FLS 6441 - Methods III: Explanation and Causation

Week 9 - Controlling for Confounding

Jonathan Phillips

May 2019

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

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- Adding control variables changes the comparison we are making: **Treatment is associated with higher values of the Outcome...holding constant the values of X**
- But when does controlling allow us to say: **Treatment *causes* higher values of the Outcome**?

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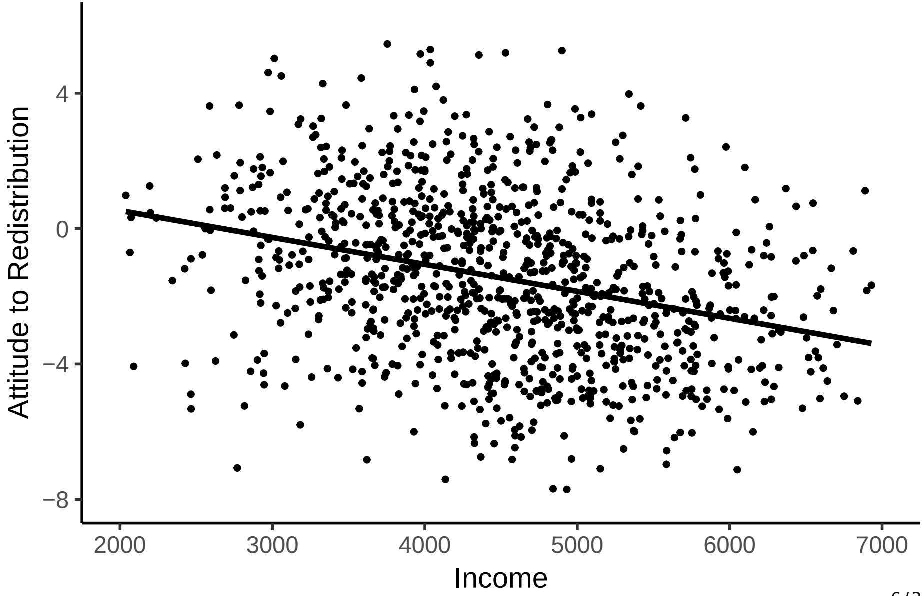
  - We have to make an argument and provide supporting evidence

Controlling for Confounding



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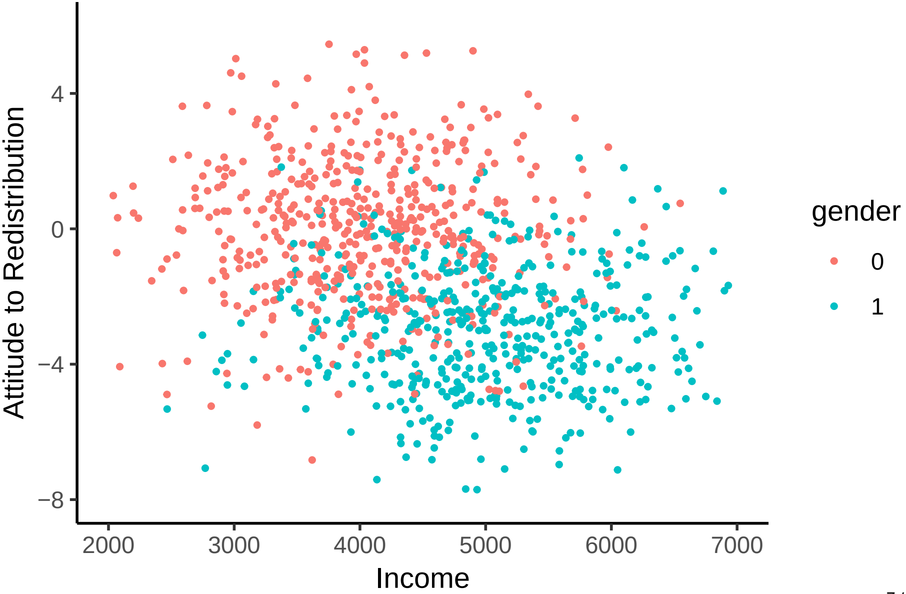

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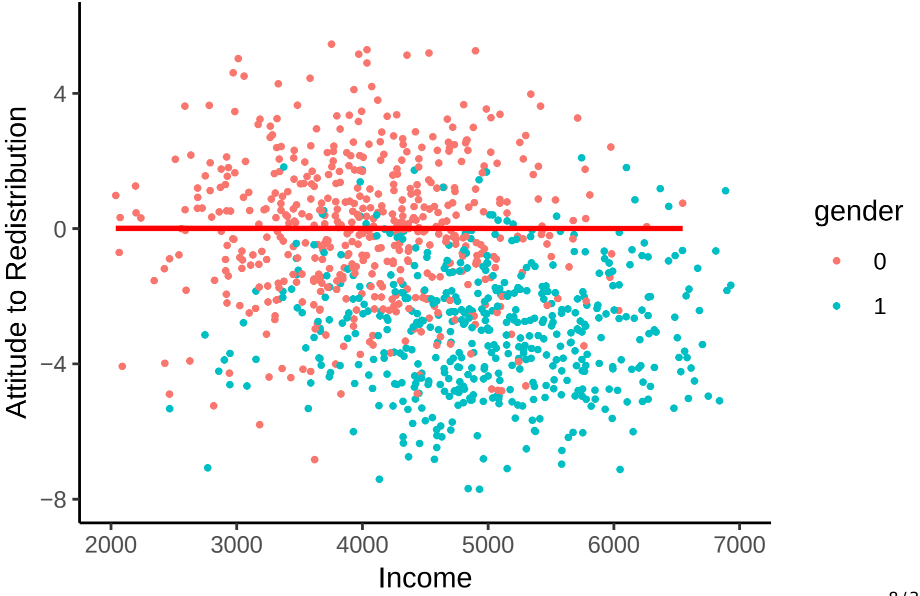

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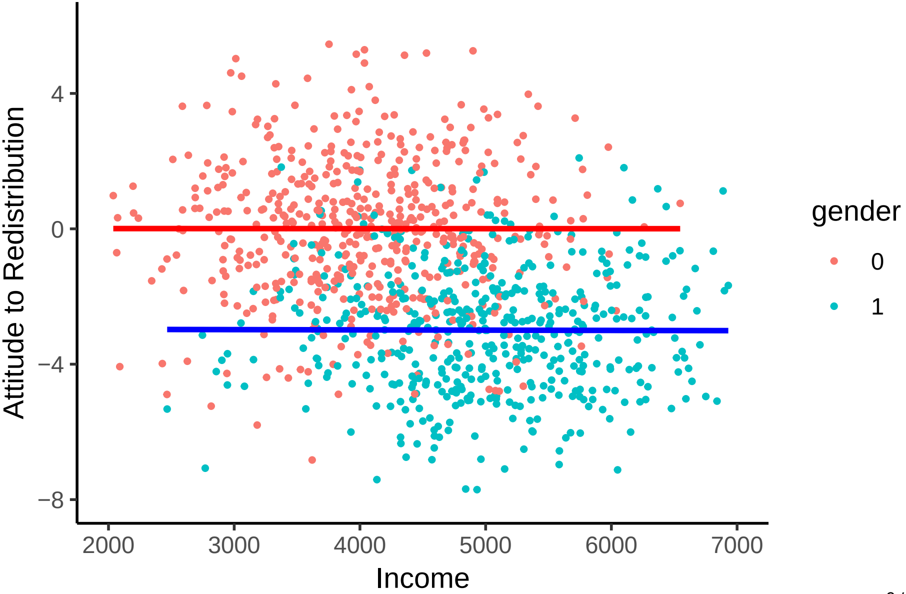

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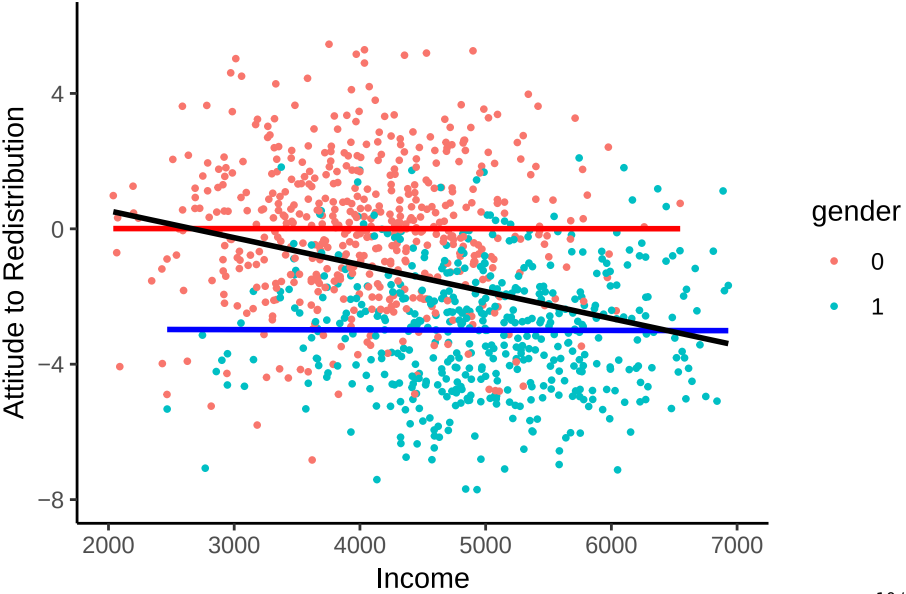

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$$\beta_{wrong} = \beta_{true} + \gamma\delta$$

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    - 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 all other characteristics

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Section 2

Which Variables to Control For

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  - A **Directed Acyclical Graph** (DAG)
  - Arrows only in one direction
  - No circular loops!

Causal Diagrams (DAGs)

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

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  - We want to focus on one ’flow’ of causation from treatment to outcomes
  - Avoiding mixing with the other flows of causation in the network

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  - Include these as control variables in our regression

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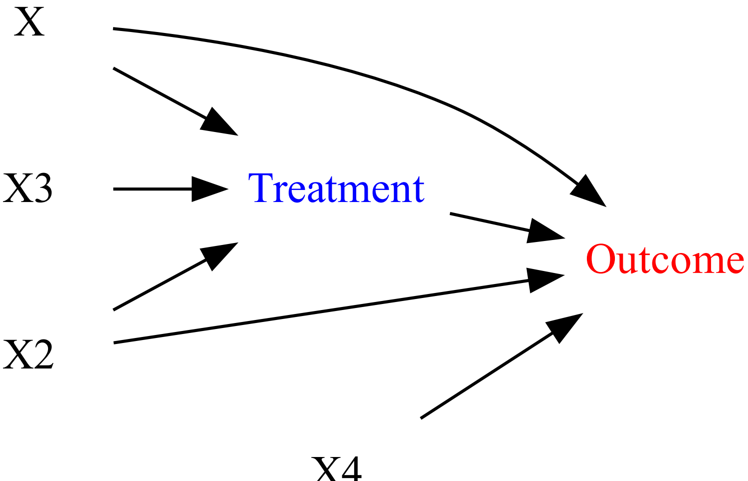

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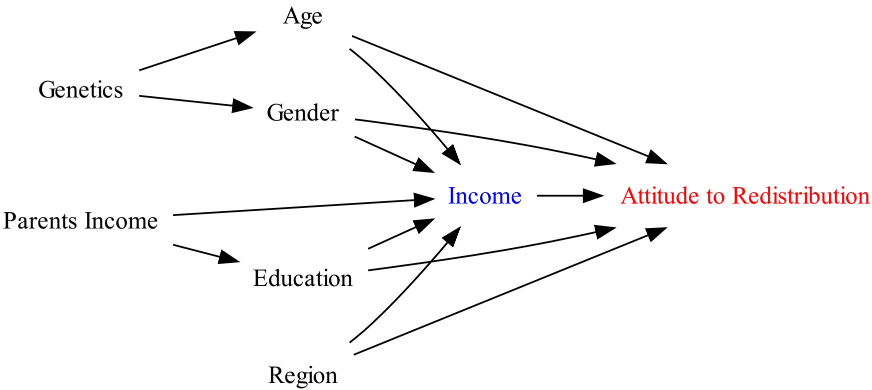

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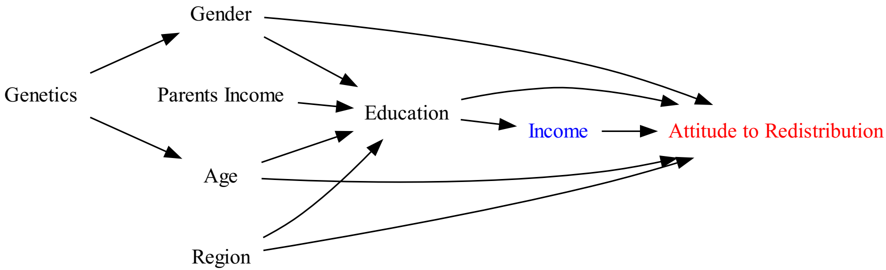

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    - Controlling for them changes the definition of the causal effect we are estimating

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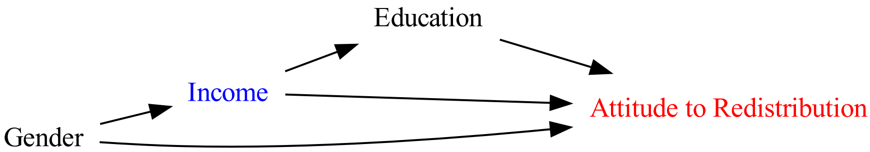

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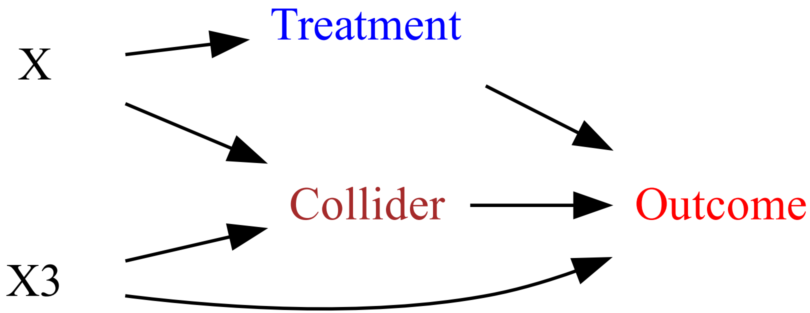

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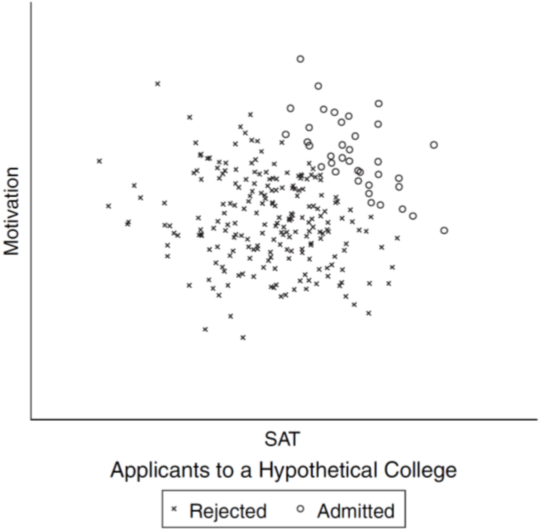

Figure 3.4: Simulation of conditional dependence within values of a collider variable.

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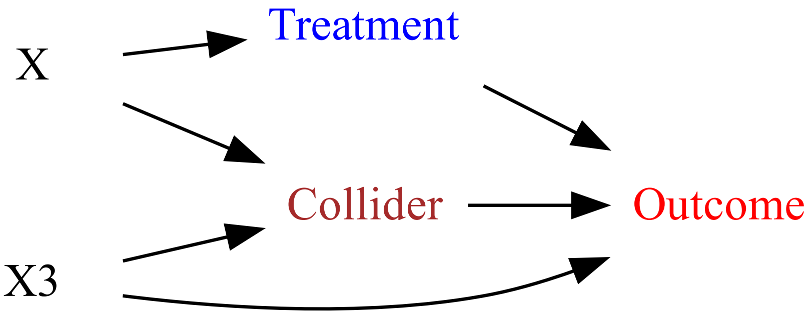
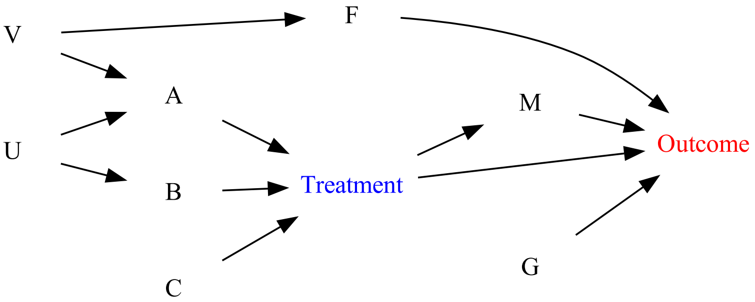


Example adapted from Morgan and Winship, p.72



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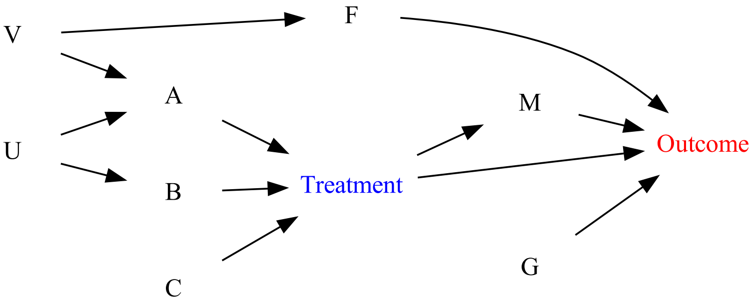

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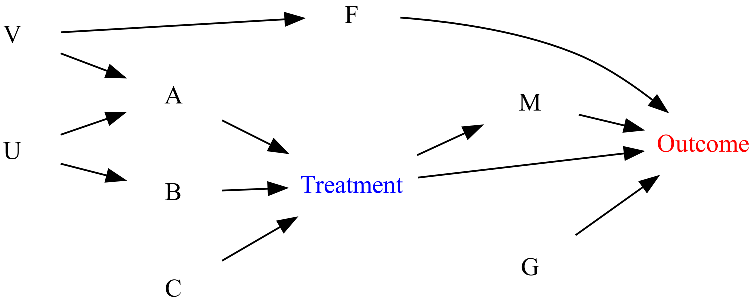

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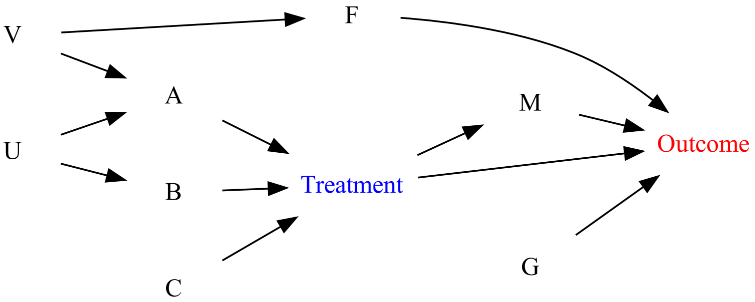

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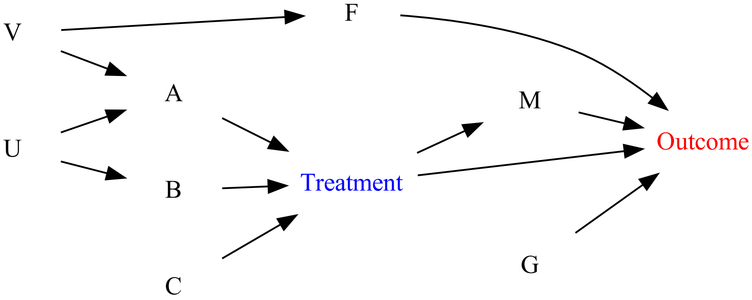

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     - In practice, don't include unnecessary controls