PSC4375: Observational Studies

Week 2: Lecture 3

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  - **Control group**: readers of papers who didn't switch

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

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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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- Threat to inference: **time-varying confounders**
  - Time trend: Labour just did better overall in 1997 compared to 1992

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  - Threat to inference: non-parallel trends

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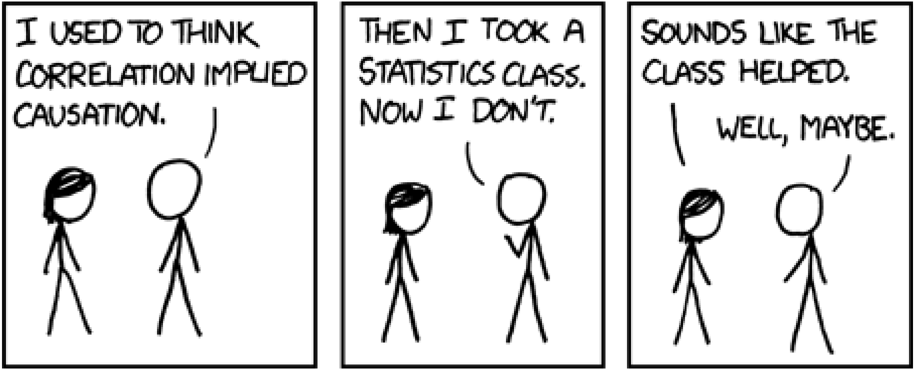
- All rely on assumptions that can't be verified to handle confounding
- RCTs handle confounding by design

Causality understanding check



See also: https://www.tylervigen.com/spurious-correlations