

# Propensity techniques

**Aleš Vomáčka**

# The Plan

- How to estimate propensity scores
- How to apply the scores
  - Propensity scores matching
  - Propensity score weighting
- Advantages and Disadvantages, assumptions

# Estimating propensity scores

# Pre-election Debates & Opinion Change

- How effective are pre-election debates at changing voter preferences?
- Data from the last presidential elections, shortly before the 2nd round.
- Variables of interest:
  - debate - have the respondent seen the last debate?
  - change - have the respondent changed candidate after debate?
  - election\_cand\_before - which candidate preferred before debate?

# The Problem

- Who sees the debate isn't random.
- Potential Outcome Framework
  - Ignorability may be violated
- Directed Acyclic Graphs Framework
  - There may be a backdoor path from debate to change.

# The (Potential) Solution

- We can try estimating probability of receiving treatment and...
  - ...achieve conditional ignorability
  - ...close the backdoor path
- How do we do it?
  - One option are propensity techniques

# Propensity Scores Techniques

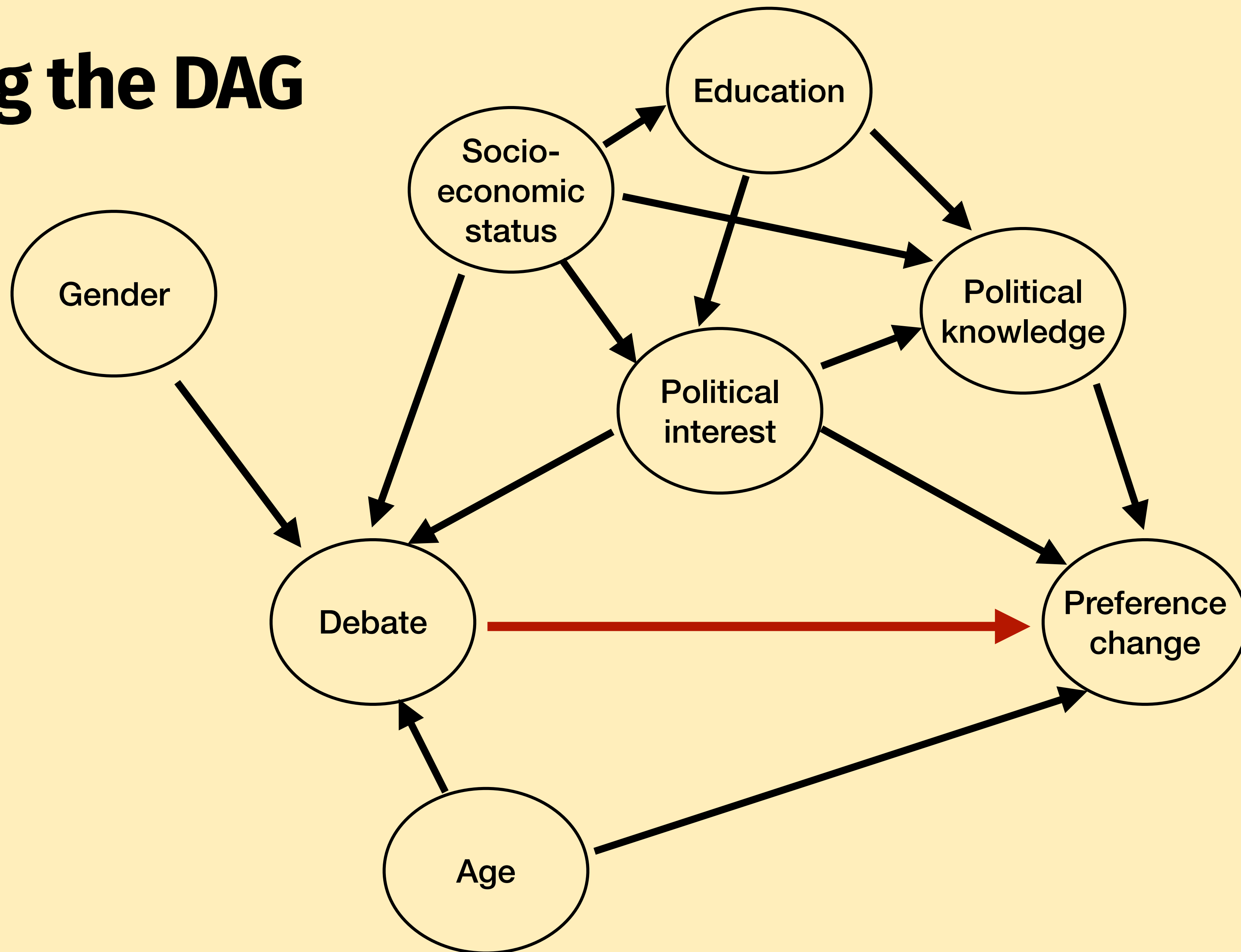
- Zhao, Q.-Y., Luo, J.-C., Su, Y., Zhang, Y.-J., Tu, G.-W., & Luo, Z. (2021). Propensity score matching with R: Conventional methods and new features. *Annals of Translational Medicine*, 9(9), 812. <https://doi.org/10.21037/atm-20-3998>
- Chesnaye, N. C., Stel, V. S., Tripepi, G., Dekker, F. W., Fu, E. L., Zoccali, C., & Jager, K. J. (2022). An introduction to inverse probability of treatment weighting in observational research. *Clinical Kidney Journal*, 15(1), 14–20. <https://doi.org/10.1093/ckj/sfab158>

# Propensity Scores

- Propensity scores - conditional probability of receiving treatment
- The probability is conditional on potential confounders.
- This means that the first step is...

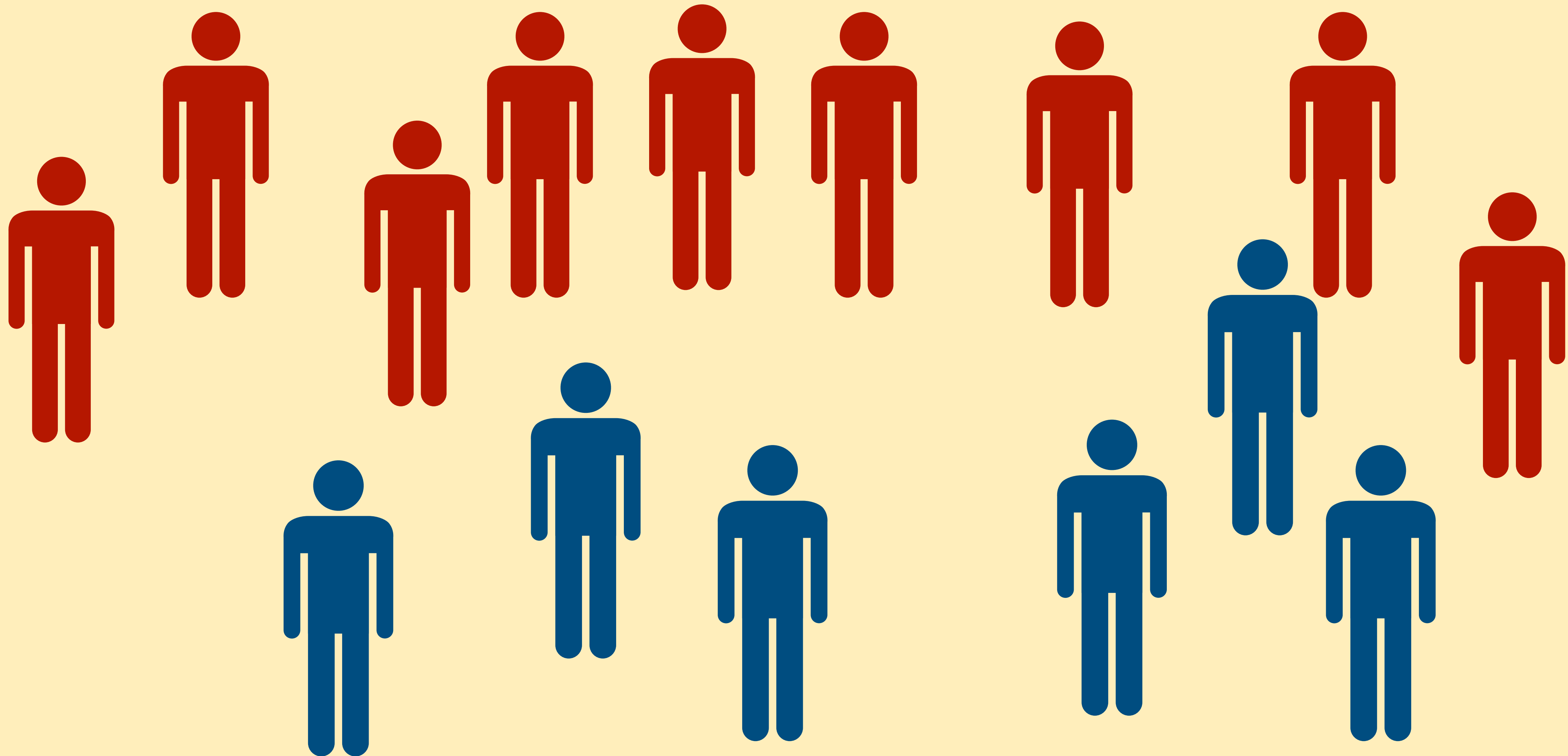


# Step 1 - Drawing the DAG

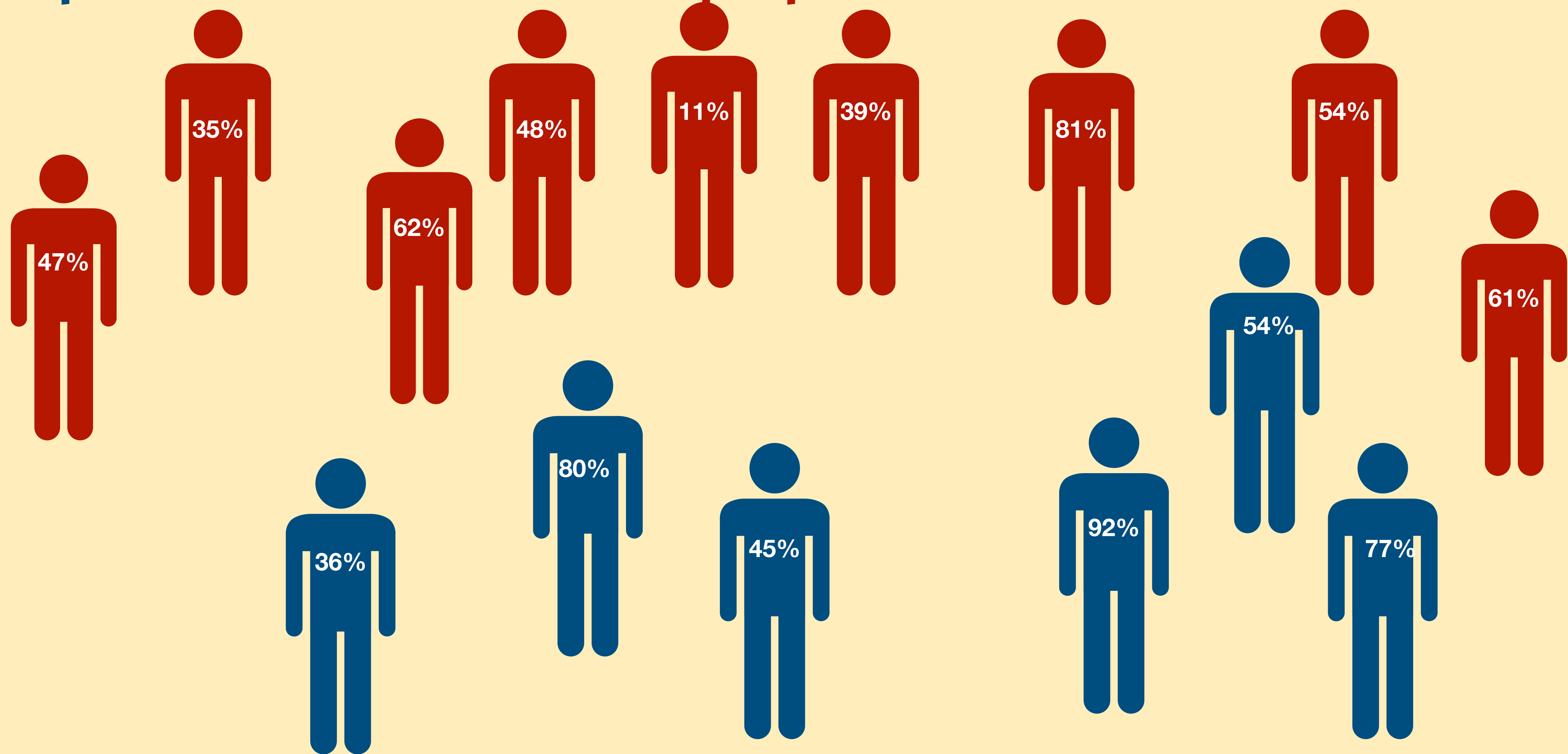


## Step 2 - Estimating propensity scores

- **People who saw the debate** and **people who didn't see the debate.**

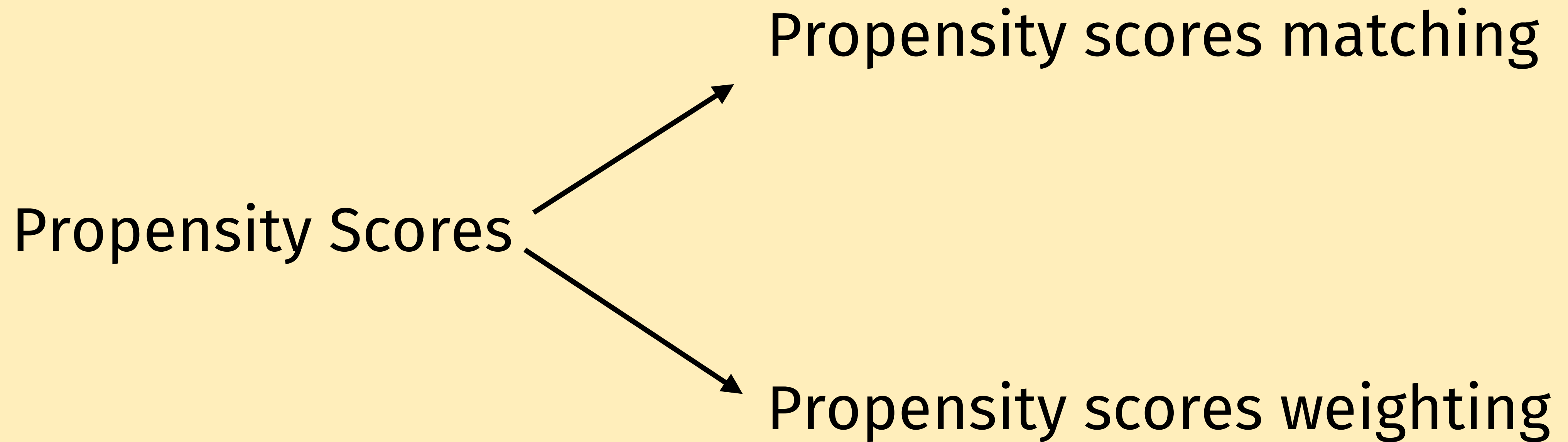


- Many models to do so, logistic regression most common (but newer methods more robust/convenient)
- **People who saw the debate** and **people who didn't see the debate.**



Questions?

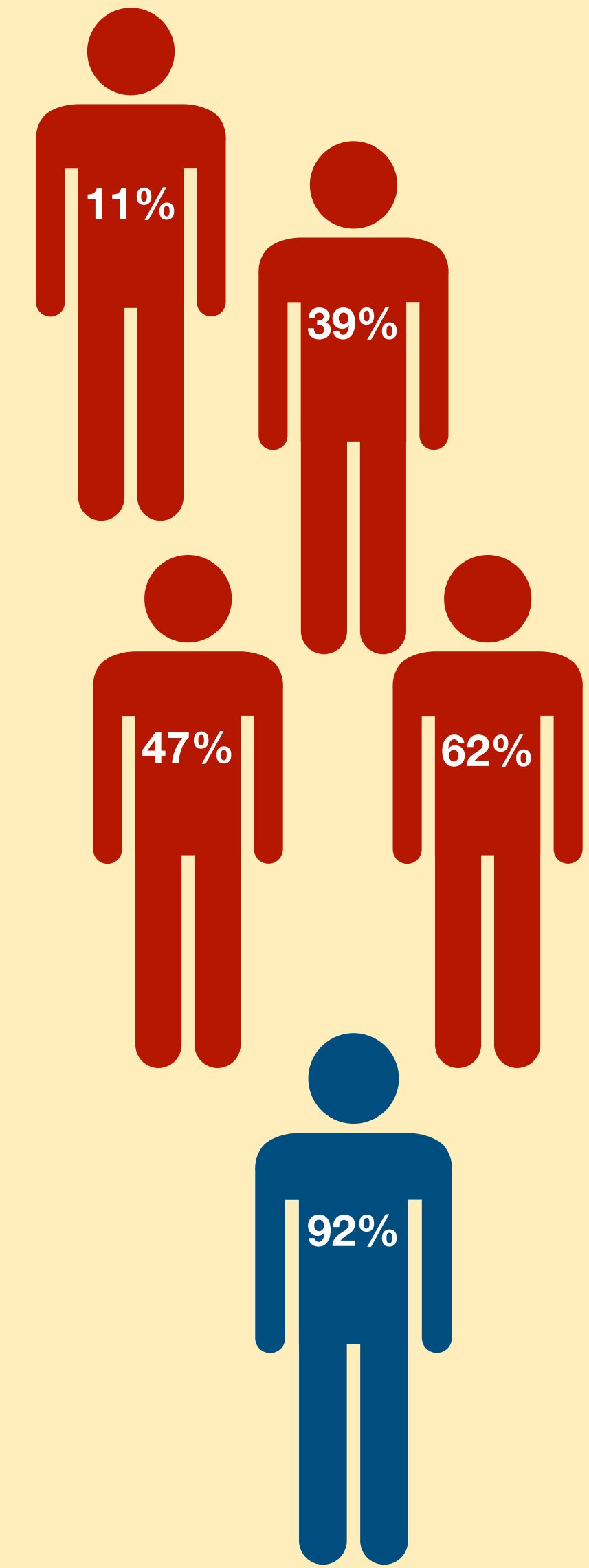
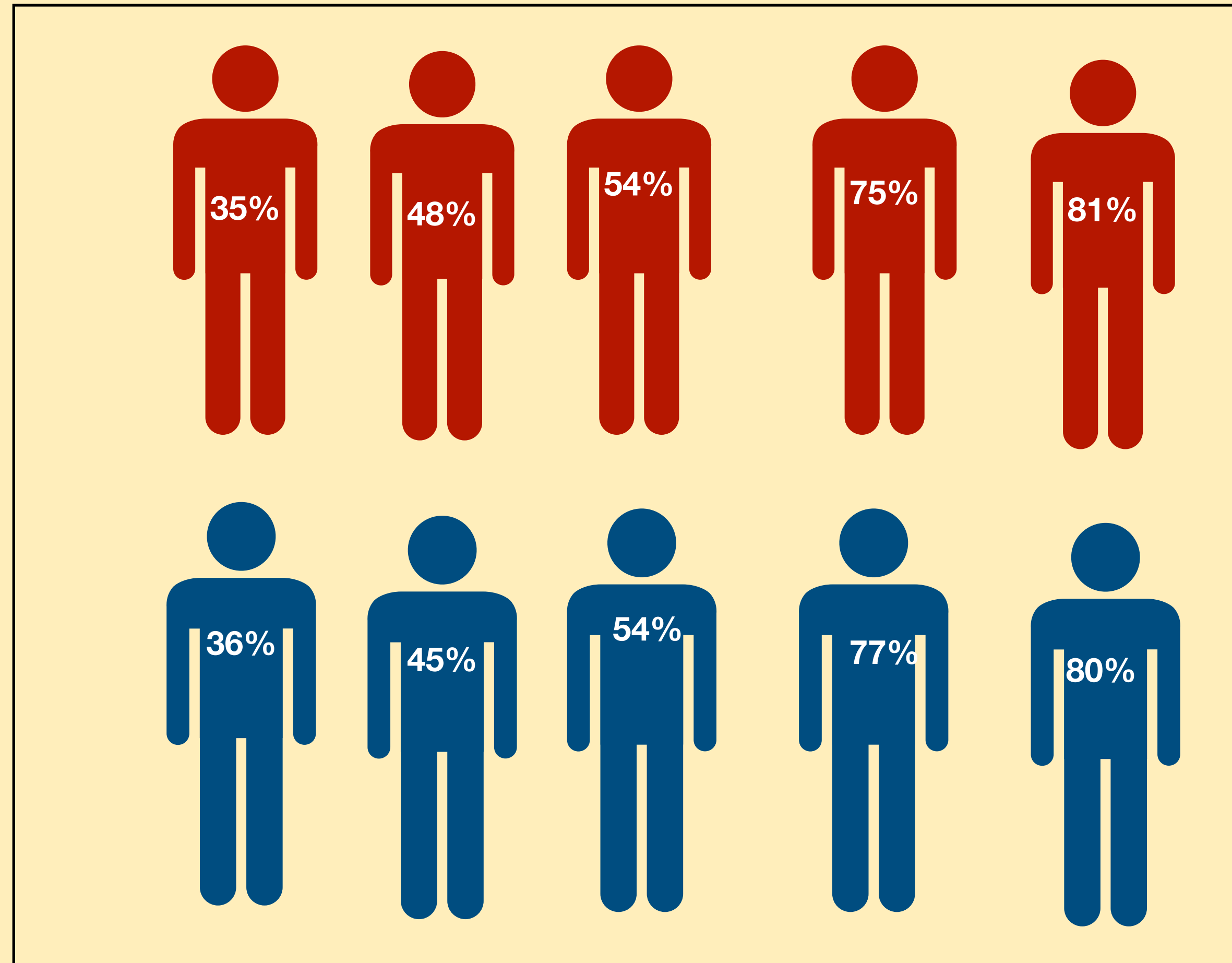
# Step 3 - Choosing Method



# Step 4a - Propensity Score Matching

Match **respondents who got the treatment** and **respondents who didn't** with similar propensity scores.

Toss the rest.



# Step 4a - Propensity Score Weighting

- Transform the probabilities of receiving treatment into weights.
- Give higher weight to respondents with:
  - Low probability of receiving treatment, but ultimately got it.
  - High probability of receiving treatment, but ultimately didn't get it.
- In short, give higher weights to the less expected outcomes.
- Many ways to do it.

# Step 4a - Inverse probability treatment weights

- OG approach - Easy to compute, widely used

$$w_i = \frac{1}{p_i} \quad \text{if } Treat = 1$$

$$w_i = \frac{1}{1 - p_i} \quad \text{if } Treat = 0$$

Where  $p_i$  is the estimated probability of receiving treatment for every respondent  $i$



# Step 4a - Full Optimal Matching

- Newer approach
- More robust, but harder to compute - combines matching and weights

$$w_i = \frac{p \cdot (m + j)}{m} \quad \text{if } Treat = 1$$
$$w_i = \frac{(1 - p) \cdot (m + j)}{j} \quad \text{if } Treat = 0$$

Where  $p$  is the marginal (average) probability of receiving treatment,  $m$  is the number of respondents in matching set who received treatment and  $j$  is the number of respondents without treatment in the matching set.

# Step 4 - IPTW vs Full Optimal Matching

Austin, P. C., & Stuart, E. A. (2017). The performance of inverse probability of treatment weighting and full matching on the propensity score in the presence of model misspecification when estimating the effect of treatment on survival outcomes. *Statistical Methods in Medical Research*, 26(4), 1654–1670. <https://doi.org/10.1177/0962280215584401>

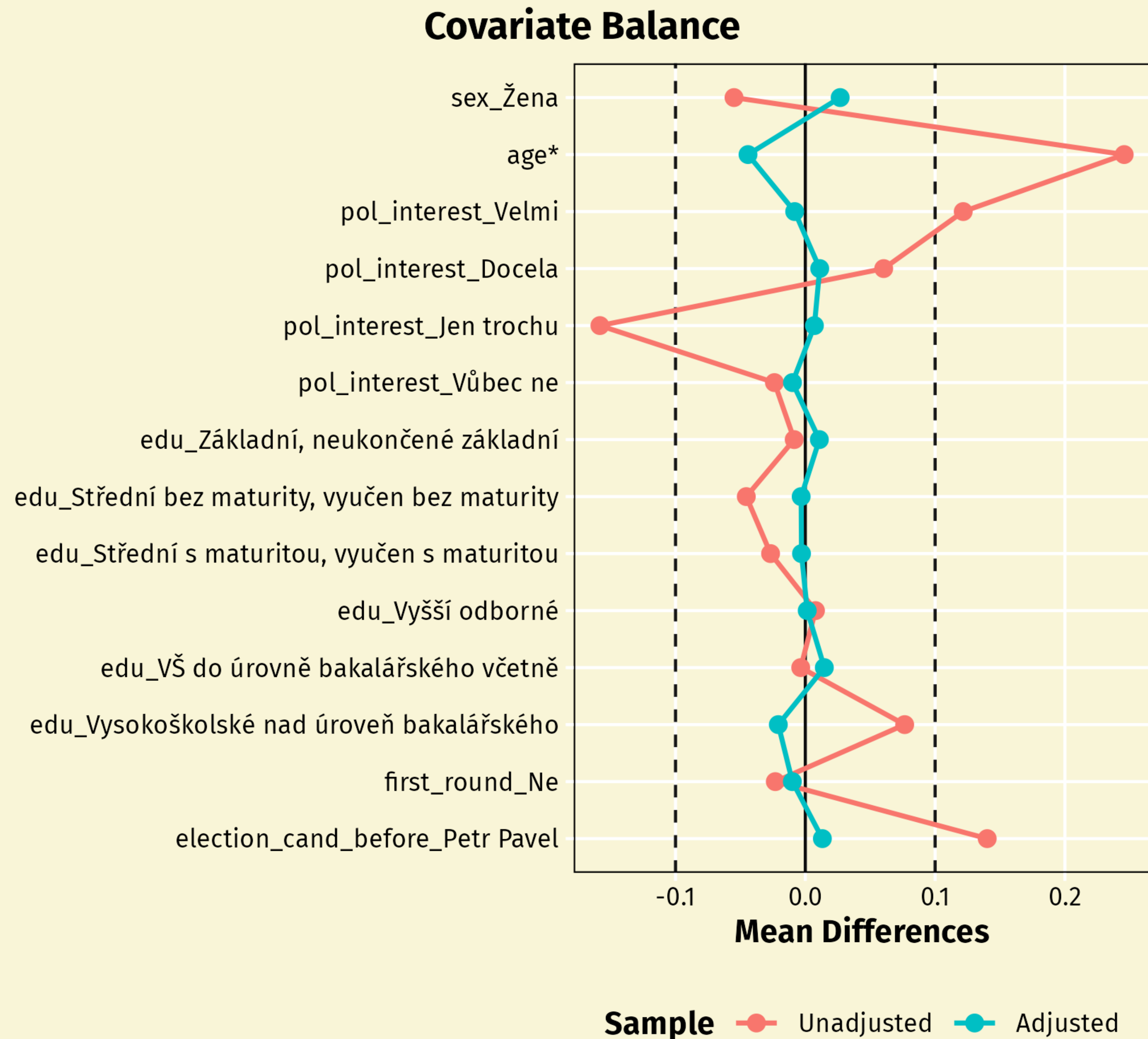
Questions?

# Step 5 - Balance checking

- Once you have matched/weighted the data, you need to check whether the treatment and control groups are balanced.
- i.e. whether they no longer differ in observed confounders.

## Step 5 - Balance checking

- Tables of visually.
- After matching/weighting, there should be no difference between treatment and control groups



## Step 6 - Estimate The Effect

- If the matching/weighting were successful, you have achieved conditional ignorability/closed backdoor paths.
- The estimated difference between between treatment and control group represents the treatment causal effect.
- Congratulations, you have made it! (maybe, you can never be sure...)

# Weighting Summary

- Advantages:
  - Doesn't throw away data.
  - Can estimate Average treatment effect on population.
- Disadvantages:
  - Can produce large weights, which makes results unstable.
  - Try explaining it to someone...

# Matching Summary

- Advantages:
  - Easy to do (explain)
  - Robust to outliers.
- Disadvantages:
  - Throws away data
  - Can only estimate **Average Treatment on Treated!!**
    - Because we threw away part of the data, we no longer have unbiased estimate for the population, only people in the sample



# No Unobserved Confounders Assumptions

- Both approaches assume you have accounted for all confounders.
- At least the important ones.
  
- Good luck proving it...

# Propensity Techniques vs Simple Conditioning

- Why use propensity scores, when we can control for variables directly?
- Propensity scores:
  - More efficient when number of predictors is large.
  - Can check balance
- But some people like to use treatment probabilities as a control variable.
- Some techniques use both (doubly robust estimators), worth checking out.

Questions?

**InteRmezzo!**