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Propensity score and measured confounding

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Thank you for scholarship ☺

Causal inference in epidemiology: recent methodological development

5-9 November 2012

Organizers:

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AIMS of course:

a) Consider sources of error and uncertainty other than sampling error

b) Discuss recent methodological developments and how they relate to each other

c) Gain some practical experience of all these methods

Course contents

Monday – Causal diagrams; Structural Equation Models; Confounding; Unmeasured confounding (instrumental variables);

Tuesday – Missing data; Multiple imputation; Sensitivity analysis;

Wednesday – Measured and unmeasured confounding; Propensity score; Inverse probability of treatment weighing

Thursday – Covariate Measurement error (instrument error, recall bias) Internal validation

Friday – Time varying exposure/confounding and mediation

Aim

- **Background**
- **Propensity score**
- **Applications of Propensity score**
- **An Example**

Randomized trials

- Randomized trials (RT)
  - » Radomization to treatment or control
  - » Unbiased treatment effect is assumed

Average treatment effect = $E(Y_1) - E(Y_0)$

(E(.)=expectation, Y_1=outcome in treated, Y_0 = outcome in control)

»but RT **not** always possible (costs, morality)

Observational studies (OS)

- Observational studies
  - » Inexpensive, Ethical, Feasible
- But limited by
  - » Not-randomized & selection bias*, different comparision groups (”apples to oranges”)
  - » High dimensional confounders with different values

*A distortion resulting from the methods used to selcet study participants(Rothman KJ (2008))

Inference in Observational studies

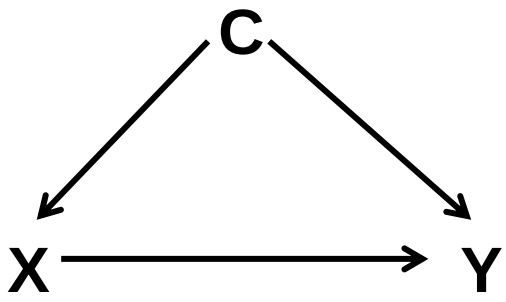
important information & important to develop better statistical analysis methods

To overcome limitations

- Strict inclusion & exclusion criterion
- Matching individuals in treated & control group
- Statistical techniques
  - » Regression, Stratification, Propensity score

Effect estimation by regression

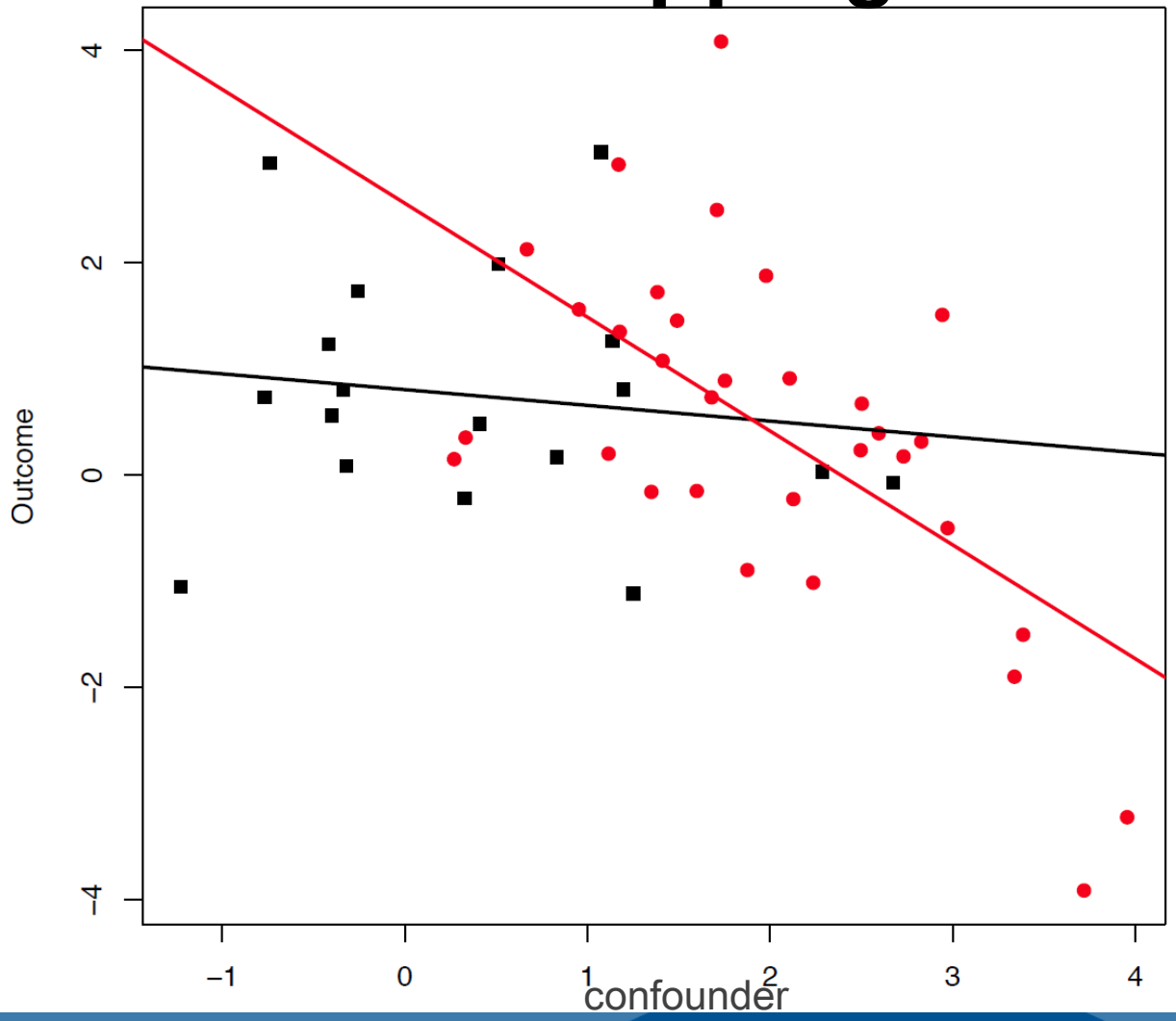
- **C** = confounders
- **X** = treatment (0,1)
- **Y** = outcome



$$\mathbf{E(Y \mid X, C)} = \alpha_0 + \alpha_1 C + \beta X$$

- The regression model compares individuals with treatment (0/1) & adjust for **C**
- When little overlap in treated & control group, extrapolation
- Well fitted models may also produce biased treatment effect estimate

Insufficient overlapping



To overcome extrapolation

- **Modelling association between exposure (X) & confounder (C) may have benefits**

Propensity score (PS) **(Rosenbaum & Rubin, Biometrika 1983)**

The conditional probablity of an individual getting treatment given her/his observed covariates (C)

$$PS = pr(X|C) = \left(\frac{exp(\beta_0 + \sum \beta_i C)}{1 + exp(\beta_0 + \sum \beta_i C)}\right)$$

***All individuals have non-zero probability of receiving each treatmet**

Propensity score

- **Propensity score summarizes confounders**
- **Individuals with same propensity score equally likely to have been treated thus comparable**
  - **Unless important cofounders are not measured**
  - **Or PS was not modeled correctly**

Using PS

1. **Stratifying (subclassifying) on PS**
2. **Matching on PS;**
3. **Adjusting for PS in linear models**

$$E(Y \mid X, p(C)) = \alpha_0 + \alpha_1 p(C) + \beta X$$

4. **Adjusting for PS & confounders in linear models**

$$E(Y \mid X, p(C)) = \alpha_0 + \alpha_1 p(C) + \alpha_2 C + \beta X$$

increases precision & doubly robust, if PS or regression model is correct (Robins, Mark & Newey, 1992)

Propensity score

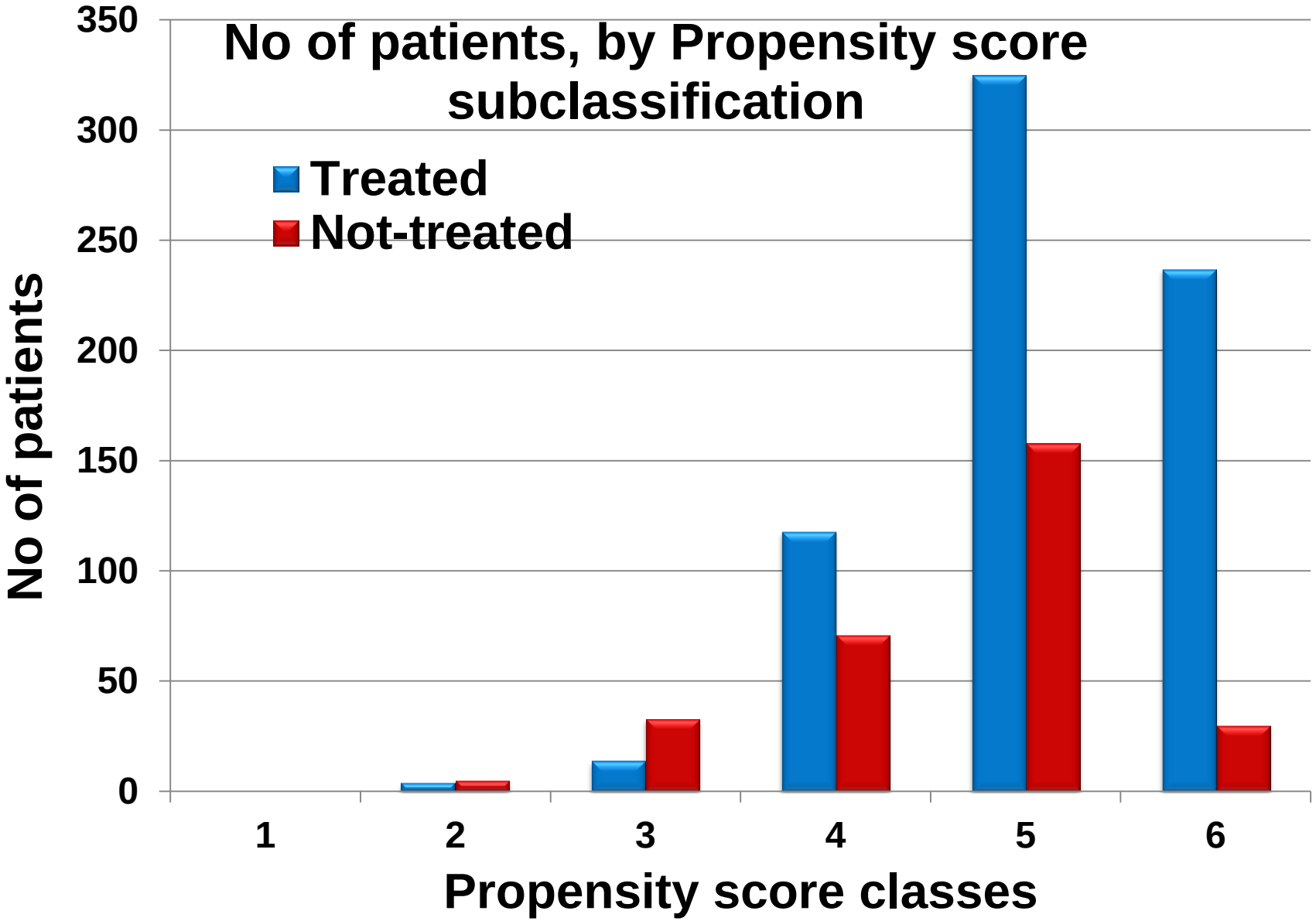
- Individuals in same strata have similar characteristic
- Outcomes are compared in each strata
- Mean or weighted mean yields overall treatment effect

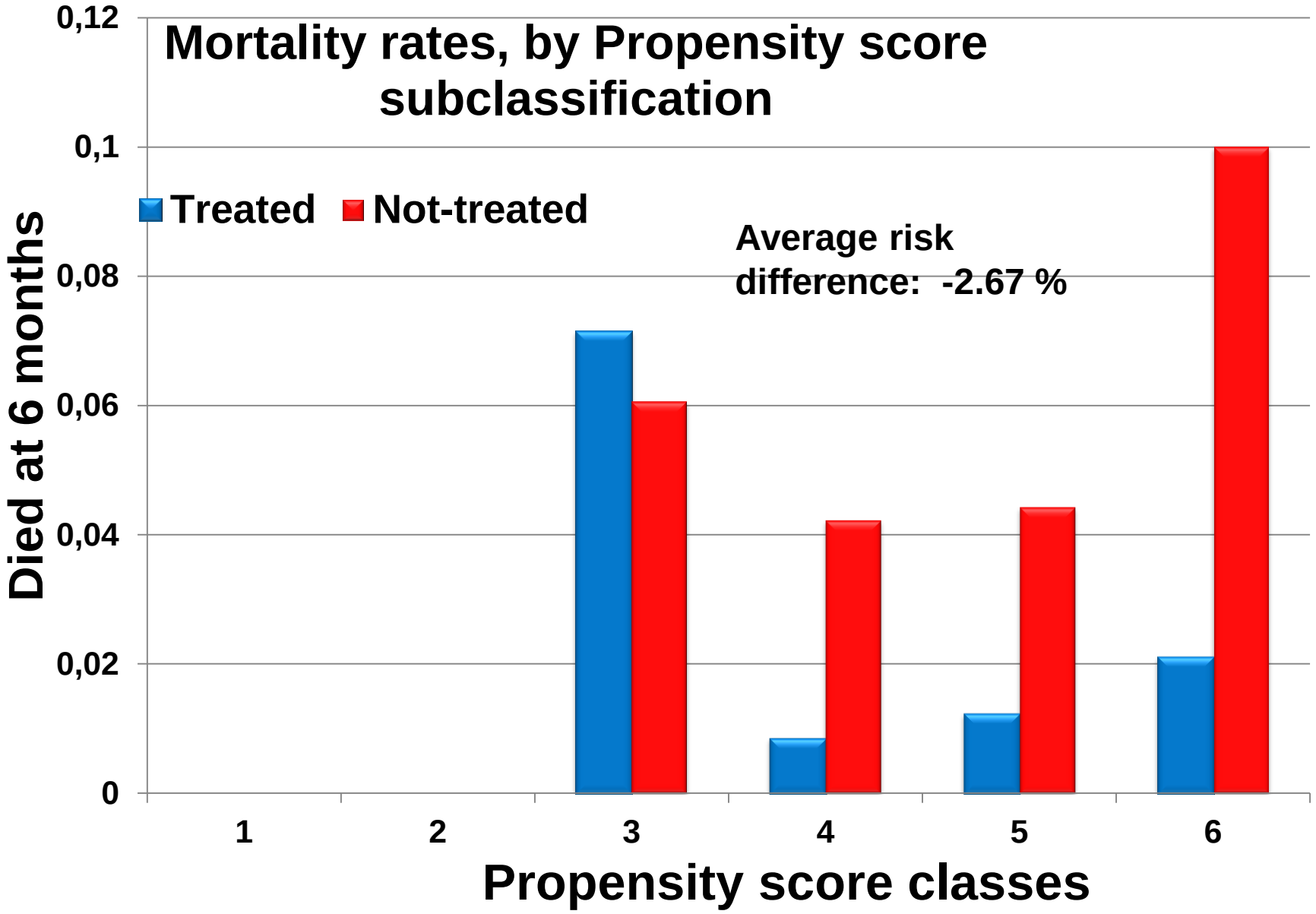
- Matching by PS, treated & control groups more balanced on covariates

An example

1. **N** = 996 patients at Ohio Heart Health in 1997
2. **Treatment**, X_1 = Augmented Percutaneous Coronary Intervention (A-PCI) and X_0 = only PCI
3. **Outcome**, Y = survival at least 6 months after treatment
4. **Confounders**, C = (gender, diabetes, height, acute myocardial infarction within 7 days before pci, no. of vessels treated, stent deployment, lower left ventricular ejection fraction)

Patients receiving **augmented PCI** **more severely** diseased than **PCI** patients


No of patients, by Propensity score subclassification
Treated
Not-treated
No of patients
350
300
250
200
150
100
50
0
1
2
3
4
5
6
Propensity score classes


Mortality rates, by Propensity score subclassification
Treated
Not-treated
Average risk difference: -2.67 %
Died at 6 months
0,12
0,1
0,08
0,06
0,04
0,02
0
1
2
3
4
5
6
Propensity score classes

Results using different methods

Method	Treated	Not-treated	Risk difference (95%CI)
No adjustment	698	298	-0.0346(-0.061, -0.008)
Adjusted for Diabetes & Vessels			-0.0319 (-0.057, -0.006)
Matching on PS	**Actual matches on PS**		**Risk difference (SE)**
Nearest neighbour matching	698	247	-0,067 (0,022)
Radius matching	698	297	-0,032 (0,014)
Regression on PS	698	298	-0,034 (0,0131)

Limitations of Propensity score

- Uncertainty due to estimating ps & sutratification/matching on ps may not be taken account by standard statistical software
- Matching algorithms? 1:1 matching? 1:N matching? how close are 2 PS?
- Incomplete matchings
- Unmeasured confounding
- Which confounders in PS model

Summary

- **PS conditional probability of treatment given confounders**
- **PS summarizes confounders**
- **PS use in stratification, matching, as a confounder**
- **Individuals with same propensity score equally likely to have been treated thus comparable**

References

1. **Rosenbaum, P.R. & Rubin, D.B. (1983)**, “The central role of the propensity score in observational studies for causal effects”, *Biometrika*, 70(1), 41-55
2. **Rosenbaum, P.R. & Rubin, D.B. (1984)**, “Reducing bias in observational studies using subclassification on the propensity score”, Journal of the American Statistical Association, 79, 516-524
3. **Robins J.M. Mark S.D. & Newey W.K. (1992)**, ”Estimating exposure effects by modelling the expectation of exposure conditional on confounders”, Biometrics 48, 479-495
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5. **Faries, D. Obenchain R.L. Haro J.M. & Leon A.C. (2010)**, ”Analysis of observational health care data using SAS® ”, Cary, NC: SAS Institute
6. **Lanehart Rheta E. et al (2012)**, ”Propensity score analysis and assesmnet of propensity score approaches using SAS® procedures”, paper 314-2012, SAS Global forum 2012

Questions & Comments