FLS 6441 - Methods III: Explanation and Causation

Week 9 - Controlling for Confounding

Jonathan Phillips

April 2020

Classification of Research Designs

		Independence of Treatment Assignment	Researcher Controls Treatment Assignment?
Controlled Experiments	Field Experiments	✓	✓
	Survey and Lab Experiments	✓	✓
Natural Experiments	Natural Experiments	✓	
	Instrumental Variables	✓	
	Discontinuities	✓	
Observational Studies	Difference-in-Differences		
	Controlling for Confounding		
	Matching		
	Comparative Cases and Process Tracing		

Section 1

Controlling for Confounding

Controlling for Confounding

- What if we don't have repeated observations over time for the same units?

Controlling for Confounding

- What if we don't have repeated observations over time for the same units?
- Or what if *everyone* is treated at the same point in time?

Controlling for Confounding

- What if we don't have repeated observations over time for the same units?
- Or what if *everyone* is treated at the same point in time?
- We cannot use Difference-in-Differences

Controlling for Confounding

- What if we don't have repeated observations over time for the same units?
- Or what if *everyone* is treated at the same point in time?
- We cannot use Difference-in-Differences
- For cross-sectional observational studies, the next-best alternative is...

Controlling for Confounding

- What if we don't have repeated observations over time for the same units?
- Or what if *everyone* is treated at the same point in time?
- We cannot use Difference-in-Differences
- For cross-sectional observational studies, the next-best alternative is...
- Controls!

Controlling for Confounding

- **What we know:** Adding control variable X changes the comparison we are making:
  - **Treatment is *associated* with higher values of the Outcome...for units with the same values of X**

Controlling for Confounding

- **What we know:** Adding control variable X changes the comparison we are making:
  - **Treatment is *associated* with higher values of the Outcome...for units with the same values of X**
- **What we don't yet know:** When does controlling allow us to say:
  - **Treatment *causes* higher values of the Outcome**?

Controlling for Confounding

- Up until now causal estimates have required treatment assignment to be **independent of potential outcomes**

Controlling for Confounding

- Up until now causal estimates have required treatment assignment to be **independent of potential outcomes**

$$(y_0, y_1) \perp D$$

Controlling for Confounding

- Up until now causal estimates have required treatment assignment to be **independent of potential outcomes**

$$(y_0, y_1) \perp D$$

- But it's also acceptable if treatment assignment is ***conditionally* independent of potential outcomes**

Controlling for Confounding

- Up until now causal estimates have required treatment assignment to be **independent of potential outcomes**

$$(y_0, y_1) \perp D$$

- But it's also acceptable if treatment assignment is ***conditionally* independent of potential outcomes**

$$(y_0, y_1) \perp D|X$$

Controlling for Confounding

- Up until now causal estimates have required treatment assignment to be **independent of potential outcomes**

$$(y_0, y_1) \perp D$$

- But it's also acceptable if treatment assignment is ***conditionally*** **independent of potential outcomes**

$$(y_0, y_1) \perp D | X$$

- After controlling for X, treatment is independent of potential outcomes: 'No unmeasured confounders'

Controlling for Confounding

- Up until now causal estimates have required treatment assignment to be **independent of potential outcomes**

$$(y_0, y_1) \perp D$$

- But it's also acceptable if treatment assignment is ***conditionally* independent of potential outcomes**

$$(y_0, y_1) \perp D|X$$

- After controlling for X, treatment is independent of potential outcomes: 'No unmeasured confounders'
- This is an *assumption*

Controlling for Confounding

- Up until now causal estimates have required treatment assignment to be **independent of potential outcomes**

$$(y_0, y_1) \perp D$$

- But it's also acceptable if treatment assignment is ***conditionally* independent of potential outcomes**

$$(y_0, y_1) \perp D|X$$

- After controlling for X, treatment is independent of potential outcomes: 'No unmeasured confounders'
- This is an *assumption*
  - We cannot directly test it

Controlling for Confounding

- Up until now causal estimates have required treatment assignment to be **independent of potential outcomes**

$$(y_0, y_1) \perp D$$

- But it's also acceptable if treatment assignment is ***conditionally* independent of potential outcomes**

$$(y_0, y_1) \perp D|X$$

- After controlling for X, treatment is independent of potential outcomes: 'No unmeasured confounders'
- This is an *assumption*
  - We cannot directly test it
  - We have to make an argument and provide supporting evidence

Controlling for Confounding

- Why does controlling for confounders help provide conditional independence?

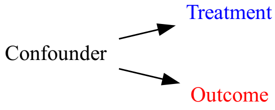
Controlling for Confounding

- Why does controlling for confounders help provide conditional independence?
- We need to know what problem - what bias - confounders create:

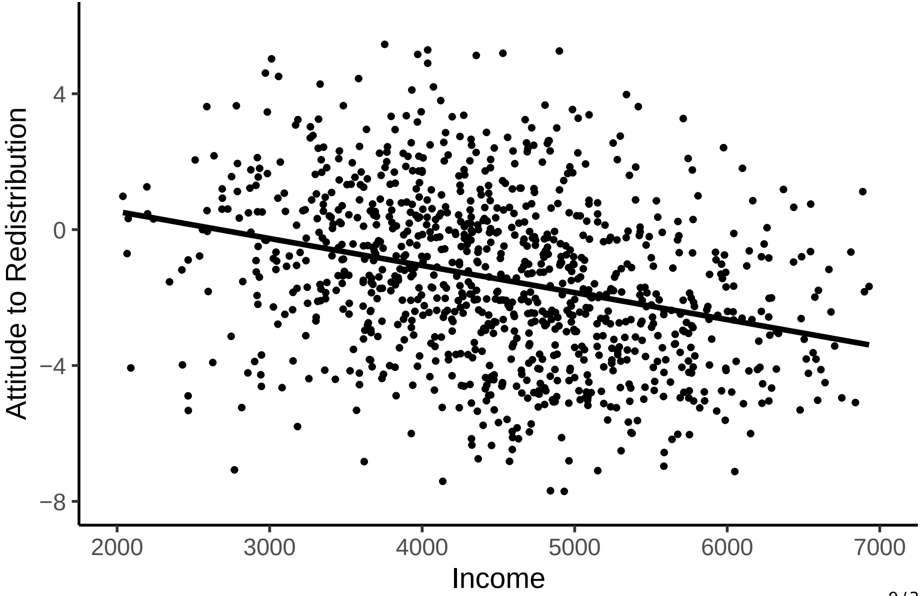
Controlling for Confounding

- Why does controlling for confounders help provide conditional independence?
- We need to know what problem - what bias - confounders create:
  - The problem is of 'fake correlations' - D and Y look like they're related, even though treatment does not affect the outcome.
- Controlling *removes these fake correlations* by only comparing D and Y for units with the same value of X

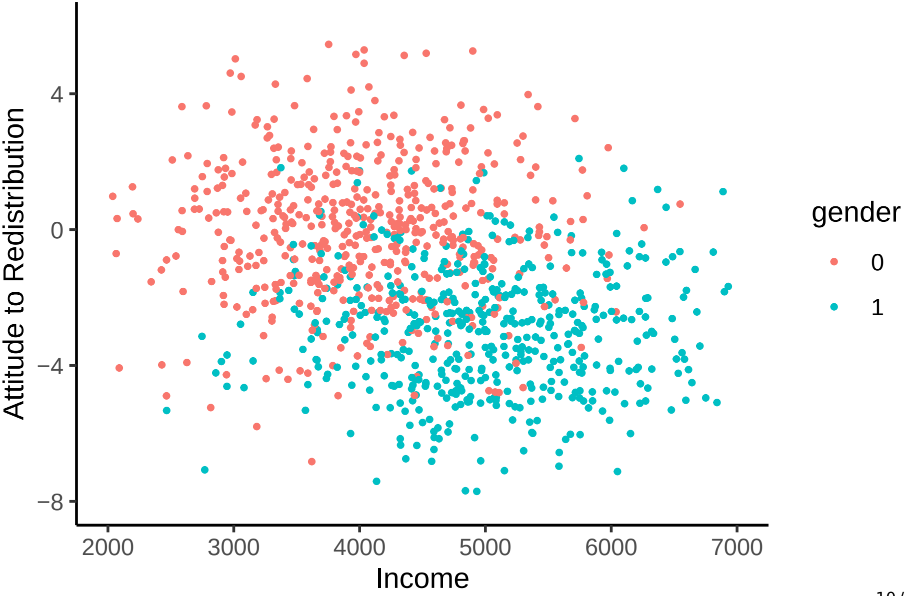
Causal Diagrams (DAGs)



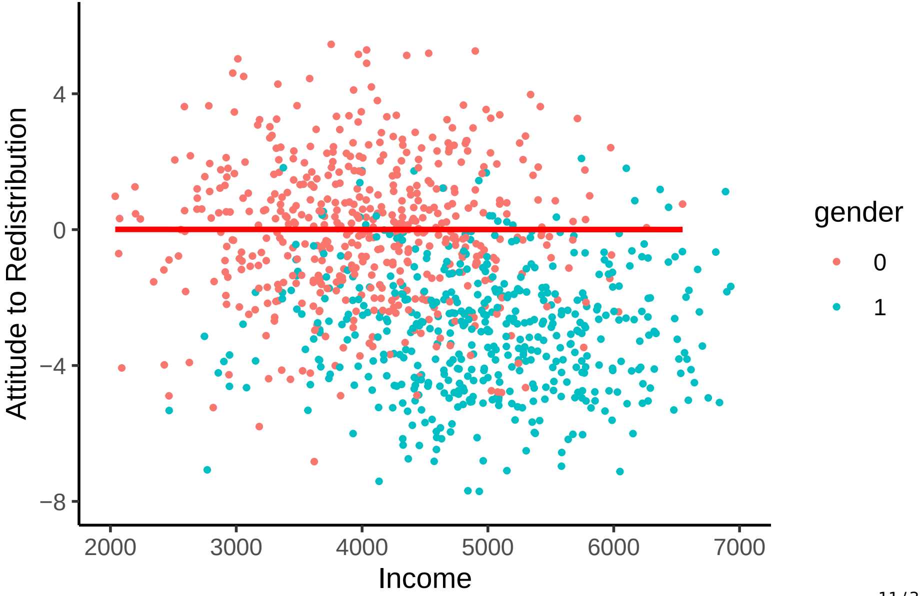
Controlling for Confounding



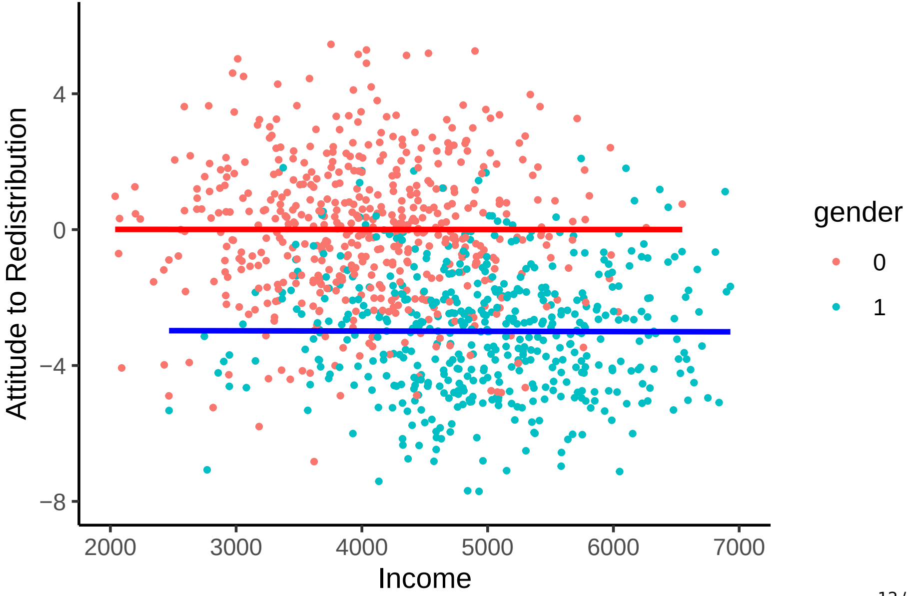
Controlling for Confounding



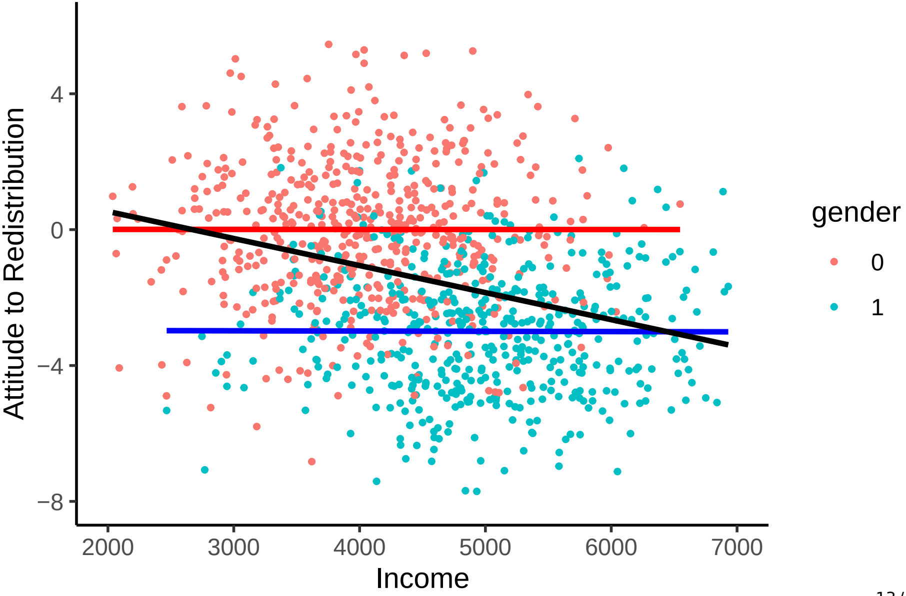
Controlling for Confounding



Controlling for Confounding



Controlling for Confounding



Controlling for Confounding

- If we omit a confounding variable, we bias our regression estimate:

Controlling for Confounding

- If we omit a confounding variable, we bias our regression estimate:
- 'True' regression with all confounders:

$$Y_i = \alpha + \beta D_i + \gamma X_i + \epsilon_i$$

Controlling for Confounding

- If we omit a confounding variable, we bias our regression estimate:
- 'True' regression with all confounders:

$$Y_i = \alpha + \beta D_i + \gamma X_i + \epsilon_i$$

- The 'wrong' regression with a missing confounder:

Controlling for Confounding

- If we omit a confounding variable, we bias our regression estimate:
- ’True’ regression with all confounders:

$$Y_i = \alpha + \beta D_i + \gamma X_i + \epsilon_i$$

- The ’wrong’ regression with a missing confounder:

$$Y_i = \alpha + \beta D_i + \epsilon_i$$

Controlling for Confounding

- If we omit a confounding variable, we bias our regression estimate:
- ’True’ regression with all confounders:

$$Y_i = \alpha + \beta D_i + \gamma X_i + \epsilon_i$$

- The ’wrong’ regression with a missing confounder:

$$Y_i = \alpha + \beta D_i + \epsilon_i$$

- What happens to our coefficient estimate?

Controlling for Confounding

- If we omit a confounding variable, we bias our regression estimate:
- 'True' regression with all confounders:

$$Y_i = \alpha + \beta D_i + \gamma X_i + \epsilon_i$$

- The 'wrong' regression with a missing confounder:

$$Y_i = \alpha + \beta D_i + \epsilon_i$$

- What happens to our coefficient estimate?

$$X_i = \psi + \delta D_i + \epsilon_i$$

Controlling for Confounding

- If we omit a confounding variable, we bias our regression estimate:
- 'True' regression with all confounders:

$$Y_i = \alpha + \beta D_i + \gamma X_i + \epsilon_i$$

- The 'wrong' regression with a missing confounder:

$$Y_i = \alpha + \beta D_i + \epsilon_i$$

- What happens to our coefficient estimate?

$$X_i = \psi + \delta D_i + \epsilon_i$$

$$Y_i = \alpha + \beta D_i + \gamma(\psi + \delta D_i + \epsilon_i) + \epsilon_i$$

Controlling for Confounding

- If we omit a confounding variable, we bias our regression estimate:
- 'True' regression with all confounders:

$$Y_i = \alpha + \beta D_i + \gamma X_i + \epsilon_i$$

- The 'wrong' regression with a missing confounder:

$$Y_i = \alpha + \beta D_i + \epsilon_i$$

- What happens to our coefficient estimate?

$$X_i = \psi + \delta D_i + \epsilon_i$$

$$Y_i = \alpha + \beta D_i + \gamma(\psi + \delta D_i + \epsilon_i) + \epsilon_i$$

$$Y_i = \alpha + D_i(\beta + \gamma\delta) + \gamma(\psi + \epsilon_i) + \epsilon_i$$

Controlling for Confounding

- If we omit a confounding variable, we bias our regression estimate:
- ’True’ regression with all confounders:

$$Y_i = \alpha + \beta D_i + \gamma X_i + \epsilon_i$$

- The ’wrong’ regression with a missing confounder:

$$Y_i = \alpha + \beta D_i + \epsilon_i$$

- What happens to our coefficient estimate?

$$X_i = \psi + \delta D_i + \epsilon_i$$

$$Y_i = \alpha + \beta D_i + \gamma(\psi + \delta D_i + \epsilon_i) + \epsilon_i$$

$$Y_i = \alpha + D_i(\beta + \gamma\delta) + \gamma(\psi + \epsilon_i) + \epsilon_i$$

- So the coefficient we estimate is wrong by this amount:

Controlling for Confounding

- If we omit a confounding variable, we bias our regression estimate:
- ’True’ regression with all confounders:

$$Y_i = \alpha + \beta D_i + \gamma X_i + \epsilon_i$$

- The ’wrong’ regression with a missing confounder:

$$Y_i = \alpha + \beta D_i + \epsilon_i$$

- What happens to our coefficient estimate?

$$X_i = \psi + \delta D_i + \epsilon_i$$

$$Y_i = \alpha + \beta D_i + \gamma(\psi + \delta D_i + \epsilon_i) + \epsilon_i$$

$$Y_i = \alpha + D_i(\beta + \gamma\delta) + \gamma(\psi + \epsilon_i) + \epsilon_i$$

- So the coefficient we estimate is wrong by this amount:

$$\beta_{wrong} = \beta_{true} + \gamma\delta$$

Controlling for Confounding

- What does controlling **do**?

Controlling for Confounding

- What does controlling **do**?
  - It means **removing the variation** in the data due to the confounder

Controlling for Confounding

- What does controlling **do**?
  - It means **removing the variation** in the data due to the confounder
  - Equivalently, it means separating our data for each value of the confounder: **Subclassification**

Controlling for Confounding

- What does controlling **do**?
  - It means **removing the variation** in the data due to the confounder
  - Equivalently, it means separating our data for each value of the confounder: **Subclassification**
  - Then, within each group, the confounder is **constant** and can't affect the relationship between D and Y.

Controlling for Confounding

- What does controlling **do**?
  - It means **removing the variation** in the data due to the confounder
  - Equivalently, it means separating our data for each value of the confounder: **Subclassification**
  - Then, within each group, the confounder is **constant** and can't affect the relationship between D and Y.
  - We have **created balance** between the treated and control groups on the confounder

Controlling for Confounding

- We receive a dataset with twenty variables: D, Y and 18 more.
    - Which variables should we include as controls?

Controlling for Confounding

- We receive a dataset with twenty variables: D, Y and 18 more.
  - Which variables should we include as controls?
- We usually should **NOT** include all of them

Controlling for Confounding

- We receive a dataset with twenty variables: D, Y and 18 more.
  - Which variables should we include as controls?
- We usually should **NOT** include all of them
  - Only the variables **necessary** to stop confounding

Controlling for Confounding

- We receive a dataset with twenty variables: D, Y and 18 more.
  - Which variables should we include as controls?
- We usually should **NOT** include all of them
  - Only the variables **necessary** to stop confounding
  - Including unnecessary variables can produce bias
    - "Bad controls"/"Post-treatment Bias"

Controlling for Confounding

- We receive a dataset with twenty variables: D, Y and 18 more.
  - Which variables should we include as controls?
- We usually should **NOT** include all of them
  - Only the variables **necessary** to stop confounding
  - Including unnecessary variables can produce bias
    - "Bad controls"/"Post-treatment Bias"
  - We lose power (degrees of freedom) for every control we add

Controlling for Confounding

- We receive a dataset with twenty variables: D, Y and 18 more.
  - Which variables should we include as controls?
- We usually should **NOT** include all of them
  - Only the variables **necessary** to stop confounding
  - Including unnecessary variables can produce bias
    - "Bad controls"/"Post-treatment Bias"
  - We lose power (degrees of freedom) for every control we add
  - And additional variables reduce overlap (increase model-dependence)

Controlling for Confounding

- We receive a dataset with twenty variables: D, Y and 18 more.
  - Which variables should we include as controls?
- We usually should **NOT** include all of them
  - Only the variables **necessary** to stop confounding
  - Including unnecessary variables can produce bias
    - "Bad controls"/"Post-treatment Bias"
  - We lose power (degrees of freedom) for every control we add
  - And additional variables reduce overlap (increase model-dependence)

Section 2

Which Variables to Control For

Causal Diagrams (DAGs)

- To know which variables to control for, it helps to draw a causal diagram

Causal Diagrams (DAGs)

- To know which variables to control for, it helps to draw a causal diagram
  - A **Directed Acyclical Graph** (DAG)

Causal Diagrams (DAGs)

- To know which variables to control for, it helps to draw a causal diagram
  - A **Directed Acyclical Graph** (DAG)
  - Arrows only in one direction

Causal Diagrams (DAGs)

- To know which variables to control for, it helps to draw a causal diagram
  - A **Directed Acyclical Graph** (DAG)
  - Arrows only in one direction
  - No circular loops!

Causal Diagrams (DAGs)

$$\text{Treatment} \longrightarrow \text{Outcome}$$

Causal Diagrams (DAGs)

- Causation is like **Water**, flowing along the graph
  - We want to focus on one 'flow' of causation from treatment to outcomes

Causal Diagrams (DAGs)

- Causation is like **Water**, flowing along the graph
  - We want to focus on one 'flow' of causation from treatment to outcomes
  - Avoiding mixing with the other flows of causation in the network

Causal Diagrams (DAGs)

Causal Diagrams (DAGs)

- Three Rules to achieve Conditional Independence:
  1. Include as controls enough variables to **block all back-door paths** from treatment to the outcome

Causal Diagrams (DAGs)

- Three Rules to achieve Conditional Independence:
    1. Include as controls enough variables to **block all back-door paths** from treatment to the outcome
    2. Exclude any variables that are **post-treatment**

Causal Diagrams (DAGs)

- Three Rules to achieve Conditional Independence:
  1. Include as controls enough variables to **block all back-door paths** from treatment to the outcome
  2. Exclude any variables that are **post-treatment**
  3. Exclude any variables that are **colliders**

1. Back-door Paths

- To identify back-door paths:

1. Back-door Paths

- To identify back-door paths:
  - Start with an arrow pointing at treatment

1. Back-door Paths

- To identify back-door paths:
  - Start with an arrow pointing at treatment
  - Trace the path 'backwards' (the direction of the arrows doesn't matter) until you reach the outcome

1. Back-door Paths

- To identify back-door paths:
  - Start with an arrow pointing at treatment
  - Trace the path 'backwards' (the direction of the arrows doesn't matter) until you reach the outcome
  - Repeat for every possible path from treatment to outcome

1. Back-door Paths

- To identify back-door paths:
  - Start with an arrow pointing at treatment
  - Trace the path 'backwards' (the direction of the arrows doesn't matter) until you reach the outcome
  - Repeat for every possible path from treatment to outcome
- **Block back-door paths** by controlling for any variable along the path

1. Back-door Paths

- To identify back-door paths:
  - Start with an arrow pointing at treatment
  - Trace the path 'backwards' (the direction of the arrows doesn't matter) until you reach the outcome
  - Repeat for every possible path from treatment to outcome
- **Block back-door paths** by controlling for any variable along the path
- Identify the **Minimum set of controls** that blocks *All* back-door paths

1. Back-door Paths

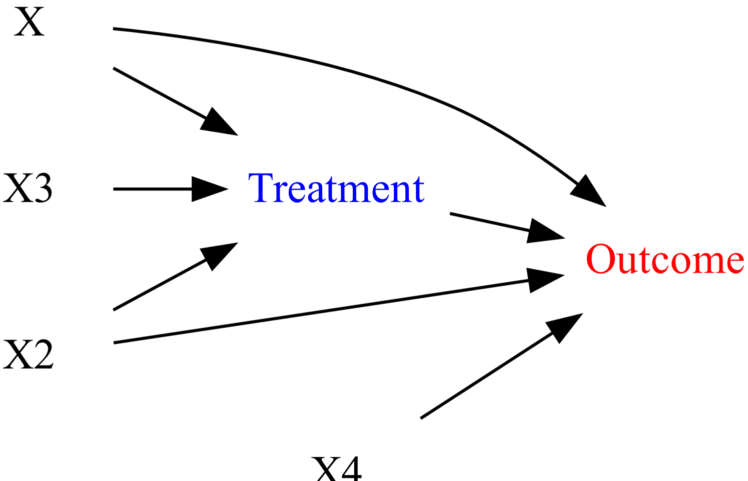
- To identify back-door paths:
  - Start with an arrow pointing at treatment
  - Trace the path 'backwards' (the direction of the arrows doesn't matter) until you reach the outcome
  - Repeat for every possible path from treatment to outcome
- **Block back-door paths** by controlling for any variable along the path
- Identify the **Minimum set of controls** that blocks *All* back-door paths
  - This achieves conditional independence of treatment from potential outcomes!

1. Back-door Paths

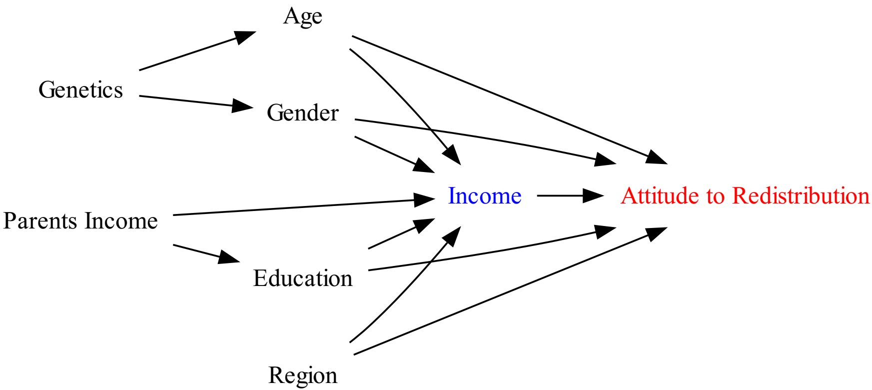
- To identify back-door paths:
  - Start with an arrow pointing at treatment
  - Trace the path ’backwards’ (the direction of the arrows doesn’t matter) until you reach the outcome
  - Repeat for every possible path from treatment to outcome
- **Block back-door paths** by controlling for any variable along the path
- Identify the **Minimum set of controls** that blocks *All* back-door paths
  - This achieves conditional independence of treatment from potential outcomes!
  - Include these as control variables in our regression

1. Back-door Paths

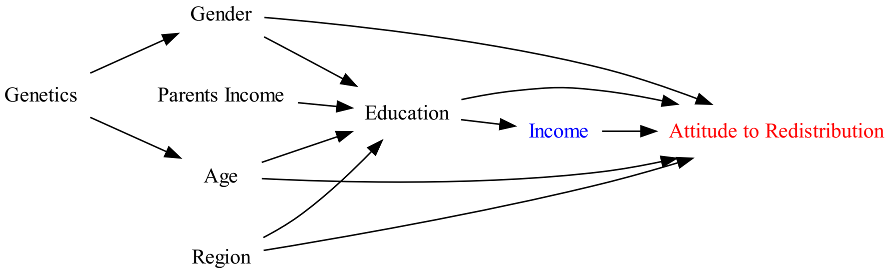
1. Back-door Paths



1. Back-door Paths



1. Back-door Paths



2. Post-treatment Variables

- Including **post-treatment** variables will introduce bias

2. Post-treatment Variables

- Including **post-treatment** variables will introduce bias
  - Because variables measured 'after' treatment can also be affected by treatment

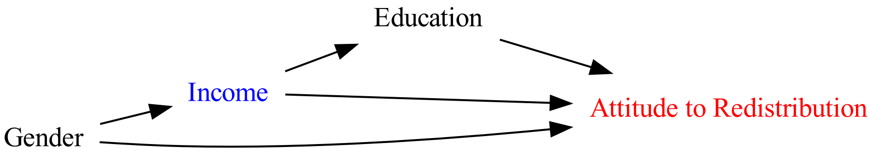
2. Post-treatment Variables

- Including **post-treatment** variables will introduce bias
  - Because variables measured ’after’ treatment can also be affected by treatment
  - They’re not confounders, but mechanisms/**mediating variables**

2. Post-treatment Variables

- Including **post-treatment** variables will introduce bias
  - Because variables measured ’after’ treatment can also be affected by treatment
  - They’re not confounders, but mechanisms/**mediating variables**
  - Controlling for them changes the definition of the causal effect we are estimating

2. Post-treatment Variables



3. Colliders

- Colliders are variables on back-door paths which have arrows pointing both into them *and* out of them

3. Colliders

- Colliders are variables on back-door paths which have arrows pointing both into them *and* out of them
- The water 'collides' in both directions so the source variables are not correlated, and produce no bias

3. Colliders

- Colliders are variables on back-door paths which have arrows pointing both into them *and* out of them
- The water 'collides' in both directions so the source variables are not correlated, and produce no bias
- But if we do accidentally 'control' for a collider we *introduce* a bias in the relationship between D and Y

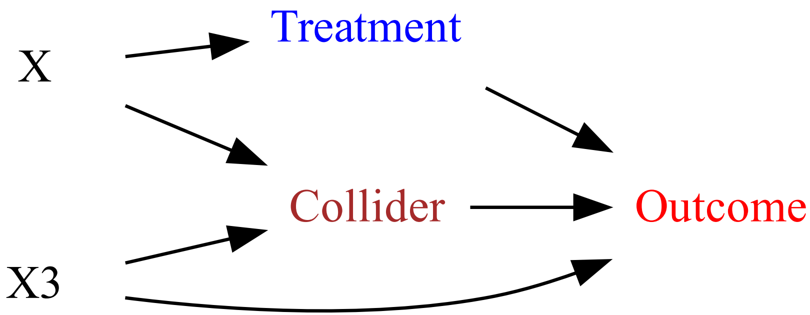
3. Colliders

- Colliders are variables on back-door paths which have arrows pointing both into them *and* out of them
- The water 'collides' in both directions so the source variables are not correlated, and produce no bias
- But if we do accidentally 'control' for a collider we *introduce* a bias in the relationship between D and Y
- So we must avoid controlling for colliders

3. Colliders

- Colliders are variables on back-door paths which have arrows pointing both into them *and* out of them
- The water 'collides' in both directions so the source variables are not correlated, and produce no bias
- But if we do accidentally 'control' for a collider we *introduce* a bias in the relationship between D and Y
- So we must avoid controlling for colliders
- Hard!

3. Colliders



3. Colliders

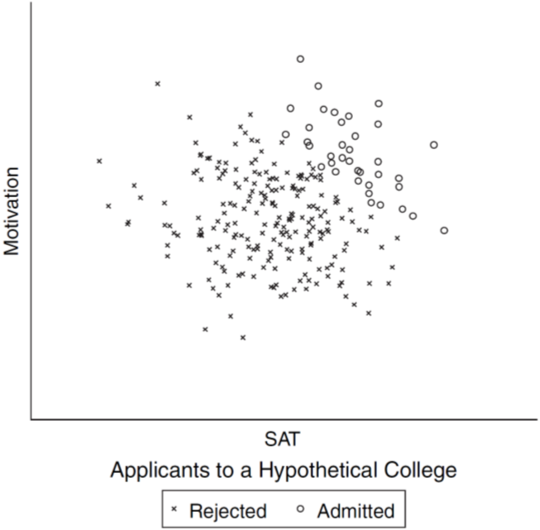
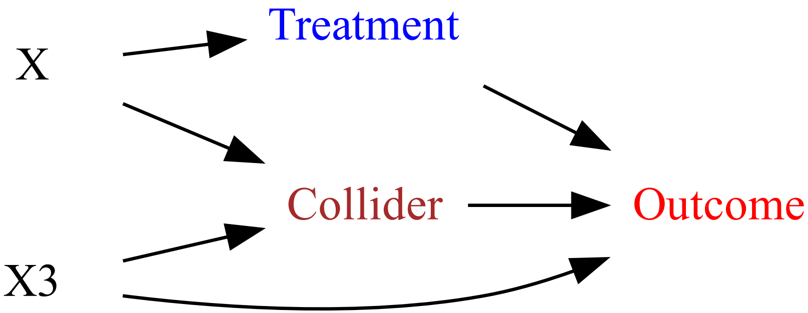


Figure 3.4: Simulation of conditional dependence within values of a collider variable.

3. Colliders



Example adapted from Morgan and Winship, p.72

1. List all of the **back-door paths** from *D* to *Y*

Example adapted from Morgan and Winship, p.72

1. List all of the **back-door paths** from D to Y
2. Identify any **post-treatment** variables: Do NOT include as controls

Example adapted from Morgan and Winship, p.72

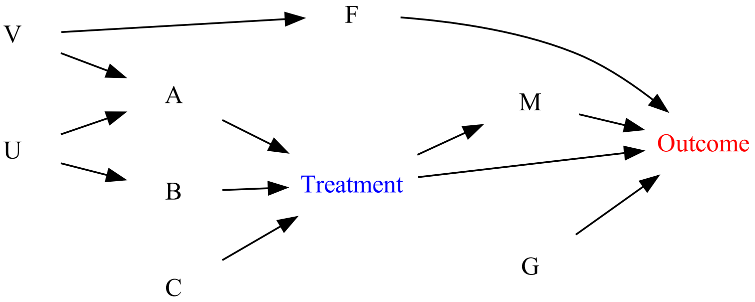
1. List all of the **back-door paths** from D to Y
2. Identify any **post-treatment** variables: Do NOT include as controls
3. Identify any back-door paths with **collider** variables: Mark these as already blocked

Example adapted from Morgan and Winship, p.72

1. List all of the **back-door paths** from D to Y
2. Identify any **post-treatment** variables: Do NOT include as controls
3. Identify any back-door paths with **collider** variables: Mark these as already blocked
4. Find a minimum set of variables that blocks all remaining back-door paths

Example adapted from Morgan and Winship, p.72

1. List all of the **back-door paths** from D to Y
2. Identify any **post-treatment** variables: Do NOT include as controls
3. Identify any back-door paths with **collider** variables: Mark these as already blocked
4. Find a minimum set of variables that blocks all remaining back-door paths
5. Double-check your minimum set of control variables does not contain any post-treatment or collider variables



Causal Diagrams (DAGs)

- Three Rules to achieve Conditional Independence:
  1. Include as controls enough variables to **block all back-door paths** from treatment to the outcome

Causal Diagrams (DAGs)

- Three Rules to achieve Conditional Independence:
  1. Include as controls enough variables to **block all back-door paths** from treatment to the outcome
     - In practice, variables which theory and past studies identify as potential confounders

Causal Diagrams (DAGs)

- Three Rules to achieve Conditional Independence:
  1. Include as controls enough variables to **block all back-door paths** from treatment to the outcome
     - In practice, variables which theory and past studies identify as potential confounders
  2. Exclude any variables that are **post-treatment**

Causal Diagrams (DAGs)

- Three Rules to achieve Conditional Independence:
  1. Include as controls enough variables to **block all back-door paths** from treatment to the outcome
     - In practice, variables which theory and past studies identify as potential confounders
  2. Exclude any variables that are **post-treatment**
     - In practice, know when your variables were measured

Causal Diagrams (DAGs)

- Three Rules to achieve Conditional Independence:
  1. Include as controls enough variables to **block all back-door paths** from treatment to the outcome
     - In practice, variables which theory and past studies identify as potential confounders
  2. Exclude any variables that are **post-treatment**
     - In practice, know when your variables were measured
  3. Exclude any variables that are **colliders**

Causal Diagrams (DAGs)

- Three Rules to achieve Conditional Independence:
  1. Include as controls enough variables to **block all back-door paths** from treatment to the outcome
     - In practice, variables which theory and past studies identify as potential confounders
  2. Exclude any variables that are **post-treatment**
     - In practice, know when your variables were measured
  3. Exclude any variables that are **colliders**
     - In practice, don't include unnecessary controls