FLS 6441 - Methods III: Explanation and Causation

Week 9 - Controlling for Confounding

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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

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- But when does controlling allow us to move from **"is associated with"** to **causes**?

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  - We have to make an argument and provide supporting evidence

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  - 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 all other characteristics

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Section 2

Which Variables to Control For

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  - No circular loops!

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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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    1. Include as controls enough variables to **block all back-door paths** from treatment to the outcome

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  2. Exclude any variables that are **post-treatment**
  3. Exclude any variables that are **colliders**

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- Identify the **Minimum set of controls** to achieve conditional independence
  - *Any* set of variables which blocks *All* back-door paths
  - Include these as control variables in our regression

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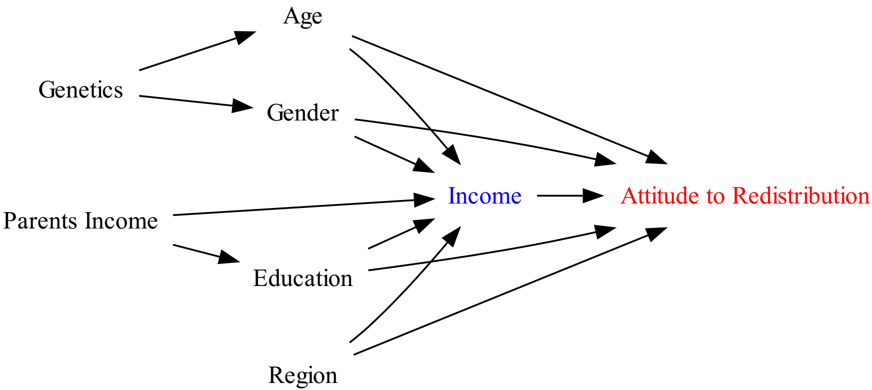

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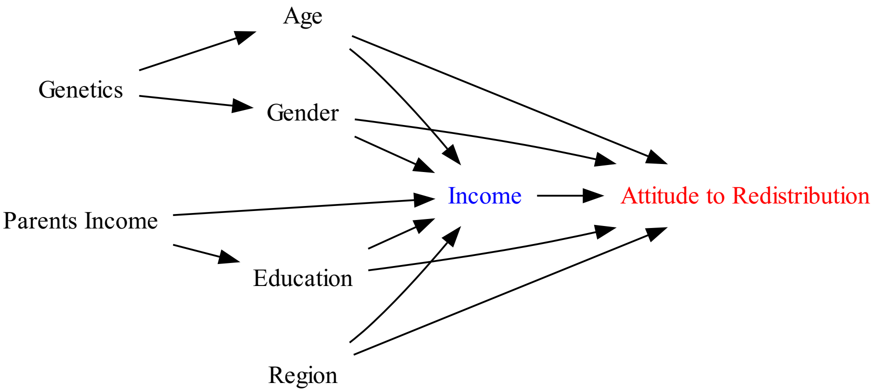

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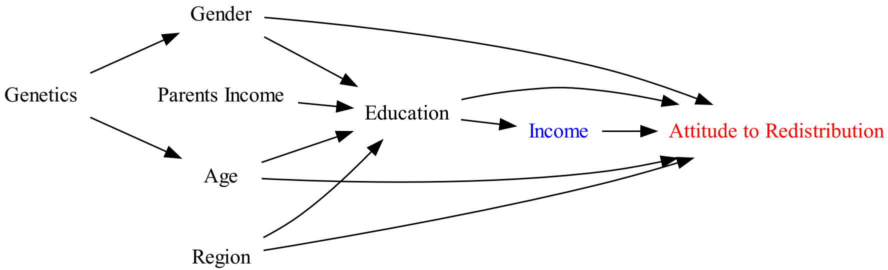

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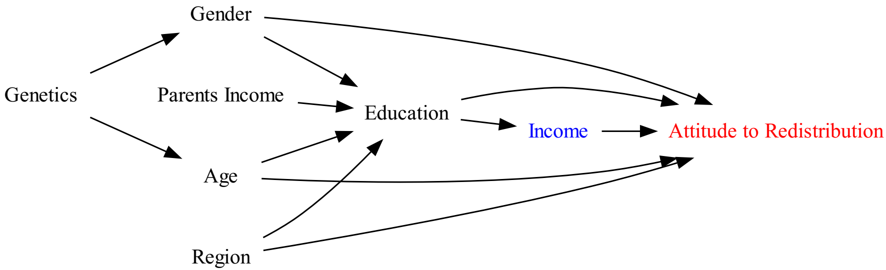

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  - Because variables measured ’after’ treatment can also be affected by treatment
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  - Controlling for them changes the definition of the causal effect we are estimating

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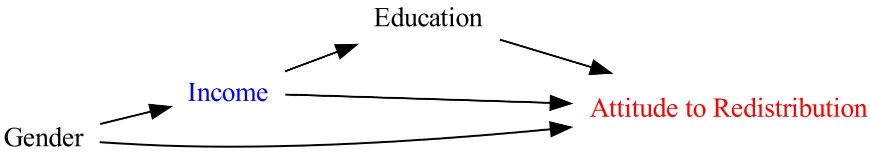

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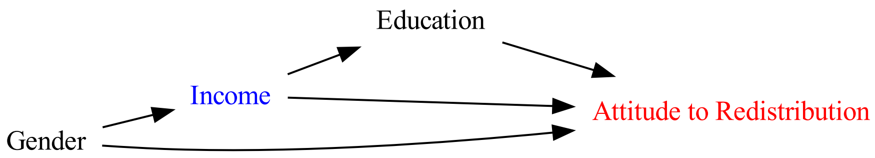

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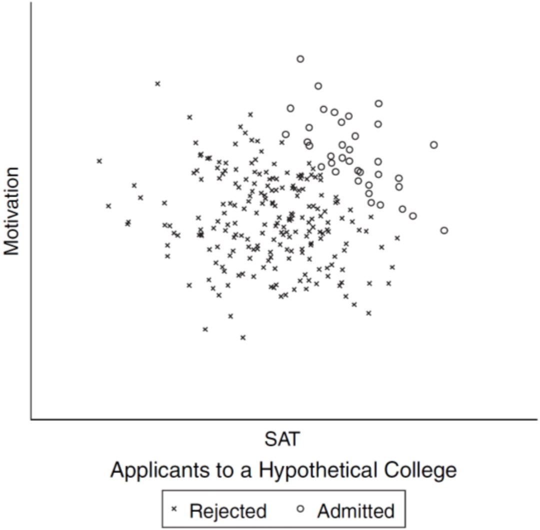

Figure 3.4: Simulation of conditional dependence within values of a collider variable.

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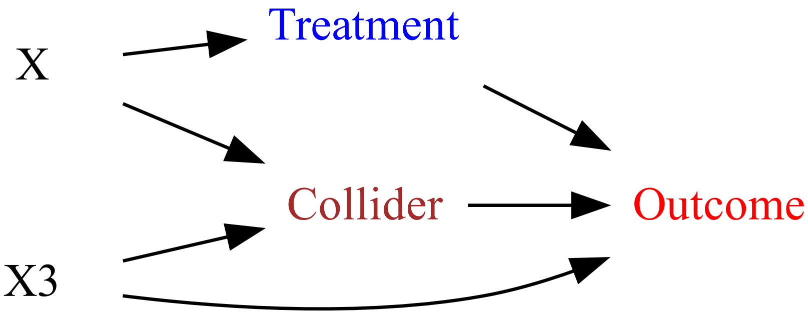

Example adapted from MW, p.72

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