PSC4375: Randomized Experiments

Week 1: Lecture 2

Prof. Weldzius

Villanova University

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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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  - 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.