EKT-816 Lecture 3

Counterfactuals, Causality, and Potential Outcomes

Jesse Naidoo

University of Pretoria

Potential Outcomes and Causality

- what do we mean by "causation"?
  - B happens after A?
  - B and A often happen together?
- suppose we have a binary "treatment", D
  - corresponding to each person i there is a pair of *potential outcomes* (Y_i^0, Y_i^1)
  - the *causal effect* or *treatment effect* for person i is $Y_i^1 - Y_i^0$
- we only observe one of the two potential outcomes
  - sometimes called "fundamental problem of causal inference"
  - thus, in order to make statements about causality, we have to fill in missing data
- the outcomes which we do not observe are called *counterfactuals*

Potential Outcomes and Causality

- what do we mean by "causation"?
    - B happens after A?
    - B and A often happen together?
- suppose we have a binary "treatment", D
    - corresponding to each person i there is a pair of *potential outcomes* (Y_i^0, Y_i^1)
    - the *causal effect* or *treatment effect* for person i is $Y_i^1 - Y_i^0$
- we only observe one of the two potential outcomes
    - sometimes called "fundamental problem of causal inference"
    - thus, in order to make statements about causality, we have to fill in missing data
- the outcomes which we do not observe are called *counterfactuals*

Potential Outcomes and Causality

- what do we mean by "causation"?
  - B happens after A?
  - B and A often happen together?
- suppose we have a binary "treatment", D
  - corresponding to each person i there is a pair of *potential outcomes* (Y_i^0, Y_i^1)
  - the *causal effect* or *treatment effect* for person i is $Y_i^1 - Y_i^0$
- we only observe one of the two potential outcomes
  - sometimes called "fundamental problem of causal inference"
  - thus, in order to make statements about causality, we have to fill in missing data
- the outcomes which we do not observe are called *counterfactuals*

Potential Outcomes and Causality

- what do we mean by "causation"?
  - B happens after A?
  - B and A often happen together?
- suppose we have a binary "treatment", D
  - corresponding to each person i there is a pair of *potential outcomes* (Y_i^0, Y_i^1)
  - the *causal effect* or *treatment effect* for person i is $Y_i^1 - Y_i^0$
- we only observe one of the two potential outcomes
  - sometimes called "fundamental problem of causal inference"
  - thus, in order to make statements about causality, we have to fill in missing data
- the outcomes which we do not observe are called *counterfactuals*

Potential Outcomes and Causality

- what do we mean by "causation"?
  - B happens after A?
  - B and A often happen together?
- suppose we have a binary "treatment", D
  - corresponding to each person i there is a pair of *potential outcomes* (Y_i^0, Y_i^1)
  - the *causal effect* or *treatment effect* for person i is $Y_i^1 - Y_i^0$
- we only observe one of the two potential outcomes
  - sometimes called "fundamental problem of causal inference"
  - thus, in order to make statements about causality, we have to fill in missing data
- the outcomes which we do not observe are called *counterfactuals*

Potential Outcomes and Causality

- what do we mean by "causation"?
  - B happens after A?
  - B and A often happen together?
- suppose we have a binary "treatment", D
  - corresponding to each person i there is a pair of *potential outcomes* (Y_i^0, Y_i^1)
  - the *causal effect* or *treatment effect* for person i is $Y_i^1 - Y_i^0$
- we only observe one of the two potential outcomes
  - sometimes called "fundamental problem of causal inference"
  - thus, in order to make statements about causality, we have to fill in missing data
- the outcomes which we do not observe are called *counterfactuals*

Potential Outcomes and Causality

- what do we mean by "causation"?
  - B happens after A?
  - B and A often happen together?
- suppose we have a binary "treatment", D
  - corresponding to each person i there is a pair of *potential outcomes* (Y_i^0, Y_i^1)
  - the *causal effect* or *treatment effect* for person i is $Y_i^1 - Y_i^0$
- we only observe one of the two potential outcomes
  - sometimes called "fundamental problem of causal inference"
  - thus, in order to make statements about causality, we have to fill in missing data
- the outcomes which we do not observe are called *counterfactuals*

Potential Outcomes and Causality

- what do we mean by "causation"?
  - B happens after A?
  - B and A often happen together?
- suppose we have a binary "treatment", D
  - corresponding to each person i there is a pair of *potential outcomes* (Y_i^0, Y_i^1)
  - the *causal effect* or *treatment effect* for person i is $Y_i^1 - Y_i^0$
- we only observe one of the two potential outcomes
  - sometimes called "fundamental problem of causal inference"
  - thus, in order to make statements about causality, we have to fill in missing data
- the outcomes which we do not observe are called *counterfactuals*

Potential Outcomes and Causality

- what do we mean by "causation"?
  - B happens after A?
  - B and A often happen together?
- suppose we have a binary "treatment", D
  - corresponding to each person i there is a pair of *potential outcomes* (Y_i^0, Y_i^1)
  - the *causal effect* or *treatment effect* for person i is $Y_i^1 - Y_i^0$
- we only observe one of the two potential outcomes
  - sometimes called "fundamental problem of causal inference"
  - thus, in order to make statements about causality, we have to fill in missing data
- the outcomes which we do not observe are called *counterfactuals*

Potential Outcomes and Causality

- what do we mean by "causation"?
  - B happens after A?
  - B and A often happen together?
- suppose we have a binary "treatment", D
  - corresponding to each person i there is a pair of *potential outcomes* (Y_i^0, Y_i^1)
  - the *causal effect* or *treatment effect* for person i is $Y_i^1 - Y_i^0$
- we only observe one of the two potential outcomes
  - sometimes called "fundamental problem of causal inference"
  - thus, in order to make statements about causality, we have to fill in missing data
- the outcomes which we do not observe are called *counterfactuals*

The Selection Problem

- notice that $Y = DY^1 + (1-D)Y^0$, for all individuals
- what does a naive comparison of mean outcomes give us?

$$\begin{aligned} E[Y|D=1] - E[Y|D=0] &= E[Y^1|D=1] - E[Y^0|D=0] \\ &= E[Y^1|D=1] - E[Y^0|D=1] \\ &\quad + E[Y^0|D=1] - E[Y^0|D=0] \\ &= E[Y^1 - Y^0|D=1] \\ &\quad + E[Y^0|D=1] - E[Y^0|D=0] \end{aligned}$$

- we call $E[Y^1 - Y^0|D=1]$ the (average) *effect of treatment on the treated* (ATT)
    - similar definitions for the effect of treatment on the *untreated* (TUT)
    - the *average treatment effect* (ATE) is just $E[Y^1 - Y^0]$
- what "policy" questions do these answer?
- the term $E[Y^0|D=1] - E[Y^0|D=0]$ is called "selection bias"
    - more specifically, it is due to selection on the *baseline* level of Y^0

The Selection Problem

- notice that $Y = DY^1 + (1-D)Y^0$, for all individuals
- what does a naive comparison of mean outcomes give us?

$$\begin{aligned}
E[Y|D=1] - E[Y|D=0] &= E[Y^1|D=1] - E[Y^0|D=0] \\
&= E[Y^1|D=1] - E[Y^0|D=1] \\
&\quad + E[Y^0|D=1] - E[Y^0|D=0] \\
&= E[Y^1 - Y^0|D=1] \\
&\quad + E[Y^0|D=1] - E[Y^0|D=0]
\end{aligned}$$

- we call $E[Y^1 - Y^0|D=1]$ the (average) *effect of treatment on the treated* (ATT)
  - similar definitions for the effect of treatment on the *untreated* (TUT)
  - the *average treatment effect* (ATE) is just $E[Y^1 - Y^0]$
- what "policy" questions do these answer?
- the term $E[Y^0|D=1] - E[Y^0|D=0]$ is called "selection bias"
  - more specifically, it is due to selection on the *baseline* level of Y^0

The Selection Problem

- notice that $Y = DY^1 + (1-D)Y^0$, for all individuals
- what does a naive comparison of mean outcomes give us?

$$
\begin{aligned}
E[Y|D=1] - E[Y|D=0] &= E[Y^1|D=1] - E[Y^0|D=0] \\
&= E[Y^1|D=1] - E[Y^0|D=1] \\
&\quad + E[Y^0|D=1] - E[Y^0|D=0] \\
&= E[Y^1 - Y^0|D=1] \\
&\quad + E[Y^0|D=1] - E[Y^0|D=0]
\end{aligned}
$$

- we call $E[Y^1 - Y^0|D=1]$ the (average) *effect of treatment on the treated* (ATT)
  - similar definitions for the effect of treatment on the *untreated* (TUT)
  - the *average treatment effect* (ATE) is just $E[Y^1 - Y^0]$
- what "policy" questions do these answer?
- the term $E[Y^0|D=1] - E[Y^0|D=0]$ is called "selection bias"
  - more specifically, it is due to selection on the *baseline* level of Y^0

The Selection Problem

- notice that $Y = DY^1 + (1-D)Y^0$, for all individuals
- what does a naive comparison of mean outcomes give us?

$$
\begin{aligned}
E[Y|D=1] - E[Y|D=0] &= E[Y^1|D=1] - E[Y^0|D=0] \\
&= E[Y^1|D=1] - E[Y^0|D=1] \\
&\quad + E[Y^0|D=1] - E[Y^0|D=0] \\
&= E[Y^1 - Y^0|D=1] \\
&\quad + E[Y^0|D=1] - E[Y^0|D=0]
\end{aligned}
$$

- we call $E[Y^1 - Y^0|D=1]$ the (average) *effect of treatment on the treated* (ATT)
    - similar definitions for the effect of treatment on the *untreated* (TUT)
    - the *average treatment effect* (ATE) is just $E[Y^1 - Y^0]$
- what "policy" questions do these answer?
- the term $E[Y^0|D=1] - E[Y^0|D=0]$ is called "selection bias"
    - more specifically, it is due to selection on the *baseline* level of Y^0

The Selection Problem

- notice that $Y = DY^1 + (1-D)Y^0$, for all individuals
- what does a naive comparison of mean outcomes give us?

$$\begin{aligned} E[Y|D=1] - E[Y|D=0] &= E[Y^1|D=1] - E[Y^0|D=0] \\ &= E[Y^1|D=1] - E[Y^0|D=1] \\ &\quad + E[Y^0|D=1] - E[Y^0|D=0] \\ &= E[Y^1 - Y^0|D=1] \\ &\quad + E[Y^0|D=1] - E[Y^0|D=0] \end{aligned}$$

- we call $E[Y^1 - Y^0|D=1]$ the (average) *effect of treatment on the treated* (ATT)
  - similar definitions for the effect of treatment on the *untreated* (TUT)
  - the *average treatment effect* (ATE) is just $E[Y^1 - Y^0]$
- what "policy" questions do these answer?
- the term $E[Y^0|D=1] - E[Y^0|D=0]$ is called "selection bias"
  - more specifically, it is due to selection on the *baseline* level of Y^0

The Selection Problem

- notice that $Y = DY^1 + (1-D)Y^0$, for all individuals
- what does a naive comparison of mean outcomes give us?

$$\begin{aligned} E[Y|D=1] - E[Y|D=0] &= E[Y^1|D=1] - E[Y^0|D=0] \\ &= E[Y^1|D=1] - E[Y^0|D=1] \\ &\quad + E[Y^0|D=1] - E[Y^0|D=0] \\ &= E[Y^1 - Y^0|D=1] \\ &\quad + E[Y^0|D=1] - E[Y^0|D=0] \end{aligned}$$

- we call $E[Y^1 - Y^0|D=1]$ the (average) *effect of treatment on the treated* (ATT)
  - similar definitions for the effect of treatment on the *untreated* (TUT)
  - the *average treatment effect* (ATE) is just $E[Y^1 - Y^0]$
- what "policy" questions do these answer?
- the term $E[Y^0|D=1] - E[Y^0|D=0]$ is called "selection bias"
  - more specifically, it is due to selection on the *baseline* level of Y^0

The Selection Problem

- notice that $Y = DY^1 + (1 - D)Y^0$, for all individuals
- what does a naive comparison of mean outcomes give us?

$$
\begin{aligned}
E[Y|D=1] - E[Y|D=0] &= E[Y^1|D=1] - E[Y^0|D=0] \\
&= E[Y^1|D=1] - E[Y^0|D=1] \\
&\quad + E[Y^0|D=1] - E[Y^0|D=0] \\
&= E[Y^1 - Y^0|D=1] \\
&\quad + E[Y^0|D=1] - E[Y^0|D=0]
\end{aligned}
$$

- we call $E[Y^1 - Y^0|D=1]$ the (average) *effect of treatment on the treated* (ATT)
    - similar definitions for the effect of treatment on the *untreated* (TUT)
    - the *average treatment effect* (ATE) is just $E[Y^1 - Y^0]$
- what "policy" questions do these answer?
- the term $E[Y^0|D=1] - E[Y^0|D=0]$ is called "selection bias"
    - more specifically, it is due to selection on the *baseline* level of Y^0

The Selection Problem

- notice that $Y = DY^1 + (1-D)Y^0$, for all individuals
- what does a naive comparison of mean outcomes give us?

$$\begin{aligned} E[Y|D=1] - E[Y|D=0] &= E[Y^1|D=1] - E[Y^0|D=0] \\ &= E[Y^1|D=1] - E[Y^0|D=1] \\ &\quad +E[Y^0|D=1] - E[Y^0|D=0] \\ &= E[Y^1 - Y^0|D=1] \\ &\quad +E[Y^0|D=1] - E[Y^0|D=0] \end{aligned}$$

- we call $E[Y^1 - Y^0|D=1]$ the (average) *effect of treatment on the treated* (ATT)
    - similar definitions for the effect of treatment on the *untreated* (TUT)
    - the *average treatment effect* (ATE) is just $E[Y^1 - Y^0]$
- what "policy" questions do these answer?
- the term $E[Y^0|D=1] - E[Y^0|D=0]$ is called "selection bias"
    - more specifically, it is due to selection on the *baseline* level of Y^0

Examples for Discussion

- what is being claimed?
  - is it a causal statement?
  - a statement of fact?
  - a normative judgement?
    - is there an implicit causal claim underlying it?
    - if yes, would there be effects on other outcomes?
    - might lead us to think about efficiency, equilibrium, etc.
  - something else?
- if there is a causal statement being made:
  - what is the counterfactual?
  - is any evidence presented in favor of the claim?

Examples for Discussion

- what is being claimed?
  - is it a causal statement?
  - a statement of fact?
  - a normative judgement?
    - is there an implicit causal claim underlying it?
    - if yes, would there be effects on other outcomes?
    - might lead us to think about efficiency, equilibrium, etc.
  - something else?
- if there is a causal statement being made:
  - what is the counterfactual?
  - is any evidence presented in favor of the claim?

Examples for Discussion

- what is being claimed?
  - is it a causal statement?
  - a statement of fact?
  - a normative judgement?
    - is there an implicit causal claim underlying it?
    - if yes, would there be effects on other outcomes?
    - might lead us to think about efficiency, equilibrium, etc.
  - something else?
- if there is a causal statement being made:
  - what is the counterfactual?
  - is any evidence presented in favor of the claim?

Examples for Discussion

- what is being claimed?
    - is it a causal statement?
    - a statement of fact?
    - a normative judgement?
        - is there an implicit causal claim underlying it?
        - if yes, would there be effects on other outcomes?
        - might lead us to think about efficiency, equilibrium, etc.
    - something else?
- if there is a causal statement being made:
    - what is the counterfactual?
    - is any evidence presented in favor of the claim?

Examples for Discussion

- what is being claimed?
  - is it a causal statement?
  - a statement of fact?
  - a normative judgement?
    - is there an implicit causal claim underlying it?
    - if yes, would there be effects on other outcomes?
    - might lead us to think about efficiency, equilibrium, etc.
  - something else?
- if there is a causal statement being made:
  - what is the counterfactual?
  - is any evidence presented in favor of the claim?

Examples for Discussion

- what is being claimed?
  - is it a causal statement?
  - a statement of fact?
  - a normative judgement?
    - is there an implicit causal claim underlying it?
    - if yes, would there be effects on other outcomes?
    - might lead us to think about efficiency, equilibrium, etc.
  - something else?
- if there is a causal statement being made:
  - what is the counterfactual?
  - is any evidence presented in favor of the claim?

Examples for Discussion

- what is being claimed?
  - is it a causal statement?
  - a statement of fact?
  - a normative judgement?
    - is there an implicit causal claim underlying it?
    - if yes, would there be effects on other outcomes?
    - might lead us to think about efficiency, equilibrium, etc.
  - something else?
- if there is a causal statement being made:
  - what is the counterfactual?
  - is any evidence presented in favor of the claim?

Examples for Discussion

- what is being claimed?
  - is it a causal statement?
  - a statement of fact?
  - a normative judgement?
    - is there an implicit causal claim underlying it?
    - if yes, would there be effects on other outcomes?
    - might lead us to think about efficiency, equilibrium, etc.
  - something else?
- if there is a causal statement being made:
  - what is the counterfactual?
  - is any evidence presented in favor of the claim?

Examples for Discussion

- what is being claimed?
  - is it a causal statement?
  - a statement of fact?
  - a normative judgement?
    - is there an implicit causal claim underlying it?
    - if yes, would there be effects on other outcomes?
    - might lead us to think about efficiency, equilibrium, etc.
  - something else?
- if there is a causal statement being made:
  - what is the counterfactual?
  - is any evidence presented in favor of the claim?

Examples for Discussion

- what is being claimed?
  - is it a causal statement?
  - a statement of fact?
  - a normative judgement?
    - is there an implicit causal claim underlying it?
    - if yes, would there be effects on other outcomes?
    - might lead us to think about efficiency, equilibrium, etc.
  - something else?
- if there is a causal statement being made:
  - what is the counterfactual?
  - is any evidence presented in favor of the claim?

Examples for Discussion

- what is being claimed?
  - is it a causal statement?
  - a statement of fact?
  - a normative judgement?
    - is there an implicit causal claim underlying it?
    - if yes, would there be effects on other outcomes?
    - might lead us to think about efficiency, equilibrium, etc.
  - something else?
- if there is a causal statement being made:
  - what is the counterfactual?
  - is any evidence presented in favor of the claim?

Randomization Solves the Selection Problem

- suppose we do an experiment, so that $D \perp\!\!\!\perp (Y^1, Y^0)$
- then our comparison of means delivers the ATE:

$$E[Y^1|D=1] - E[Y^0|D=0] = E[Y^1] - E[Y^0] = E[Y^1 - Y^0]$$

- Tennessee STAR experiment
  - affected about 11 600 children over 4 years (1985 - 1988)
  - 3 treatments:
    - small class (13 - 17)
    - normal class (22 - 25) + part-time TA
    - normal class + full-time TA
  - Table 2.2.1: descriptive statistics
    - do we have covariate balance?
    - what about attrition rates?
  - Table 2.2.2: experimental results

Randomization Solves the Selection Problem

- suppose we do an experiment, so that $D \perp\!\!\!\perp (Y^1, Y^0)$
- then our comparison of means delivers the ATE:

$$E[Y^1|D = 1] - E[Y^0|D = 0] = E[Y^1] - E[Y^0] = E[Y^1 - Y^0]$$

- Tennessee STAR experiment
  - affected about 11 600 children over 4 years (1985 - 1988)
  - 3 treatments:
    - small class (13 - 17)
    - normal class (22 - 25) + part-time TA
    - normal class + full-time TA
  - Table 2.2.1: descriptive statistics
    - do we have covariate balance?
    - what about attrition rates?
  - Table 2.2.2: experimental results

Randomization Solves the Selection Problem

- suppose we do an experiment, so that $D \perp\!\!\!\perp (Y^1, Y^0)$
- then our comparison of means delivers the ATE:

$$E[Y^1|D=1] - E[Y^0|D=0] = E[Y^1] - E[Y^0] = E[Y^1 - Y^0]$$

- Tennessee STAR experiment
  - affected about 11 600 children over 4 years (1985 - 1988)
  - 3 treatments:
    - small class (13 - 17)
    - normal class (22 - 25) + part-time TA
    - normal class + full-time TA
  - Table 2.2.1: descriptive statistics
    - do we have covariate balance?
    - what about attrition rates?
  - Table 2.2.2: experimental results

Randomization Solves the Selection Problem

- suppose we do an experiment, so that $D \perp\!\!\!\perp (Y^1, Y^0)$
- then our comparison of means delivers the ATE:

$$E[Y^1|D=1] - E[Y^0|D=0] = E[Y^1] - E[Y^0] = E[Y^1 - Y^0]$$

- Tennessee STAR experiment
  - affected about 11 600 children over 4 years (1985 - 1988)
  - 3 treatments:
    - small class (13 - 17)
    - normal class (22 - 25) + part-time TA
    - normal class + full-time TA
  - Table 2.2.1: descriptive statistics
    - do we have covariate balance?
    - what about attrition rates?
  - Table 2.2.2: experimental results

Randomization Solves the Selection Problem

- suppose we do an experiment, so that $D \perp\!\!\!\perp (Y^1, Y^0)$
- then our comparison of means delivers the ATE:

$$E[Y^1|D=1] - E[Y^0|D=0] = E[Y^1] - E[Y^0] = E[Y^1 - Y^0]$$

- Tennessee STAR experiment
  - affected about 11 600 children over 4 years (1985 - 1988)
  - 3 treatments:
    - small class (13 - 17)
    - normal class (22 - 25) + part-time TA
    - normal class + full-time TA
  - Table 2.2.1: descriptive statistics
    - do we have covariate balance?
    - what about attrition rates?
  - Table 2.2.2: experimental results

Randomization Solves the Selection Problem

- suppose we do an experiment, so that $D \perp\!\!\!\perp (Y^1, Y^0)$
- then our comparison of means delivers the ATE:

$$E[Y^1|D=1] - E[Y^0|D=0] = E[Y^1] - E[Y^0] = E[Y^1 - Y^0]$$

- Tennessee STAR experiment
  - affected about 11 600 children over 4 years (1985 - 1988)
  - 3 treatments:
    - small class (13 - 17)
    - normal class (22 - 25) + part-time TA
    - normal class + full-time TA
  - Table 2.2.1: descriptive statistics
    - do we have covariate balance?
    - what about attrition rates?
  - Table 2.2.2: experimental results

Randomization Solves the Selection Problem

- suppose we do an experiment, so that $D \perp\!\!\!\perp (Y^1, Y^0)$
- then our comparison of means delivers the ATE:

$$E[Y^1|D=1] - E[Y^0|D=0] = E[Y^1] - E[Y^0] = E[Y^1 - Y^0]$$

- Tennessee STAR experiment
  - affected about 11 600 children over 4 years (1985 - 1988)
  - 3 treatments:
    - small class (13 - 17)
    - normal class (22 - 25) + part-time TA
    - normal class + full-time TA
  - Table 2.2.1: descriptive statistics
    - do we have covariate balance?
    - what about attrition rates?
  - Table 2.2.2: experimental results

Randomization Solves the Selection Problem

- suppose we do an experiment, so that $D \perp\!\!\!\perp (Y^1, Y^0)$
- then our comparison of means delivers the ATE:

$$E[Y^1|D=1] - E[Y^0|D=0] = E[Y^1] - E[Y^0] = E[Y^1 - Y^0]$$

- Tennessee STAR experiment
  - affected about 11 600 children over 4 years (1985 - 1988)
  - 3 treatments:
    - small class (13 - 17)
    - normal class (22 - 25) + part-time TA
    - normal class + full-time TA
  - Table 2.2.1: descriptive statistics
    - do we have covariate balance?
    - what about attrition rates?
  - Table 2.2.2: experimental results

Randomization Solves the Selection Problem

- suppose we do an experiment, so that $D \perp\!\!\!\perp (Y^1, Y^0)$
- then our comparison of means delivers the ATE:

$$E[Y^1|D=1] - E[Y^0|D=0] = E[Y^1] - E[Y^0] = E[Y^1 - Y^0]$$

- Tennessee STAR experiment
  - affected about 11 600 children over 4 years (1985 - 1988)
  - 3 treatments:
    - small class (13 - 17)
    - normal class (22 - 25) + part-time TA
    - normal class + full-time TA
  - Table 2.2.1: descriptive statistics
    - do we have covariate balance?
    - what about attrition rates?
  - Table 2.2.2: experimental results

Randomization Solves the Selection Problem

- suppose we do an experiment, so that $D \perp\!\!\!\perp (Y^1, Y^0)$
- then our comparison of means delivers the ATE:

$$E[Y^1|D=1] - E[Y^0|D=0] = E[Y^1] - E[Y^0] = E[Y^1 - Y^0]$$

- Tennessee STAR experiment
  - affected about 11 600 children over 4 years (1985 - 1988)
  - 3 treatments:
    - small class (13 - 17)
    - normal class (22 - 25) + part-time TA
    - normal class + full-time TA
  - Table 2.2.1: descriptive statistics
    - do we have covariate balance?
    - what about attrition rates?
  - Table 2.2.2: experimental results

Randomization Solves the Selection Problem

- suppose we do an experiment, so that $D \perp\!\!\!\perp (Y^1, Y^0)$
- then our comparison of means delivers the ATE:

$$E[Y^1|D=1] - E[Y^0|D=0] = E[Y^1] - E[Y^0] = E[Y^1 - Y^0]$$

- Tennessee STAR experiment
  - affected about 11 600 children over 4 years (1985 - 1988)
  - 3 treatments:
    - small class (13 - 17)
    - normal class (22 - 25) + part-time TA
    - normal class + full-time TA
  - Table 2.2.1: descriptive statistics
    - do we have covariate balance?
    - what about attrition rates?
  - Table 2.2.2: experimental results

Randomization Solves the Selection Problem

- suppose we do an experiment, so that $D \perp\!\!\!\perp (Y^1, Y^0)$
- then our comparison of means delivers the ATE:

$$E[Y^1|D=1] - E[Y^0|D=0] = E[Y^1] - E[Y^0] = E[Y^1 - Y^0]$$

- Tennessee STAR experiment
  - affected about 11 600 children over 4 years (1985 - 1988)
  - 3 treatments:
    - small class (13 - 17)
    - normal class (22 - 25) + part-time TA
    - normal class + full-time TA
  - Table 2.2.1: descriptive statistics
    - do we have covariate balance?
    - what about attrition rates?
  - Table 2.2.2: experimental results

SUTVA, General Equilibrium and External Validity

- "stable unit treatment value assumption"
- this is actually two assumptions
  - potential outcomes for a given individual don't depend on treatment for others
    - earnings effects of education for a given person vs mass school construction
    - Bill Gates' proposal to give 30% of families in rural sub-Saharan African chickens
    - peer effects in schooling?
    - often economists think of these as "general equilibrium effects"
  - potential outcomes for a given individual don't depend on the way treatment was assigned
    - voluntary migration vs kidnapping!
    - being raised by a single parent: voluntary divorce vs spousal death vs never married?

SUTVA, General Equilibrium and External Validity

- "stable unit treatment value assumption"
- this is actually two assumptions
  - potential outcomes for a given individual don't depend on treatment for others
    - earnings effects of education for a given person vs mass school construction
    - Bill Gates' proposal to give 30% of families in rural sub-Saharan African chickens
    - peer effects in schooling?
    - often economists think of these as "general equilibrium effects"
  - potential outcomes for a given individual don't depend on the way treatment was assigned
    - voluntary migration vs kidnapping!
    - being raised by a single parent: voluntary divorce vs spousal death vs never-married?

SUTVA, General Equilibrium and External Validity

- "stable unit treatment value assumption"
- this is actually two assumptions
  - potential outcomes for a given individual don't depend on treatment for others
    - earnings effects of education for a given person vs mass school construction
    - Bill Gates' proposal to give 30% of families in rural sub-Saharan African chickens
    - peer effects in schooling?
    - often economists think of these as "general equilibrium effects"
  - potential outcomes for a given individual don't depend on the way treatment was assigned
    - voluntary migration vs kidnapping!
    - being raised by a single parent: voluntary divorce vs spousal death vs never-married?

SUTVA, General Equilibrium and External Validity

- "stable unit treatment value assumption"
- this is actually two assumptions
  - potential outcomes for a given individual don't depend on treatment for others
    - earnings effects of education for a given person vs mass school construction
    - Bill Gates' proposal to give 30% of families in rural sub-Saharan African chickens
    - peer effects in schooling?
    - often economists think of these as "general equilibrium effects"
  - potential outcomes for a given individual don't depend on the way treatment was assigned
    - voluntary migration vs kidnapping!
    - being raised by a single parent: voluntary divorce vs spousal death vs never-married?

SUTVA, General Equilibrium and External Validity

- "stable unit treatment value assumption"
- this is actually two assumptions
  - potential outcomes for a given individual don't depend on treatment for others
    - earnings effects of education for a given person vs mass school construction
    - Bill Gates' proposal to give 30% of families in rural sub-Saharan African chickens
    - peer effects in schooling?
    - often economists think of these as "general equilibrium effects"
  - potential outcomes for a given individual don't depend on the way treatment was assigned
    - voluntary migration vs kidnapping!
    - being raised by a single parent: voluntary divorce vs spousal death vs never-married?

SUTVA, General Equilibrium and External Validity

- "stable unit treatment value assumption"
- this is actually two assumptions
  - potential outcomes for a given individual don't depend on treatment for others
    - earnings effects of education for a given person vs mass school construction
    - Bill Gates' proposal to give 30% of families in rural sub-Saharan African chickens
    - peer effects in schooling?
    - often economists think of these as "general equilibrium effects"
  - potential outcomes for a given individual don't depend on the way treatment was assigned
    - voluntary migration vs kidnapping!
    - being raised by a single parent: voluntary divorce vs spousal death vs never-married?

SUTVA, General Equilibrium and External Validity

- "stable unit treatment value assumption"
- this is actually two assumptions
  - potential outcomes for a given individual don't depend on treatment for others
    - earnings effects of education for a given person vs mass school construction
    - Bill Gates' proposal to give 30% of families in rural sub-Saharan African chickens
    - peer effects in schooling?
    - often economists think of these as "general equilibrium effects"
  - potential outcomes for a given individual don't depend on the way treatment was assigned
    - voluntary migration vs kidnapping!
    - being raised by a single parent: voluntary divorce vs spousal death vs never-married?

SUTVA, General Equilibrium and External Validity

- "stable unit treatment value assumption"
- this is actually two assumptions
    - potential outcomes for a given individual don't depend on treatment for others
        - earnings effects of education for a given person vs mass school construction
        - Bill Gates' proposal to give 30% of families in rural sub-Saharan African chickens
        - peer effects in schooling?
        - often economists think of these as "general equilibrium effects"
    - potential outcomes for a given individual don't depend on the way treatment was assigned
        - voluntary migration vs kidnapping!
        - being raised by a single parent: voluntary divorce vs spousal death vs never-married?

SUTVA, General Equilibrium and External Validity

- “stable unit treatment value assumption”
- this is actually two assumptions
    - potential outcomes for a given individual don’t depend on treatment for others
        - earnings effects of education for a given person vs mass school construction
        - Bill Gates’ proposal to give 30% of families in rural sub-Saharan African chickens
        - peer effects in schooling?
        - often economists think of these as “general equilibrium effects”
    - potential outcomes for a given individual don’t depend on the way treatment was assigned
        - voluntary migration vs kidnapping!
        - being raised by a single parent: voluntary divorce vs spousal death vs never-married?

SUTVA, General Equilibrium and External Validity

- "stable unit treatment value assumption"
- this is actually two assumptions
  - potential outcomes for a given individual don't depend on treatment for others
    - earnings effects of education for a given person vs mass school construction
    - Bill Gates' proposal to give 30% of families in rural sub-Saharan African chickens
    - peer effects in schooling?
    - often economists think of these as "general equilibrium effects"
  - potential outcomes for a given individual don't depend on the way treatment was assigned
    - voluntary migration vs kidnapping!
    - being raised by a single parent: voluntary divorce vs spousal death vs never-married?

Causal Mechanisms vs Treatment Effects

- often, we do not just want to know “what works”
  - also want to know *why* it works
- Keane (2010) gives a medical example: gastric distension from abdominal wounds
  - belief at the time was this was due to buildup of toxicity in intestines
  - Wangsteen's experiments showed that in fact it was just swallowed air
  - estimated to have saved about 100,000 lives of US soldiers in WWII
- completely naive attempts to see “what works” quickly run into combinatorial problems
  - there are many more combinations of policies than you can run experiments for!
  - a model (even implicit) is an essential device to fill in missing information
    - “data and assumptions are perfect substitutes” – Charles Manski
- of course, we want to be clear about where our conclusions come from:
  - which facts in the data drive our estimates?
  - under which assumptions are these facts informative about the parameters of interest?

Causal Mechanisms vs Treatment Effects

- often, we do not just want to know “what works”
  - also want to know *why* it works
- Keane (2010) gives a medical example: gastric distension from abdominal wounds
  - belief at the time was this was due to buildup of toxicity in intestines
  - Wangsteen's experiments showed that in fact it was just swallowed air
  - estimated to have saved about 100,000 lives of US soldiers in WWII
- completely naive attempts to see “what works” quickly run into combinatorial problems
  - there are many more combinations of policies than you can run experiments for!
  - a model (even implicit) is an essential device to fill in missing information
    - “data and assumptions are perfect substitutes” – Charles Manski
- of course, we want to be clear about where our conclusions come from:
  - which facts in the data drive our estimates?
  - under which assumptions are these facts informative about the parameters of interest?

Causal Mechanisms vs Treatment Effects

- often, we do not just want to know “what works”
  - also want to know *why* it works
- Keane (2010) gives a medical example: gastric distension from abdominal wounds
  - belief at the time was this was due to buildup of toxicity in intestines
  - Wangsteen’s experiments showed that in fact it was just swallowed air
  - estimated to have saved about 100,000 lives of US soldiers in WWII
- completely naive attempts to see “what works” quickly run into combinatorial problems
  - there are many more combinations of policies than you can run experiments for!
  - a model (even implicit) is an essential device to fill in missing information
    - “data and assumptions are perfect substitutes”
- of course, we want to be clear about where our conclusions come from:
  - which facts in the data drive our estimates?
  - under which assumptions are these facts informative about the parameters of interest?

Causal Mechanisms vs Treatment Effects

- often, we do not just want to know "what works"
  - also want to know *why* it works
- Keane (2010) gives a medical example: gastric distension from abdominal wounds
  - belief at the time was this was due to buildup of toxicity in intestines
  - Wangsteen's experiments showed that in fact it was just swallowed air
  - estimated to have saved about 100,000 lives of US soldiers in WWII
- completely naive attempts to see "what works" quickly run into combinatorial problems
  - there are many more combinations of policies than you can run experiments for!
  - a model (even implicit) is an essential device to fill in missing information
    - "data and assumptions are perfect substitutes" – Charles Manski
- of course, we want to be clear about where our conclusions come from:
  - which facts in the data drive our estimates?
  - under which assumptions are these facts informative about the parameters of interest?

Causal Mechanisms vs Treatment Effects

- often, we do not just want to know “what works”
  - also want to know *why* it works
- Keane (2010) gives a medical example: gastric distension from abdominal wounds
  - belief at the time was this was due to buildup of toxicity in intestines
  - Wangsteen’s experiments showed that in fact it was just swallowed air
  - estimated to have saved about 100,000 lives of US soldiers in WWII
- completely naive attempts to see “what works” quickly run into combinatorial problems
  - there are many more combinations of policies than you can run experiments for!
  - a model (even implicit) is an essential device to fill in missing information
    - “Data and assumptions are perfect substitutes”
- of course, we want to be clear about where our conclusions come from:
  - which facts in the data drive our estimates?
  - under which assumptions are these facts informative about the parameters of interest?

Causal Mechanisms vs Treatment Effects

- often, we do not just want to know "what works"
  - also want to know *why* it works
- Keane (2010) gives a medical example: gastric distension from abdominal wounds
  - belief at the time was this was due to buildup of toxicity in intestines
  - Wangsteen's experiments showed that in fact it was just swallowed air
  - estimated to have saved about 100,000 lives of US soldiers in WWII
- completely naive attempts to see "what works" quickly run into combinatorial problems
  - there are many more combinations of policies than you can run experiments for!
  - a model (even implicit) is an essential device to fill in missing information
- of course, we want to be clear about where our conclusions come from:
  - which facts in the data drive our estimates?
  - under which assumptions are these facts informative about the parameters of interest?

Causal Mechanisms vs Treatment Effects

- often, we do not just want to know “what works”
  - also want to know *why* it works
- Keane (2010) gives a medical example: gastric distension from abdominal wounds
  - belief at the time was this was due to buildup of toxicity in intestines
  - Wangsteen’s experiments showed that in fact it was just swallowed air
  - estimated to have saved about 100,000 lives of US soldiers in WWII
- completely naive attempts to see “what works” quickly run into combinatorial problems
  - there are many more combinations of policies than you can run experiments for!
  - a model (even implicit) is an essential device to fill in missing information
    - “data and assumptions are perfect substitutes” - Charles Manski
- of course, we want to be clear about where our conclusions come from:
  - which facts in the data drive our estimates?
  - under which assumptions are these facts informative about the parameters of interest?

Causal Mechanisms vs Treatment Effects

- often, we do not just want to know "what works"
  - also want to know *why* it works
- Keane (2010) gives a medical example: gastric distension from abdominal wounds
  - belief at the time was this was due to buildup of toxicity in intestines
  - Wangsteen's experiments showed that in fact it was just swallowed air
  - estimated to have saved about 100,000 lives of US soldiers in WWII
- completely naive attempts to see "what works" quickly run into combinatorial problems
  - there are many more combinations of policies than you can run experiments for!
  - a model (even implicit) is an essential device to fill in missing information
    - "data and assumptions are perfect substitutes" - Charles Manski
- of course, we want to be clear about where our conclusions come from:
  - which facts in the data drive our estimates?
  - under which assumptions are these facts informative about the parameters of interest?

Causal Mechanisms vs Treatment Effects

- often, we do not just want to know "what works"
  - also want to know *why* it works
- Keane (2010) gives a medical example: gastric distension from abdominal wounds
  - belief at the time was this was due to buildup of toxicity in intestines
  - Wangsteen's experiments showed that in fact it was just swallowed air
  - estimated to have saved about 100,000 lives of US soldiers in WWII
- completely naive attempts to see "what works" quickly run into combinatorial problems
  - there are many more combinations of policies than you can run experiments for!
  - a model (even implicit) is an essential device to fill in missing information
    - "data and assumptions are perfect substitutes" - Charles Manski
- of course, we want to be clear about where our conclusions come from:
  - which facts in the data drive our estimates?
  - under which assumptions are these facts informative about the parameters of interest?

Causal Mechanisms vs Treatment Effects

- often, we do not just want to know "what works"
  - also want to know *why* it works
- Keane (2010) gives a medical example: gastric distension from abdominal wounds
  - belief at the time was this was due to buildup of toxicity in intestines
  - Wangsteen's experiments showed that in fact it was just swallowed air
  - estimated to have saved about 100,000 lives of US soldiers in WWII
- completely naive attempts to see "what works" quickly run into combinatorial problems
  - there are many more combinations of policies than you can run experiments for!
  - a model (even implicit) is an essential device to fill in missing information
    - "data and assumptions are perfect substitutes" - Charles Manski
- of course, we want to be clear about where our conclusions come from:
  - which facts in the data drive our estimates?
  - under which assumptions are these facts informative about the parameters of interest?

Causal Mechanisms vs Treatment Effects

- often, we do not just want to know "what works"
  - also want to know *why* it works
- Keane (2010) gives a medical example: gastric distension from abdominal wounds
  - belief at the time was this was due to buildup of toxicity in intestines
  - Wangsteen's experiments showed that in fact it was just swallowed air
  - estimated to have saved about 100,000 lives of US soldiers in WWII
- completely naive attempts to see "what works" quickly run into combinatorial problems
  - there are many more combinations of policies than you can run experiments for!
  - a model (even implicit) is an essential device to fill in missing information
    - "data and assumptions are perfect substitutes" - Charles Manski
- of course, we want to be clear about where our conclusions come from:
  - which facts in the data drive our estimates?
  - under which assumptions are these facts informative about the parameters of interest?

Causal Mechanisms vs Treatment Effects

- often, we do not just want to know "what works"
  - also want to know *why* it works
- Keane (2010) gives a medical example: gastric distension from abdominal wounds
  - belief at the time was this was due to buildup of toxicity in intestines
  - Wangsteen's experiments showed that in fact it was just swallowed air
  - estimated to have saved about 100,000 lives of US soldiers in WWII
- completely naive attempts to see "what works" quickly run into combinatorial problems
  - there are many more combinations of policies than you can run experiments for!
  - a model (even implicit) is an essential device to fill in missing information
    - "data and assumptions are perfect substitutes" - Charles Manski
- of course, we want to be clear about where our conclusions come from:
  - which facts in the data drive our estimates?
  - under which assumptions are these facts informative about the parameters of interest?

Causal Mechanisms vs Treatment Effects

- often, we do not just want to know "what works"
  - also want to know *why* it works
- Keane (2010) gives a medical example: gastric distension from abdominal wounds
  - belief at the time was this was due to buildup of toxicity in intestines
  - Wangsteen's experiments showed that in fact it was just swallowed air
  - estimated to have saved about 100,000 lives of US soldiers in WWII
- completely naive attempts to see "what works" quickly run into combinatorial problems
  - there are many more combinations of policies than you can run experiments for!
  - a model (even implicit) is an essential device to fill in missing information
    - "data and assumptions are perfect substitutes" - Charles Manski
- of course, we want to be clear about where our conclusions come from:
  - which facts in the data drive our estimates?
  - under which assumptions are these facts informative about the parameters of interest?

The "Four FAQs"

- Angrist and Pischke outline their four FAQs:
  - 1: what is the causal relationship of interest?
  - 2: what would be the ideal experiment?
  - 3: what is your identification strategy?
  - 4: what is your mode of statistical inference?
- there is more to research than this, but:
  - answers to these questions are the core of a project
- evaluating whether given strategies are appropriate
  - given the question
  - given the data
  - will be our agenda for the rest of the course
- conversely, thinking through whether a particular strategy would deliver a credible estimate
  - helps you design a project
  - helps focus attention on the biggest potential weaknesses (and how to overcome them)

The "Four FAQs"

- Angrist and Pischke outline their four FAQs:
  - 1: what is the causal relationship of interest?
  - 2: what would be the ideal experiment?
  - 3: what is your identification strategy?
  - 4: what is your mode of statistical inference?
- there is more to research than this, but:
  - answers to these questions are the core of a project
- evaluating whether given strategies are appropriate
  - given the question
  - given the data
  - will be our agenda for the rest of the course
- conversely, thinking through whether a particular strategy would deliver a credible estimate
  - helps you design a project
  - helps focus attention on the biggest potential weaknesses (and how to overcome them)

The "Four FAQs"

- Angrist and Pischke outline their four FAQs:
  - 1: what is the causal relationship of interest?
  - 2: what would be the ideal experiment?
  - 3: what is your identification strategy?
  - 4: what is your mode of statistical inference?
- there is more to research than this, but:
  - answers to these questions are the core of a project
- evaluating whether given strategies are appropriate
  - given the question
  - given the data
  - will be our agenda for the rest of the course
- conversely, thinking through whether a particular strategy would deliver a credible estimate
  - helps you design a project
  - helps focus attention on the biggest potential weaknesses (and how to overcome them)

The "Four FAQs"

- Angrist and Pischke outline their four FAQs:
  - 1: what is the causal relationship of interest?
  - 2: what would be the ideal experiment?
  - 3: what is your identification strategy?
  - 4: what is your mode of statistical inference?
- there is more to research than this, but:
  - answers to these questions are the core of a project
- evaluating whether given strategies are appropriate
  - given the question
  - given the data
  - will be our agenda for the rest of the course
- conversely, thinking through whether a particular strategy would deliver a credible estimate
  - helps you design a project
  - helps focus attention on the biggest potential weaknesses (and how to overcome them)

The "Four FAQs"

- Angrist and Pischke outline their four FAQs:
  - 1: what is the causal relationship of interest?
  - 2: what would be the ideal experiment?
  - 3: what is your identification strategy?
  - 4: what is your mode of statistical inference?
- there is more to research than this, but:
  - answers to these questions are the core of a project
- evaluating whether given strategies are appropriate
  - given the question
  - given the data
  - will be our agenda for the rest of the course
- conversely, thinking through whether a particular strategy would deliver a credible estimate
  - helps you design a project
  - helps focus attention on the biggest potential weaknesses (and how to overcome them)

The "Four FAQs"

- Angrist and Pischke outline their four FAQs:
  - 1: what is the causal relationship of interest?
  - 2: what would be the ideal experiment?
  - 3: what is your identification strategy?
  - 4: what is your mode of statistical inference?
- there is more to research than this, but:
  - answers to these questions are the core of a project
- evaluating whether given strategies are appropriate
  - given the question
  - given the data
  - will be our agenda for the rest of the course
- conversely, thinking through whether a particular strategy would deliver a credible estimate
  - helps you design a project
  - helps focus attention on the biggest potential weaknesses (and how to overcome them)

The “Four FAQs”

- Angrist and Pischke outline their four FAQs:
  - 1: what is the causal relationship of interest?
  - 2: what would be the ideal experiment?
  - 3: what is your identification strategy?
  - 4: what is your mode of statistical inference?
- there is more to research than this, but:
  - answers to these questions are the core of a project
- evaluating whether given strategies are appropriate
  - given the question
  - given the data
  - will be our agenda for the rest of the course
- conversely, thinking through whether a particular strategy would deliver a credible estimate
  - helps you design a project
  - helps focus attention on the biggest potential weaknesses (and how to overcome them)

The “Four FAQs”

- Angrist and Pischke outline their four FAQs:
  - 1: what is the causal relationship of interest?
  - 2: what would be the ideal experiment?
  - 3: what is your identification strategy?
  - 4: what is your mode of statistical inference?
- there is more to research than this, but:
  - answers to these questions are the core of a project
- evaluating whether given strategies are appropriate
  - given the question
  - given the data
  - will be our agenda for the rest of the course
- conversely, thinking through whether a particular strategy would deliver a credible estimate
  - helps you design a project
  - helps focus attention on the biggest potential weaknesses (and how to overcome them)

The "Four FAQs"

- Angrist and Pischke outline their four FAQs:
    - 1: what is the causal relationship of interest?
    - 2: what would be the ideal experiment?
    - 3: what is your identification strategy?
    - 4: what is your mode of statistical inference?
- there is more to research than this, but:
    - answers to these questions are the core of a project
- evaluating whether given strategies are appropriate
    - given the question
    - given the data
    - will be our agenda for the rest of the course
- conversely, thinking through whether a particular strategy would deliver a credible estimate
    - helps you design a project
    - helps focus attention on the biggest potential weaknesses (and how to overcome them)

The "Four FAQs"

- Angrist and Pischke outline their four FAQs:
  - 1: what is the causal relationship of interest?
  - 2: what would be the ideal experiment?
  - 3: what is your identification strategy?
  - 4: what is your mode of statistical inference?
- there is more to research than this, but:
  - answers to these questions are the core of a project
- evaluating whether given strategies are appropriate
  - given the question
  - given the data
  - will be our agenda for the rest of the course
- conversely, thinking through whether a particular strategy would deliver a credible estimate
  - helps you design a project
  - helps focus attention on the biggest potential weaknesses (and how to overcome them)

The "Four FAQs"

- Angrist and Pischke outline their four FAQs:
  - 1: what is the causal relationship of interest?
  - 2: what would be the ideal experiment?
  - 3: what is your identification strategy?
  - 4: what is your mode of statistical inference?
- there is more to research than this, but:
  - answers to these questions are the core of a project
- evaluating whether given strategies are appropriate
  - given the question
  - given the data
  - will be our agenda for the rest of the course
- conversely, thinking through whether a particular strategy would deliver a credible estimate
  - helps you design a project
  - helps focus attention on the biggest potential weaknesses (and how to overcome them)

The "Four FAQs"

- Angrist and Pischke outline their four FAQs:
  - 1: what is the causal relationship of interest?
  - 2: what would be the ideal experiment?
  - 3: what is your identification strategy?
  - 4: what is your mode of statistical inference?
- there is more to research than this, but:
  - answers to these questions are the core of a project
- evaluating whether given strategies are appropriate
  - given the question
  - given the data
  - will be our agenda for the rest of the course
- conversely, thinking through whether a particular strategy would deliver a credible estimate
  - helps you design a project
  - helps focus attention on the biggest potential weaknesses (and how to overcome them)

The "Four FAQs"

- Angrist and Pischke outline their four FAQs:
  - 1: what is the causal relationship of interest?
  - 2: what would be the ideal experiment?
  - 3: what is your identification strategy?
  - 4: what is your mode of statistical inference?
- there is more to research than this, but:
  - answers to these questions are the core of a project
- evaluating whether given strategies are appropriate
  - given the question
  - given the data
  - will be our agenda for the rest of the course
- conversely, thinking through whether a particular strategy would deliver a credible estimate
  - helps you design a project
  - helps focus attention on the biggest potential weaknesses (and how to overcome them)

The "Four FAQs"

- Angrist and Pischke outline their four FAQs:
  - 1: what is the causal relationship of interest?
  - 2: what would be the ideal experiment?
  - 3: what is your identification strategy?
  - 4: what is your mode of statistical inference?
- there is more to research than this, but:
  - answers to these questions are the core of a project
- evaluating whether given strategies are appropriate
  - given the question
  - given the data
  - will be our agenda for the rest of the course
- conversely, thinking through whether a particular strategy would deliver a credible estimate
  - helps you design a project
  - helps focus attention on the biggest potential weaknesses (and how to overcome them)

What is the Causal Relationship of Interest?

- not all good research is about causal relationships
  - wage and productivity trends
  - flow approach to labor markets
- still, a large majority of economic research at least aims at causality
  - might correspond to a parameter in an economic model
    - a labor supply elasticity
    - an elasticity of substitution (in production)
  - might be "policy relevant"
    - have to think carefully about external validity here
    - would the policy change itself alter the causal relationship?
    - e.g. is the "causal effect of schooling" a supply-side or a demand-side parameter?

What is the Causal Relationship of Interest?

- not all good research is about causal relationships
  - wage and productivity trends
  - flow approach to labor markets
- still, a large majority of economic research at least aims at causality
  - might correspond to a parameter in an economic model
    - a labor supply elasticity
    - an elasticity of substitution (in production)
  - might be "policy relevant"
    - have to think carefully about external validity here
    - would the policy change itself alter the causal relationship?
    - e.g. is the "causal effect of schooling" a supply-side or a demand-side parameter?

What is the Causal Relationship of Interest?

- not all good research is about causal relationships
  - wage and productivity trends
  - flow approach to labor markets
- still, a large majority of economic research at least aims at causality
  - might correspond to a parameter in an economic model
    - a labor supply elasticity
    - an elasticity of substitution (in production)
  - might be "policy relevant"
    - have to think carefully about external validity here
    - would the policy change itself alter the causal relationship

What is the Causal Relationship of Interest?

- not all good research is about causal relationships
  - wage and productivity trends
  - flow approach to labor markets
- still, a large majority of economic research at least aims at causality
  - might correspond to a parameter in an economic model
    - a labor supply elasticity
    - an elasticity of substitution (in production)
  - might be "policy relevant"
    - have to think carefully about external validity here
    - would the policy change itself alter the causal relationship?
    - e.g. is the "causal effect of schooling" a supply-side or a demand-side parameter?

What is the Causal Relationship of Interest?

- not all good research is about causal relationships
  - wage and productivity trends
  - flow approach to labor markets
- still, a large majority of economic research at least aims at causality
  - might correspond to a parameter in an economic model
    - a labor supply elasticity
    - an elasticity of substitution (in production)
  - might be "policy relevant"
    - have to think carefully about external validity here
    - would the policy change itself alter the causal relationship?
    - e.g. is the "causal effect of schooling" a supply-side or a demand-side parameter?

What is the Causal Relationship of Interest?

- not all good research is about causal relationships
  - wage and productivity trends
  - flow approach to labor markets
- still, a large majority of economic research at least aims at causality
  - might correspond to a parameter in an economic model
    - a labor supply elasticity
    - an elasticity of substitution (in production)
  - might be "policy relevant"
    - have to think carefully about external validity here
    - would the policy change itself alter the causal relationship?
    - e.g. is the "causal effect of schooling" a supply-side or a demand-side parameter?

What is the Causal Relationship of Interest?

- not all good research is about causal relationships
  - wage and productivity trends
  - flow approach to labor markets
- still, a large majority of economic research at least aims at causality
  - might correspond to a parameter in an economic model
    - a labor supply elasticity
    - an elasticity of substitution (in production)
  - might be "policy relevant"
    - have to think carefully about external validity here
    - would the policy change itself alter the causal relationship?
    - e.g. is the "causal effect of schooling" a supply-side or a demand-side parameter?

What is the Causal Relationship of Interest?

- not all good research is about causal relationships
  - wage and productivity trends
  - flow approach to labor markets
- still, a large majority of economic research at least aims at causality
  - might correspond to a parameter in an economic model
    - a labor supply elasticity
    - an elasticity of substitution (in production)
  - might be "policy relevant"
    - have to think carefully about external validity here
    - would the policy change itself alter the causal relationship?
    - e.g. is the "causal effect of schooling" a supply-side or a demand-side parameter?

What is the Causal Relationship of Interest?

- not all good research is about causal relationships
  - wage and productivity trends
  - flow approach to labor markets
- still, a large majority of economic research at least aims at causality
  - might correspond to a parameter in an economic model
    - a labor supply elasticity
    - an elasticity of substitution (in production)
  - might be "policy relevant"
    - have to think carefully about external validity here
    - would the policy change itself alter the causal relationship?
    - e.g. is the "causal effect of schooling" a supply-side or a demand-side parameter?

What is the Causal Relationship of Interest?

- not all good research is about causal relationships
  - wage and productivity trends
  - flow approach to labor markets
- still, a large majority of economic research at least aims at causality
  - might correspond to a parameter in an economic model
    - a labor supply elasticity
    - an elasticity of substitution (in production)
  - might be "policy relevant"
    - have to think carefully about external validity here
    - would the policy change itself alter the causal relationship?
    - e.g. is the "causal effect of schooling" a supply-side or a demand-side parameter?

What is the Causal Relationship of Interest?

- not all good research is about causal relationships
  - wage and productivity trends
  - flow approach to labor markets
- still, a large majority of economic research at least aims at causality
  - might correspond to a parameter in an economic model
    - a labor supply elasticity
    - an elasticity of substitution (in production)
  - might be "policy relevant"
    - have to think carefully about external validity here
    - would the policy change itself alter the causal relationship?
    - e.g. is the "causal effect of schooling" a supply-side or a demand-side parameter?

What Would Be the Ideal Experiment?

- example: Milgram experiment
- racial or gender discrimination
  - do we want to manipulate race or gender itself? or the *perception* of race?
  - Goldin and Rouse (2000) experiment on blind auditions for orchestras
  - resume audit studies
- school start age and test scores
  - if maturity has an effect (ability to sit still, concentrate), inherently confounded with age
  - option 1: randomize start age (e.g. 6 vs 7) and test in Gr 1
  - option 2: randomize start age but test at age 8
  - what if you had a cohort who were *not* in school?

What Would Be the Ideal Experiment?

- example: Milgram experiment
- racial or gender discrimination
  - do we want to manipulate race or gender itself? or the *perception* of race?
  - Goldin and Rouse (2000) experiment on blind auditions for orchestras
  - resume audit studies
- school start age and test scores
  - if maturity has an effect (ability to sit still, concentrate), inherently confounded with age
  - option 1: randomize start age (e.g. 6 vs 7) and test in Gr 1
  - option 2: randomize start age but test at age 8
  - what if you had a cohort who were *not* in school?

What Would Be the Ideal Experiment?

- example: Milgram experiment
- racial or gender discrimination
  - do we want to manipulate race or gender itself? or the *perception* of race?
  - Goldin and Rouse (2000) experiment on blind auditions for orchestras
  - resume audit studies
- school start age and test scores
  - if maturity has an effect (ability to sit still, concentrate), inherently confounded with age
  - option 1: randomize start age (e.g. 6 vs 7) and test in Gr 1
  - option 2: randomize start age but test at age 8
  - what if you had a cohort who were *not* in school?

What Would Be the Ideal Experiment?

- example: Milgram experiment
- racial or gender discrimination
  - do we want to manipulate race or gender itself? or the *perception* of race?
  - Goldin and Rouse (2000) experiment on blind auditions for orchestras
  - resume audit studies
- school start age and test scores
  - if maturity has an effect (ability to sit still, concentrate), inherently confounded with age
  - option 1: randomize start age (e.g. 6 vs 7) and test in Gr 1
  - option 2: randomize start age but test at age 8
  - what if you had a cohort who were *not* in school?

What Would Be the Ideal Experiment?

- example: Milgram experiment
- racial or gender discrimination
  - do we want to manipulate race or gender itself? or the *perception* of race?
  - Goldin and Rouse (2000) experiment on blind auditions for orchestras
  - resume audit studies
- school start age and test scores
  - if maturity has an effect (ability to sit still, concentrate), inherently confounded with age
  - option 1: randomize start age (e.g. 6 vs 7) and test in Gr 1
  - option 2: randomize start age but test at age 8
  - what if you had a cohort who were *not* in school?

What Would Be the Ideal Experiment?

- example: Milgram experiment
- racial or gender discrimination
  - do we want to manipulate race or gender itself? or the *perception* of race?
  - Goldin and Rouse (2000) experiment on blind auditions for orchestras
  - resume audit studies
- school start age and test scores
  - if maturity has an effect (ability to sit still, concentrate), inherently confounded with age
  - option 1: randomize start age (e.g. 6 vs 7) and test in Gr 1
  - option 2: randomize start age but test at age 8
  - what if you had a cohort who were *not* in school?

What Would Be the Ideal Experiment?

- example: Milgram experiment
- racial or gender discrimination
  - do we want to manipulate race or gender itself? or the *perception* of race?
  - Goldin and Rouse (2000) experiment on blind auditions for orchestras
  - resume audit studies
- school start age and test scores
  - if maturity has an effect (ability to sit still, concentrate), inherently confounded with age
  - option 1: randomize start age (e.g. 6 vs 7) and test in Gr 1
  - option 2: randomize start age but test at age 8
  - what if you had a cohort who were *not* in school?

What Would Be the Ideal Experiment?

- example: Milgram experiment
- racial or gender discrimination
    - do we want to manipulate race or gender itself? or the *perception* of race?
    - Goldin and Rouse (2000) experiment on blind auditions for orchestras
    - resume audit studies
- school start age and test scores
    - if maturity has an effect (ability to sit still, concentrate), inherently confounded with age
    - option 1: randomize start age (e.g. 6 vs 7) and test in Gr 1
    - option 2: randomize start age but test at age 8
    - what if you had a cohort who were *not* in school?

What Would Be the Ideal Experiment?

- example: Milgram experiment
- racial or gender discrimination
  - do we want to manipulate race or gender itself? or the *perception* of race?
  - Goldin and Rouse (2000) experiment on blind auditions for orchestras
  - resume audit studies
- school start age and test scores
  - if maturity has an effect (ability to sit still, concentrate), inherently confounded with age
  - option 1: randomize start age (e.g. 6 vs 7) and test in Gr 1
  - option 2: randomize start age but test at age 8
  - what if you had a cohort who were *not* in school?

What Would Be the Ideal Experiment?

- example: Milgram experiment
- racial or gender discrimination
  - do we want to manipulate race or gender itself? or the *perception* of race?
  - Goldin and Rouse (2000) experiment on blind auditions for orchestras
  - resume audit studies
- school start age and test scores
  - if maturity has an effect (ability to sit still, concentrate), inherently confounded with age
  - option 1: randomize start age (e.g. 6 vs 7) and test in Gr 1
  - option 2: randomize start age but test at age 8
  - what if you had a cohort who were *not* in school?

What is Your Identification Strategy?

- also known as: "what is the source of the identifying variation?"
  - this will make more sense later when we discuss OLS and IV
  - basic idea: *what, precisely, is the evidence for your causal claim?*
- if we don't understand what aspects of the data drive the conclusions, how can we assess the credibility of the claims?
  - if you cannot answer this clearly, no one will take your claims seriously

What is Your Identification Strategy?

- also known as: "what is the source of the identifying variation?"
  - this will make more sense later when we discuss OLS and IV
  - basic idea: *what, precisely, is the evidence for your causal claim?*
- if we don't understand what aspects of the data drive the conclusions, how can we assess the credibility of the claims?
  - if you cannot answer this clearly, no one will take your claims seriously

What is Your Identification Strategy?

- also known as: "what is the source of the identifying variation?"
  - this will make more sense later when we discuss OLS and IV
  - basic idea: *what, precisely, is the evidence for your causal claim?*
- if we don't understand what aspects of the data drive the conclusions, how can we assess the credibility of the claims?
  - if you cannot answer this clearly, no one will take your claims seriously

What is Your Identification Strategy?

- also known as: "what is the source of the identifying variation?"
  - this will make more sense later when we discuss OLS and IV
  - basic idea: *what, precisely, is the evidence for your causal claim?*
- if we don't understand what aspects of the data drive the conclusions, how can we assess the credibility of the claims?
  - if you cannot answer this clearly, no one will take your claims seriously

What is Your Identification Strategy?

- also known as: “what is the source of the identifying variation?”
  - this will make more sense later when we discuss OLS and IV
  - basic idea: *what, precisely, is the evidence for your causal claim?*
- if we don’t understand what aspects of the data drive the conclusions, how can we assess the credibility of the claims?
  - if you cannot answer this clearly, no one will take your claims seriously

What is Your Mode of Statistical Inference?

- need to quantify the precision of estimates and test hypotheses
- with more complex research designs this can be very involved
- when your data are clustered, grouped or aggregated, need to adjust for correlated unobservables

What is Your Mode of Statistical Inference?

- need to quantify the precision of estimates and test hypotheses
- with more complex research designs this can be very involved
- when your data are clustered, grouped or aggregated, need to adjust for correlated unobservables

What is Your Mode of Statistical Inference?

- need to quantify the precision of estimates and test hypotheses
- with more complex research designs this can be very involved
- when your data are clustered, grouped or aggregated, need to adjust for correlated unobservables

References

Goldin, Claudia, and Cecilia Rouse. 2000. "The Impact of "Blind" Auditions on Female Musicians." *American Economic Review* 90 (4): 715–41.

Keane, Michael. 2010. "A Structural Perspective on the Experimentalist School." *Journal of Economic Perspectives* 24 (2): 47–58. https://doi.org/10.1257/jep.24.2.47.

Table of Contents