Gov 51: Observational Studies

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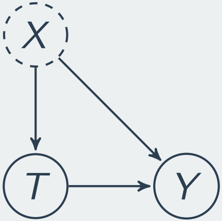
  - Observational studies often have larger/more representative samples that improve external validity.

Confounding



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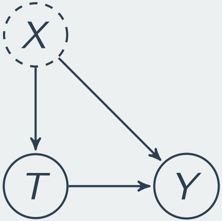

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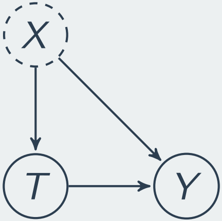

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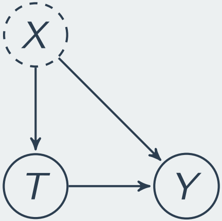

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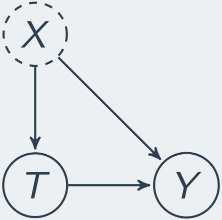

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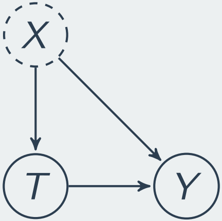

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  - one type: **selection bias** from self-selection into treatment

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  3. **Difference-in-differences design**: use before/after information for the treated and control group; need over-time on treated & control group.

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- Could there be confounders?

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- Threat to inference: we can only control for observed variables $\rightsquigarrow$ threat of **unmeasured confounding**

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  - Time trend: Labour just did better overall in 1997 compared to 1992.

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- RCTs handle confounding by design.

Causality understanding check