Observational Studies & Descriptive Statistics

PSC7475: Week 2

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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

Summarizing approaches:

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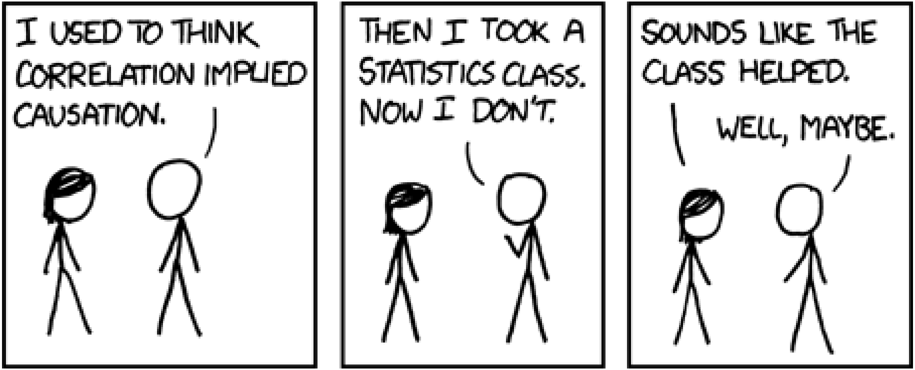
- All rely on assumptions that can't be verified to handle confounding
- RCTs handle confounding by design

Causality understanding check



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

Lots of data

- Data from study of the effect of minimum wage

```
##        chain location wageBefore wageAfter fullBefore
## 1     wendys       PA       5.00      5.25         20
## 2     wendys       PA       5.50      4.75          6
## 3 burgerking       PA       5.00      4.75         50
## 4 burgerking       PA       5.00      5.00         10
## 5        kfc       PA       5.25      5.00          2
## 6        kfc       PA       5.00      5.00          2
##   fullAfter partBefore partAfter
## 1         0         20        36
## 2        28         26         3
## 3        15         35        18
## 4        26         17         9
## 5         3          8        12
## 6         2         10         9
```

Lots and lots of data

```
head(minwage$wageAfter, n = 200)
```

```
##   [1] 5.25 4.75 4.75 5.00 5.00 5.00 4.75 5.00 4.50 4.75 4.5
##  [12] 5.00 4.75 4.75 4.75 4.25 5.00 4.90 5.00 4.75 5.00 4.2
##  [23] 4.75 4.25 4.25 4.25 4.25 4.25 4.25 4.38 4.75 4.25 4.5
##  [34] 4.50 4.25 4.25 4.25 4.25 5.05 4.25 4.25 4.25 4.25 4.3
##  [45] 4.50 4.50 5.00 4.75 5.00 4.35 4.25 4.90 4.50 4.50 4.7
##  [56] 6.25 4.35 4.50 4.50 5.00 4.75 4.50 4.75 4.25 4.91 4.4
##  [67] 4.25 5.05 5.05 5.05 5.05 5.05 5.05 5.05 5.05 5.05 5.0
##  [78] 5.05 5.05 5.05 5.50 5.05 5.05 5.05 5.05 5.05 5.05 5.2
##  [89] 5.25 5.05 5.05 5.50 5.05 5.05 5.05 5.05 5.05 5.05 5.0
## [100] 5.05 5.05 5.05 5.05 5.05 5.05 5.05 5.05 5.05 5.05 5.2
## [111] 5.05 5.05 5.05 5.05 5.05 5.05 5.05 5.05 5.05 5.67 5.0
## [122] 5.05 5.05 5.05 5.25 5.25 5.05 5.50 5.05 5.05 5.05 5.5
## [133] 5.50 5.05 5.05 5.25 5.05 5.05 5.15 5.05 5.05 5.05 5.0
## [144] 5.00 5.05 5.05 5.05 5.05 5.05 5.05 5.05 5.05 5.05 5.0
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- Two salient features of a variable that we want to know:
  - **Central tendency**: where is the middle/typical/average value
  - **Spread** around the center: are all values to the center or spread out?

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- **Median**:

$$\text{median} = \begin{cases} \text{middle value} & \text{if number of entries is odd} \\ \frac{\text{sum of two middle values}}{2} & \text{if number of entries is even} \end{cases}$$

- In **R**: `mean()` and `median()`

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- What does Mark Zuckerberg do to the mean vs. median income?

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- **R** function: `range()`, `summary()`, `IQR()`

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- Why not just take the average deviations from mean without squaring?

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- Today she got \$0.56, what about that?