# **Propensity Scores**

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#### Four Learning Objectives

- Why observational studies have little ability to make causal claims
- 2. Understanding the niche that observational studies fill
- 3. What is a propensity score
- 4. Ways to implement a propensity score

#### **Outline**

- Background on assessing causation
- 2. Define propensity score (PS)
- Calculate the PS
- Use the PS
- 5. Limitations of the PS

## Causality

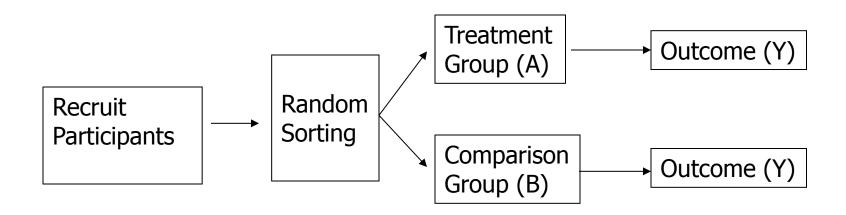
- Researchers are often interested in understanding causal relationships
  - Does drinking red wine affect health?
  - Does a new treatment reduce symptoms?
  - Does job burnout affect risk of suicidality?
  - Does the Veterans Crisis Line reduce the likelihood of suicide?

#### **Randomized Clinical Trial**

 RCT provides a methodological approach for understanding causation

 Understanding propensity score is assisted by understanding randomized trials.

#### Randomization



Note: random sorting can, by chance, lead to unbalanced groups. Most trials use checks and balances to preserve randomization

Just because a RCT can speak to causality, you must ask the question for whom— generalizability is often very limited

# **Trial analysis**

The expected effect of treatment is

$$E(Y)=E(Y^A)-E(Y^B)$$

Expected effect on group A minus expected effect on group B (i.e., mean difference).

# **Trial Analysis (II)**

 E(Y)=E(Y<sup>A</sup>)-E(Y<sup>B</sup>) can be analyzed using the following general model

$$y_i = \alpha + \beta x_i + \varepsilon_i$$

#### Where

- y is the outcome
- $\alpha$  is the intercept
- x is the mean difference in the outcome between treatment A relative to treatment B
- ε is the error term
- i denotes the unit of analysis (person)

# **Trial Analysis (III)**

The model can be expanded to control for baseline characteristics

$$y_i = \alpha + \beta x_i + \delta Z_i + \varepsilon_i$$

#### Where

- y is outcome
- $\alpha$  is the intercept
- x is the added value of the treatment A relative to treatment B
- Z is a vector of baseline characteristics (predetermined prior to randomization)
- ε is the error term
- i denotes the unit of analysis (person)

#### **Assumptions**

- Right hand side variables are measured without noise (i.e., considered fixed in repeated samples)
- There is no correlation between the right hand side variables and the error term

$$E(x_i \varepsilon_i) = 0$$



If these conditions hold, β is an unbiased estimate of the causal effect of the treatment on the outcome

#### What if...

the assumptions don't hold in the RCT, then what?

You lose the unbiased estimate of causality.

#### **Observational Studies**

- Randomized trials may be
  - Unethical
  - Infeasible
  - Impractical
  - Not scientifically justified

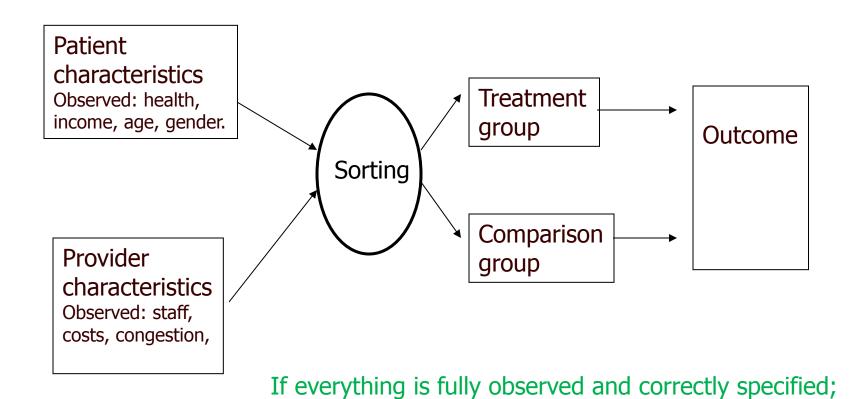
## **Endogenous**

- Poll-
- Has anyone heard of this term?
  - Yes, I use the term frequently when talking to friends and family
  - Yes, I have heard others use the term related to methods
  - Yes, I have heard the term related to medicine or endocrinology
  - No, and I like being honest

## **Endogenous**

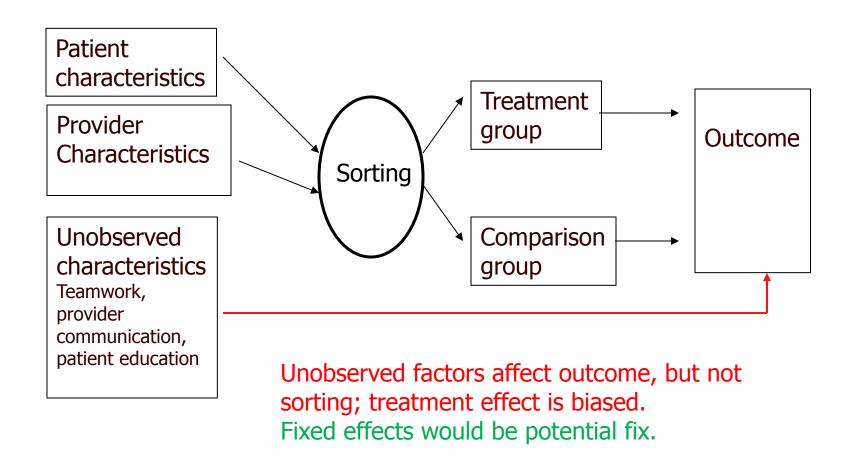
- Not attributable to any external factor.
- Example: Does smoking lead to cancer cancer<sub>i</sub> =  $\alpha$  + βsmoking<sub>i</sub> +  $\epsilon$ <sub>i</sub>
  - Smoking is correlated with income, education, parental exposure, etc.
  - We aren't controlling for any of those factors, thus E(smoking  $_i$ ,  $ε_i$ )≠0
  - Thus, smoking is endogenous

## Sorting without randomization

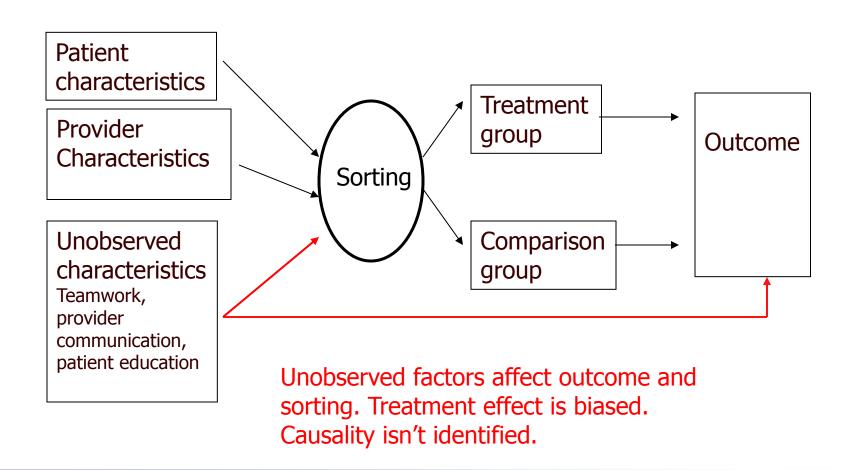


results are not biased. Never happens in reality.

## Sorting without randomization



## Sorting without randomization



## **Propensity Score Defined**

- The PS uses observed information, which is multi-dimensional, to calculate a single variable (the score)
- The score is the predicted propensity to get sorted (usually thought of as propensity to get treatment).

Expected treatment effect:  $E(Y)=E(Y^A)-E(Y^B)$ 

Propensity Score is:  $Pr(Y=A \mid X_i)$ 

#### **Propensity Scores**

What it is: Another way to correct for observable characteristics

What it is not: A way to adjust for unobserved characteristics

The only way to make causal claims is to make huge assumptions.

# Strong Ignorability

- To make statements about causation, you would need to make an assumption that treatment assignment is strongly ignorable.
  - Similar to assumptions of missing at random
  - Equivalent to stating that all variables of interest are observed

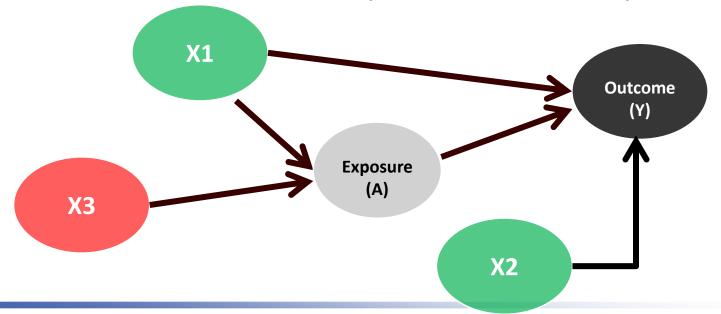
# Creating a Propensity Score

# **Calculating the Propensity Score**

- You observe treatment: One group receives it and another group doesn't
- Use multivariate logistic regression to estimate the probability that a person received treatment
- The predicted probability from the logistic model is the propensity score

#### Variables to Include

- Include variables that are related to the observed outcome
- This will decrease the variance of an estimated exposure effect without increasing bias
- Do not include variables affect only correlated with exposure



#### Variables to Exclude

- Exclude variables that are related to the exposure but not to the outcome
- These variables will increase the variance of the estimated exposure effect without decreasing bias
- Variable selection is particularly important in small studies (n<500)</li>

## **Example: Resident Surgery**

Do cardiac bypass patients have better / worse outcomes when their surgery is conducted by a resident or an attending?

We had a datasets that tracked the primary surgeon for heart bypass

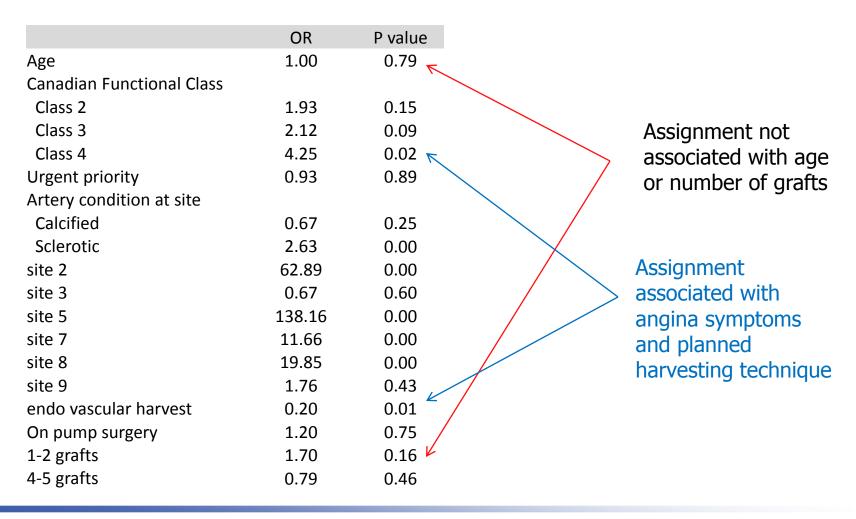
#### Uses

- Understanding sorting and balance
  - Sorting is multidimensional
  - The PS provides a simple way of reducing this dimensionality to understand the similarity of the treatment groups
- Adjusting for covariance

#### **Example**

- Are surgical outcomes worse when the surgeon is a resident?
- Resident assignment may depend on
  - Patient risk
  - Availability of resident
  - Resident skill
  - Local culture

#### **Resident Assignment**

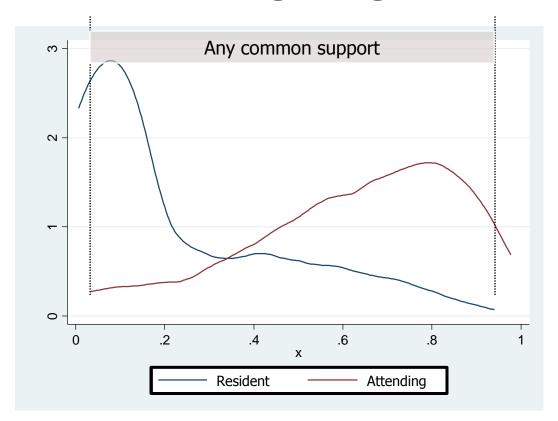


Bakaeen F, Sethi G, Wagner T, et al. Coronary Artery Bypass Graft Patency: Residents Versus Attending Surgeons. *Annals of Thoracic Surgery.* 

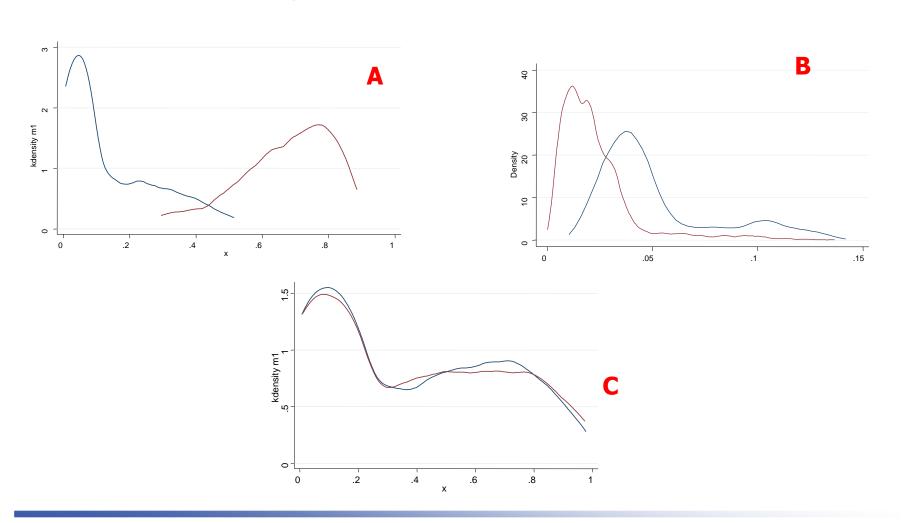
## **Shared or Common Support**

- Concept that measures overlap of people in both treatments
- Conditional on covariates, there exist people who choose both treatments.
- Poor common support suggests that conditional on observables, we cannot control for sorting.

# Propensity Score for Resident vs Attending Surgeon



# **Compare Three Scores**



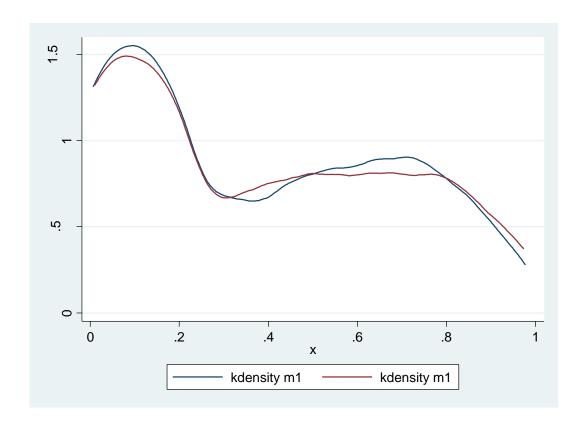
#### Poll

- Do any of these distributions concern you? Choose one
- B
- All of them
- None of them

#### **RCTs and Propensity Scores**

What would happen if you used a propensity score with data from a RCT?

# **Shared Common Support**



#### **Common Support**

 Growing evidence in economics that propensity scores provide some advantages when there is considerable shared support

# **Using the Propensity Score**

# **Using the Propensity Score**

- Compare individuals based on similar PS scores (a matched analysis)
- Conduct subgroup analyses on similar groups (stratification)
- Include it as a covariate (quintiles of the PS) in the regression model
- 4. Use it to weight the regression (i.e., place more weight on similar cases)
- Use both 3 and 4 together (doubly robust)

#### **PS** as a Covariate

- There seems to be little advantage to using PS over multivariate analyses in most cases.<sup>1</sup>
- PS provides flexibility in the functional form
- Propensity scores may be preferable if the sample size is small and the outcome of interest is rare.<sup>2</sup>

<sup>1.</sup> Winkelmeyer. Nephrol. Dial. Transplant 2004; 19(7): 1671-1673.

<sup>2.</sup> Cepeda et al. Am J Epidemiol 2003; 158: 280-287

# **Matched Analyses**

- The idea is to select controls that resemble the treatment group in all dimensions, except for treatment
- You can exclude cases and controls that don't match, which can reduce the sample size/power.
- Different matching methods

## **Matching Methods**

- Nearest Neighbor: rank the propensity score and choose control that is closest to case.
- Caliper: choose your common support and from within randomly draw controls

Choice of matching estimator important

### **Recent Areas of Research**

- Economics: choice of matching estimators
  - Busso M et al. New Evidence on the Finite Sample Properties of Propensity Score Reweighting and Matching Estimators. Review of Economics and Statistics, 96.5 (2014): 885-897
- Biostatistics: high dimensional propensity scores using big data
  - Schneeweiss, Sebastian, et al. "High-dimensional propensity score adjustment in studies of treatment effects using health care claims data." *Epidemiology* 20.4 (2009): 512.

## **Limitations**

### Do the Unobservables Matter?

- Propensity scores focus only on observed characteristics, not on unobserved.
- Improbable that we fully observe the sorting process
  - − Thus E(x<sub>i</sub> ε<sub>i</sub>)≠0
  - Multivariate (including propensity score) is biased and we need instrumental variables, fixed effects or RCT

# Does Using PS Exacerbate Imbalance of Unobservables

PS is based on observables.

Brooks and Ohsfeldt, using simulated data, showed that PS models can create greater imbalance among unobserved variables.

Brooks and Ohsfeldt (2013): Squeezing the balloon: propensity scores and unmeasured covariate balance. *Health Services Research*.

# **Summary**

### **Overview**

- Propensity scores offer another way to adjust for confound by observables
- Reducing the multidimensional nature of confounding can be helpful
- There are many ways to implement propensity scores and a growing interest in matching estimators

# Strengths

 Allow one to check for balance between control and treatment

Without balance, average treatment effects can be very sensitive to the choice of the estimators.<sup>1</sup>

1. Imbens and Wooldridge 2007 http://www.nber.org/WNE/lect\_1\_match\_fig.pdf

# Challenges

- Propensity scores are often misunderstood
- Not enough attention is placed on the PS model, itself
- Not enough attention is placed on robustness checks
- While a PS can help create balance on observables, PS models do not control for unobservables or selection bias

# **Further Reading**

- Imbens and Wooldridge (2007) www.nber.org/WNE/lect\_1\_match\_fig.pdf
- Imbens, Guido W. "The role of the propensity score in estimating dose-response functions." *Biometrika* 87.3 (2000): 706-710.
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- Imai, Kosuke, and Marc Ratkovic. "Covariate balancing propensity score." *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*76.1 (2014): 243-263.