PSC7475: Introduction to Causality

Lecture 1

Prof. Weldzius

Villanova University

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What is causal effect?

Factual vs. **Counterfactual**

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- **Fundamental problem of causal inference:**
  - Can never observe counterfactuals, must be inferred.

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- Outcome of interest: receiving a callback from a potential employer.

A tale of two applications

	Criminal Record	Callback?
Applicant 1	Ex-felon	No
Applicant 2	No criminal record	Yes

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- Did the first applicant not get a callback **because** they had a criminal record?

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- **Outcome variable** Y_i: callback

	T_i (ex-felon)	Y_i (callback)
Ex-felon applicant	1	0
Non-ex-felon applicant	0	1

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  - Observe $Y_i = Y_i(1)$ if $T_i = 1$ or $Y_i = Y_i(0)$ if $T_i = 0$
- To infer causal effect, we need to infer the missing counterfactuals!

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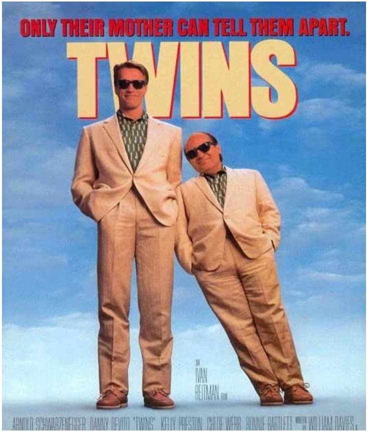
- NJ increased the minimum wage. Causal effect on unemployment?
  - $\rightsquigarrow$ find a state similar to NJ that didn't increase minimum wage.

Imperfect matches



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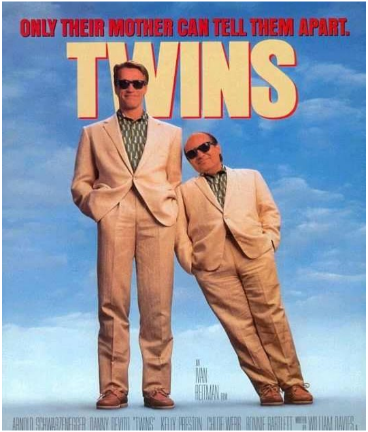

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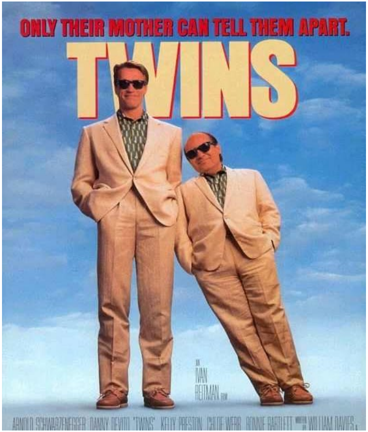

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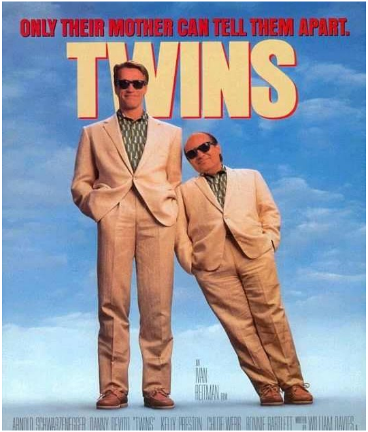

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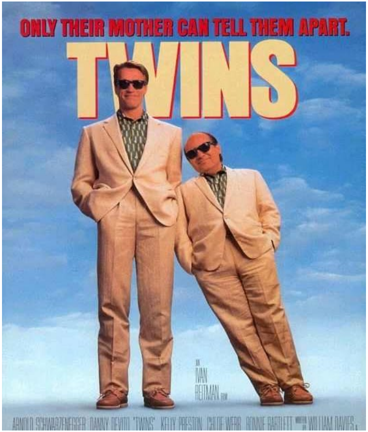

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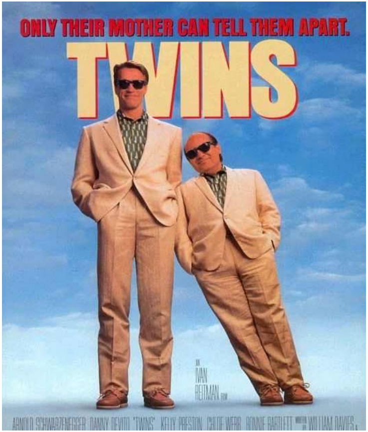

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- How can we correct for that?

Break time

- Space here for a break in the action

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    - $T_i =$ contact with member of the LGBT community (1) or not (0)

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- Suppose we surveyed 6 people and 3 supported gay marriage:

$$\bar{Y} = \frac{1}{6}(1+1+1+0+0+0) = 0.5$$

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- When will the difference-in-means be a good estimate of the SATE?

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  - $\bar{Y}_{control} \approx \frac{1}{n} \sum_{i=1}^{n} Y_i(0)$

Randomized control trials (RCTs)

- **Randomize control trial**: each unit's treatment assignment is determined by chance
  - e.g., flip a coin; draw read and blue chips from a hat; etc.
- Randomization ensures **balance** between treatment and control group.
  - Treatment and control group are identical **on average**
  - Similar on both observable and unobservable characteristics.
- Control group $\approx$ what would have happened to treatment group if they had taken control
  - $\bar{Y}_{control} \approx \frac{1}{n}\sum_{i=1}^{n} Y_i(0)$
  - $\bar{Y}_{treated} - \bar{Y}_{control} \approx$ SATE

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- **Hawthorne effects**:
  - Respondents act differently just knowing that they are under study.

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  - $\bar{X}_{treated}$: average value of variable for treated group
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  - Under randomization, $\bar{X}_{treated} - \bar{X}_{control} \approx 0$

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- If treatment arms are randomly assigned, these differences will be good estimators for each causal contrast.