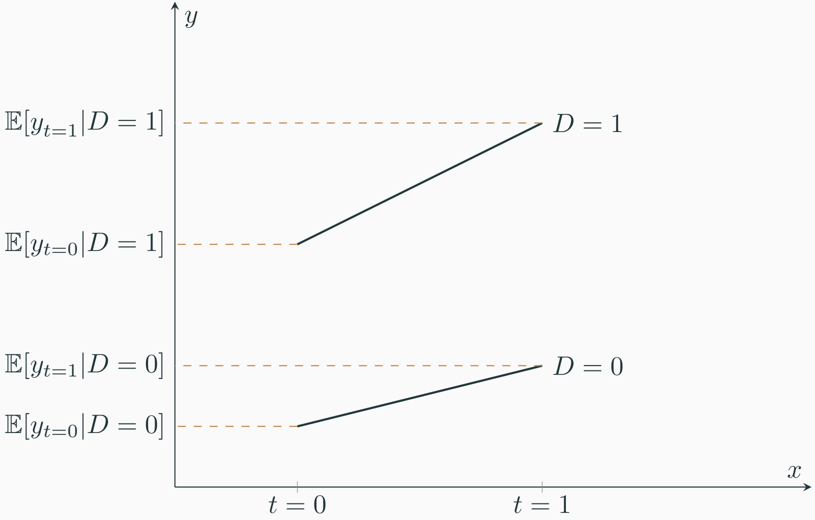

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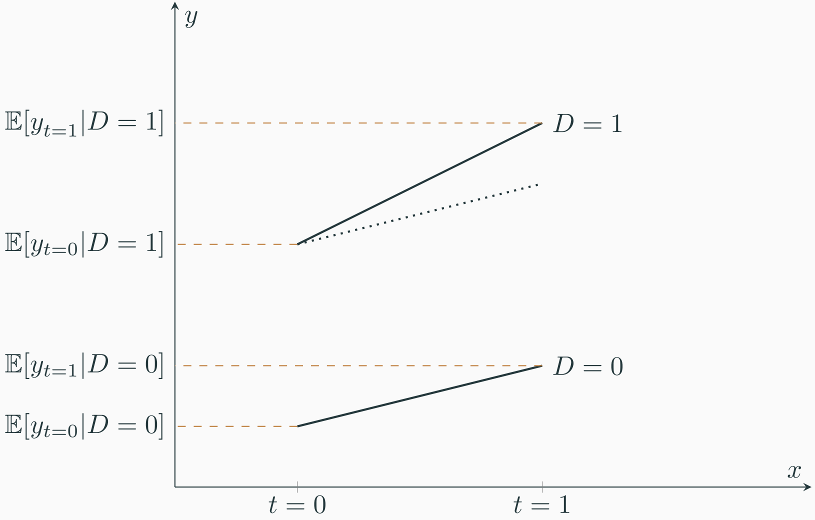

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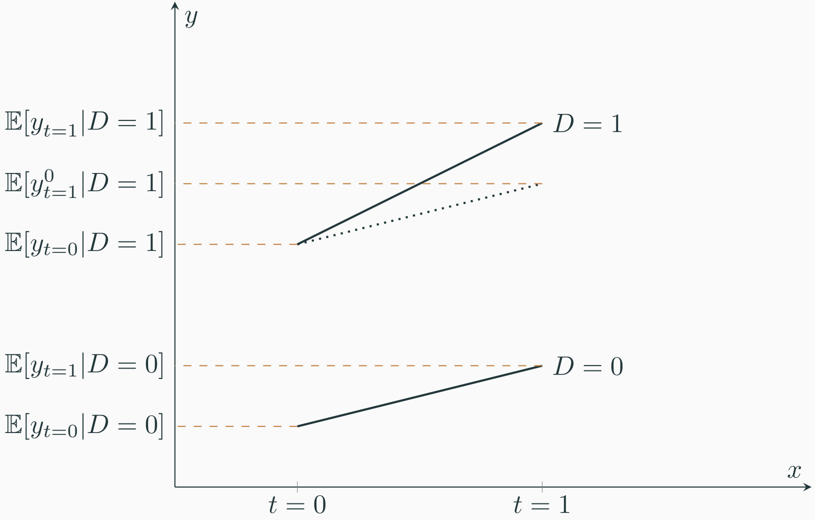

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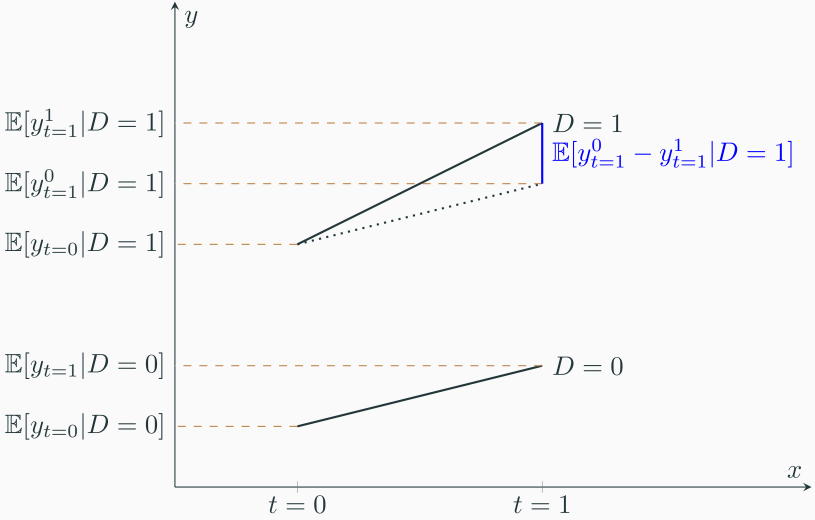

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  - assumes treated and control observations would have developed in parallel without treatment
- algebraically, DD 'nets out' pre-existing differences in outcomes

Recap

1. In randomized experiments: Treatment is randomly assigned
   - effect is identified by the difference in means
2. RD: Treatment is discontinuous along some running variable
   - effect is identified by the jump in outcomes at the cutoff
   - RDs often arise from administrative or legal rules

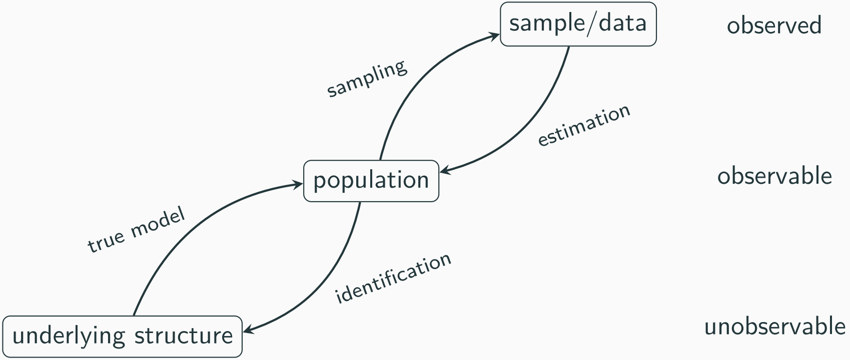
Recap

1. In randomized experiments: Treatment is randomly assigned
   - effect is identified by the difference in means
2. RD: Treatment is discontinuous along some running variable
   - effect is identified by the jump in outcomes at the cutoff
   - RDs often arise from administrative or legal rules
3. DD: 2 groups, 2 periods. Only one group gets treated in the second period
   - effect is identified by the difference-in-differences

Next

- Estimation

Identification, estimation, inference



Estimation

Estimation and inference

The first part was on identification:

- How do things we care about (causal effects) relate to population moments (differences is means).

Not covered:

- How to estimate these?
  - While the population is hypothetically observable, we usually only have a sample of observations

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  - While the population is hypothetically observable, we usually only have a sample of observations
- Need to estimate population moments from the sample
  - Estimation: Obtaining “best guesses” for population moments.
    - E.g., using sample means to estimate population means.
  - Inference: Test hypotheses, assess uncertainty in estimates.
    - E.g., checking if an estimated difference could be the result of chance (during sampling) or is an actual difference in population means

Usually estimation is done by means of some regression.

Further topics

Basics on estimation

▸ Estimation ▸ Estimators in the most basic forms

Inference

▸ Sources of uncertainty ▸ Two ways to think about uncertainty ▸ Inference

Bootstrapping

▸ Inference – Sampling-based uncertainty ▸ Bootstrap - Example

Randomization inference

▸ Randomization inference – Design-based uncertainty ▸ Randomization inference - Example (1)

▸ Randomization inference - Example of an insignificant estimate ▸ Randomization inference - Example of a significant estimate

▸ More on randomization inference

Recap and outlook

Section recap

- Many relevant research questions are causal questions

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Section recap

- Many relevant research questions are causal questions
- Comparing groups in observational data says little about causality
  - Because of selection bias
- Identification results imply certain relationships between population moments and underlying structure
  1. RCTs imply that means between groups correspond to causal effects
  2. RD and DD are alternative identification strategies where (under certain identifying assumptions) causal effects can be identified

Outlook

- Rest of today
  - RCTs
- Session 2: Regression discontinuity
  - Identification and estimation
  - Suri, Bharadwaj, and Jack (2021)
- Section 3: Difference-in-differences

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Let's have a break.

Additional resources

Books:

- Cunningham (2021)
- Angrist and Pischke (2008)
- Imbens and Rubin (2015)

Videos:

- Videos by Josh Angrist on RCTs and related topics
  mru.orgcourses/mastering-econometrics/introduction-randomized-trials

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Appendix

Back

Estimation

- Identification results are statements linking underlying structure to the population distribution

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Estimation

- Identification results are statements linking underlying structure to the population distribution
- The easiest approach to estimation is to replace properties of the population distribution by sample analogues. E.g.,

$$
\begin{aligned}
E[y] &\to \bar{y} &&= \frac{1}{n}\sum_i y_i && \text{(sample means)} \\
E[y|D=1] &\to \bar{y}|_{D=1} &&= \frac{1}{\sum_i D_i}\sum_i D_i y_i && \text{(subsample means)} \\
E[y|x] &\to \hat{y}|_x &&= \widehat{\alpha} + \hat{\beta}x && \text{(fitted regression values)} \\
&\dots
\end{aligned}
$$

Back

Estimators in the most basic forms

- Randomized experiments

$$\widehat{ATE} = \bar{y}|_{D=1} - \bar{y}|_{D=0}$$

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$$\widehat{ATE} = \bar{y}|_{D=1} - \bar{y}|_{D=0}$$

- Sharp regression discontinuity, choose bandwidth b:

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- Difference-in-differences:

$$\widehat{ATT} = (\bar{y_1}|_{D=1} - \bar{y_1}|_{D=0}) - (\bar{y_0}|_{D=1} - \bar{y_0}|_{D=0})$$

Back

Sources of uncertainty

Ex.: Evaluation of a job training program

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  - Tails: Person participates, Heads: Person does not receive training.

Where is uncertainty in coming from?

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- Thus: US$1 is our estimate for the ATE.

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  - Since the sample was randomly selected, we can say that difference in means, $\bar{y}|_{D=1} - \bar{y}|_{D=0}$, estimates the difference in expectations
- Thus: US$1 is our estimate for the ATE.

Where is uncertainty in coming from?

- random sampling
- random treatment assignment

◂ Back Two ways to think about uncertainty

1. Uncertainty about individuals
   - There is a population (say 4m working-age Austrians) half are treated, half control
   - Our random sampling only draws 100 from those
2. Uncertainty about other potential outcomes
   - Even if there is no sampling uncertainty (we observe the whole population) maybe we randomly gave treatment to those who had a good outcome anyways.;

Often that distinction make a negligible difference for results.

- in some cases (small samples) it matters for how we think about uncertainty (see Abadie et al. 2020 for a discussion)

Back

Inference

Typically standard OLS asymptotics are sufficient to give us decent ...

- standard errors
- p-values
- confidence bands

For other cases we might resort to

1. bootstrapping

Back

Inference – Sampling-based uncertainty

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◂ Back Inference – Sampling-based uncertainty

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- Bootstrap solution:
  - Pretend the sample is the population and repeatedly draw new samples (with replacement) from it.
    - Mimics the infeasible solution.
    - Allows to study how conclusions (i.e. estimates) vary across draws.

Back Bootstrap - Example

- Recall: 5 cities were randomly sampled and in each city 20 random people where interviewed.

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- Bootstrap "Algorithm":
  1. Draw, with replacement, 20 people for each of the 5 cities from the sample, to obtain a bootstrap sample of 100 people.
  2. Estimate the treatment effect in the bootstrap sample, $\widehat{\tau}_b$.
  3. Repeat steps 1-2 B times (e.g., 10,000): $\{\widehat{\tau}_b\}_{b=1,\ldots,B}$.
  4. Compute summary statistics for the distribution of bootstrap estimates.
- standard deviation of $\{\widehat{\tau}_b\}$ $\Rightarrow$ standard error of the estimate.
- 2.5% and 97.5% percentile of $\{\widehat{\tau}_b\}$ $\Rightarrow$ the 95% confidence interval.
- This quantifies the sampling-based uncertainty.
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  - This ignores sampling uncertainty from the selection of the 5 villages: $\Rightarrow$ Alternative: Draw (with repl.) a sample of 5 villages in step 1

Back Randomization inference – Design-based uncertainty

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- Infeasible solution:
  - Repeat the whole experiment 1000 times giving placebo treatments.
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- Randomization inference solution (aka, permutation tests):
  - Estimate the effect for 1000 hypothetical treatment assignments.
    - Mimics the distribution of effect estimator if there's no effect.
    - Allows to study if our true estimate is [un]likely to be the result of chance.

Back

Randomization inference - Example (1)

- Recall: For each person a coin flip determined participation.
- Randomization inference (RI) "Algorithm":
  1. Simulate a new coin flip for each participant
  2. Estimate the treatment effect (difference in means) using the real outcome data but the "fake" treatment dummy, $\widehat{\tau}_r$.
  3. Repeat steps 1-2 R times (e.g., 10,000): $\{\widehat{\tau}_r\}_{r=1,\ldots,R}$.
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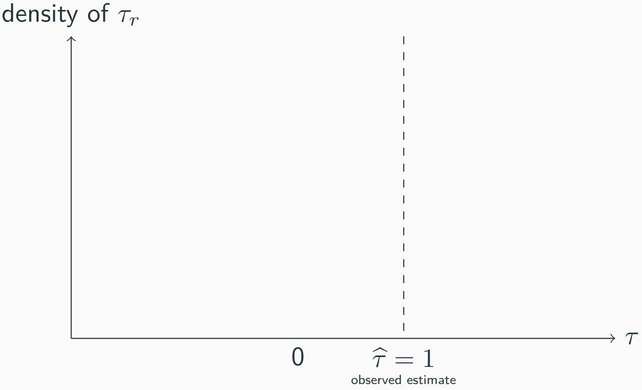
- If the true estimate falls “outside” the distribution of RI-estimates:
  - The estimate is not what we would expect if there was no effect.
  - We contradicted our imposed assumption, so there must be an effect.
- If the true estimate lies “well within” the distribution:
  - The estimate is consistent with what we expect if there was no effect.

Back

Randomization inference - Example of an insignificant estimate



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Back

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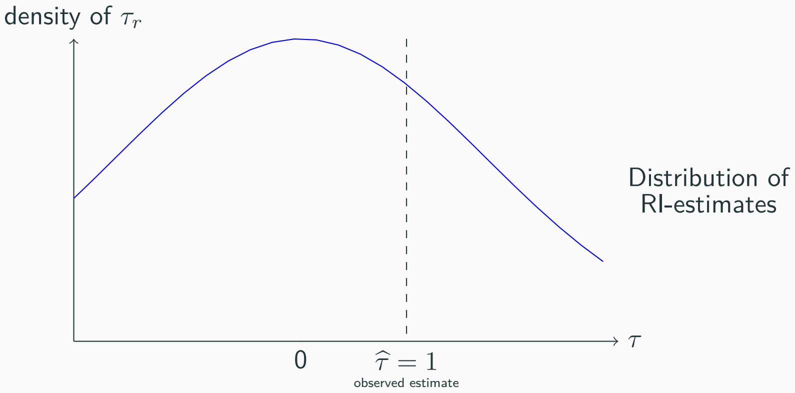

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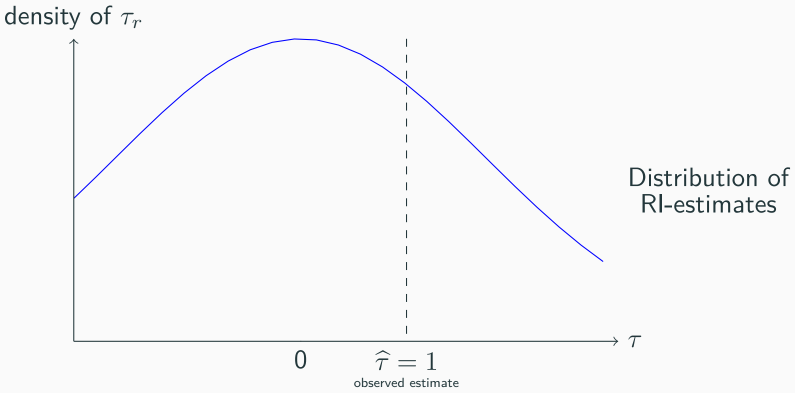
Back Randomization inference - Example of an insignificant estimate



- The estimated treatment effect, $\widehat{\tau}$, is not very different from the R "treatment effects" we estimated using "fake" coin tosses.
  - i.e, the observed difference is not significant.

Back

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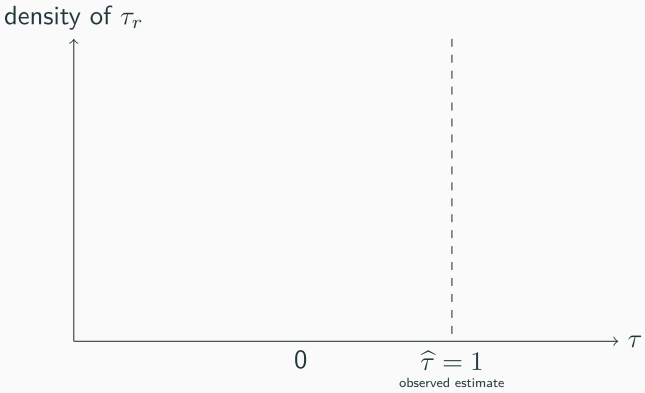

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Back

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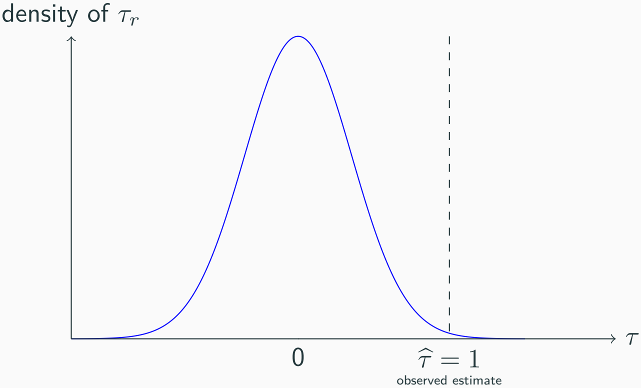

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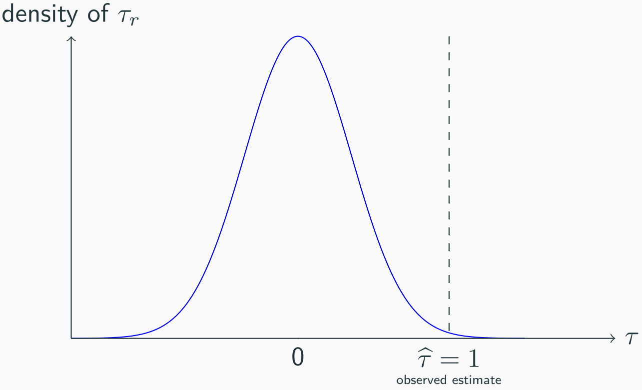

- The estimated treatment effect, $\widehat{\tau}$, is very different from the R "treatment effects" we estimated using "fake" coin tosses.
  - the observed difference is inconsistent with the H_0 of no effect.

Back

More on randomization inference

- Goal: Understand if we would observe our estimate $\hat{\beta}$ under $H_0 : \beta = 0$.
- Basic idea behind randomization inference straightforward:
  - If H_0, then D does not matter. I.e., values for D should explain our data equally well.
  - If we reshuffle D we mimic data from "parallel universes".
  - If H_0, these are as 'valid' as our actual data.
- Draw R alternative treatment assignments and compute the treatment effect estimate on those data.
- If H_0, then our actual estimate $\hat{\beta}$ can is a draw from the distribution of the R estimates.
- If not H_0, then our actual estimate may be entirely different.
- $\Rightarrow$ Reject the H_0, if our estimate is far outside the distribution.