PSC7475: Introduction to Causality

Lecture 1

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What is causal effect?

Factual vs. **Counterfactual**

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A tale of two applications

	Criminal Record	Callback?
Applicant 1		
Applicant 2		

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

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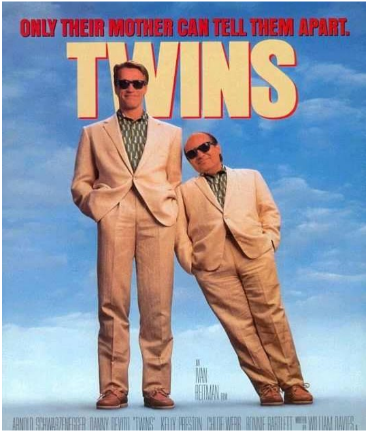
  - $\rightsquigarrow$ find a state similar to NJ that didn't increase minimum wage.

Imperfect matches



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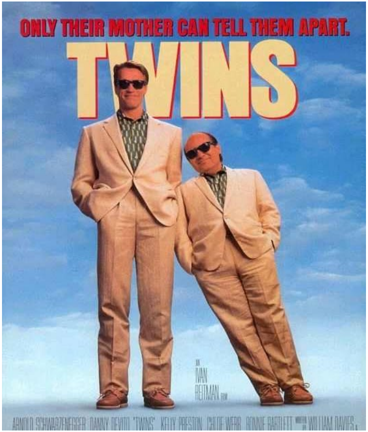

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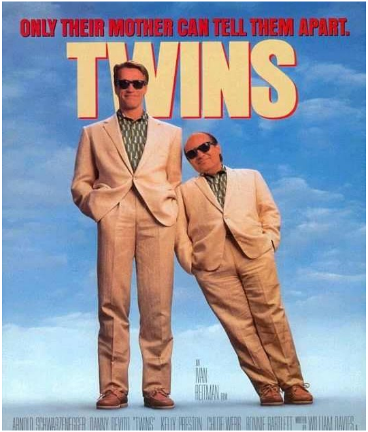

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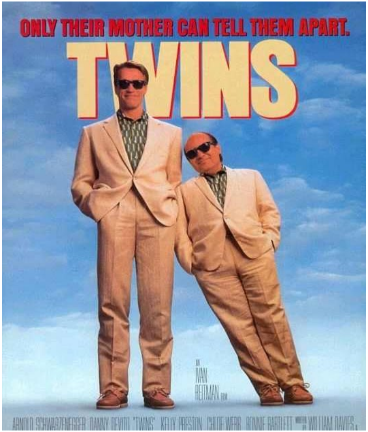

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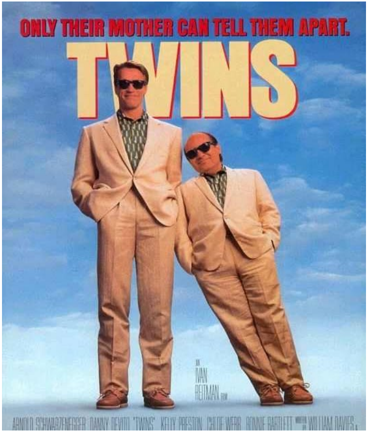

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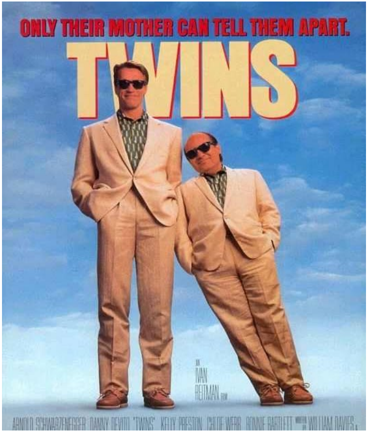

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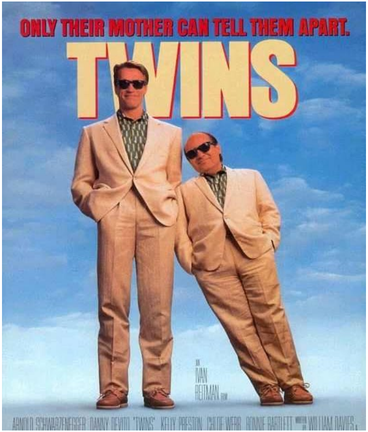

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Break time

- Space here for a break in the action

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  - $Y_i =$ support for gay marriage (1) or not (0)
  - $T_i =$ contact with member of the LGBT community (1) or not (0)

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- **Fundamental problem of causal inference**: only one of the two potential outcomes is observable.

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

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- $\bar{Y}_{treated}$: observed average outcome for treated group - $\bar{Y}_{control}$: observed average outcome for control group * When will the difference-in-means be a good estimate of the SATE?

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