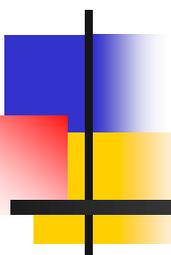


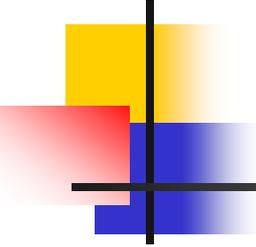
**CLEAR Center-PM&R Journal
Methods Webinar Series**

Methods for Dealing with
Confounding in Observational
Studies: Propensity Scores



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Propensity scores

- A data compression technique specifically for confounders

Why propensity scores?

- Observational treatment studies are limited by the lack of randomization.
 - Factors that affect treatment selection also affect outcomes (confounding by indication).
- Propensity scores aim to address this treatment selection bias.



Treatment groups differ greatly!

Examples of imbalances, from Table 1:

Table 1. Baseline Characteristics: Unmatched Cohort

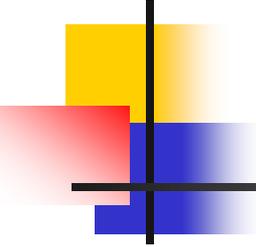
Covariates	Mechanical AVR (n=406)	Ross Procedure (n=918)	P
Male gender, n (%)	310 (76.4)	691 (75.3)	0.672
Mean age at surgical intervention, y	49.5±10.3	41.6±11.0	<0.001
Cause, n (%)			
Rheumatic	23 (5.7)	37 (4.0)	0.054
Missing	58 (14.3)		
Calcified/degenerative	311 (76.6)	333 (36.3)	<0.001
Preoperative DM, n (%)	20 (4.9)	26 (2.8)	0.055
Preoperative hypertension, n (%)	161 (39.7)	245 (26.7)	<0.001
Concomitant CABG, n (%)	145 (35.7)	38 (4.1)	<0.001

●AVR indicates aortic valve replacement; NYHA, New York Heart Association; DM, diabetes mellitus; LVEF, left ventricular ejection fraction; LVH, left ventricular hypertrophy; LVEDD, left ventricular end-diastolic diameter; LVESD, left ventricular end-systolic diameter; CABG, coronary artery bypass grafting; and MV, mitral valve.

Example 2: rehabilitation vs. no rehabilitation post-stroke

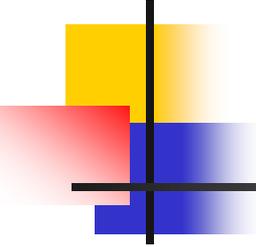
- Retrospective cohort study comparing rehabilitation in nursing homes versus no rehabilitation for stroke patients
- Outcome: community discharge; functional status
- Patients who receive rehabilitation have better outcomes than those who do not receive rehabilitation, but they are also less disabled, better insured, and have more social support at baseline.
 - Does the rehabilitation itself improve outcomes or would these patients have done well regardless?





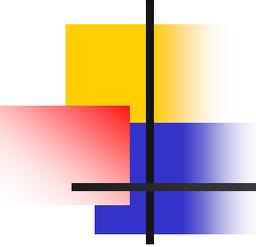
Traditional ways to control for these confounders...

- Stratification
- Matching
- Statistical adjustment



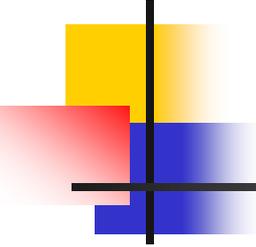
Issues with these methods...

- Stratification
 - How can we stratify on so many confounders?
- Matching
 - How can we match on so many confounders?
- Statistical adjustment
 - Groups may simply be incomparable.
 - High chance of residual confounding.
 - Cannot control for 24 confounders when there are only 36 events (36 deaths)!



With propensity scores...

- Stratification
 - Easy to stratify on a single number!
- Matching
 - Easy to match on a single number!
- Statistical adjustment
 - Easy to adjust for a single number, even if event rate is low!



Propensity scores

- In a randomized trial, all participants have the same probability of receiving each treatment.
- In an observational study, participants vary in these probabilities.
 - Propensity scores estimate these probabilities for each individual, given their covariates (clinical, social, demographic characteristics).

Propensity scores

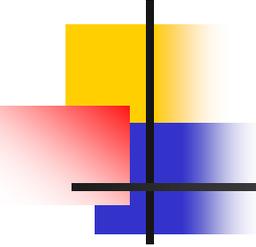
- The propensity score is the probability of receiving a treatment given one's covariates:
 - $P(\text{treatment A} / \text{covariates})$
- For example, a young patient in good physical condition might have a 70% chance of receiving a Ross procedure; an older patient in poor physical condition might have a 30% chance.



70% chance of Ross procedure



30% chance of Ross procedure



Propensity scores

- Propensity scores are estimated using logistic regression:
Logit (treatment A) = intercept + covariate 1 + covariate 2 + covariate 3 + covariate 4...
- Yields a predicted probability of treatment A for each individual.
- Reduces a large number of covariates to a single number (a probability).

Propensity scores

- Patients with similar propensity scores are comparable, even if they vary greatly in their underlying characteristics.
 - If a patient with a 70% propensity score received the Ross procedure and another with a 70% propensity score received a mechanical valve, then, in theory, any difference in outcome can be attributed to the treatment rather than to patient selection.

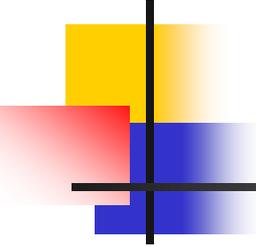


70% chance of Ross procedure; and HAD ROSS PROCEDURE

VS.



70% chance of Ross procedure; and HAD MECHANICAL VALVE

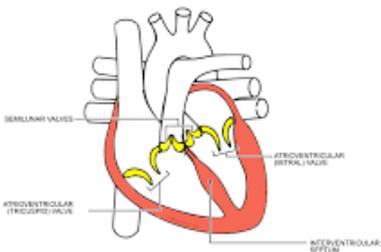


Propensity scores vs. Randomization

- Matching or stratifying participants based on propensity scores yields treatment groups that are balanced with respect to *measured* covariates.
- Randomization yields treatment groups that are balanced with respect to *measured and unmeasured* covariates.
- Propensity scores do not eliminate unmeasured or residual confounding!

Building the propensity score model

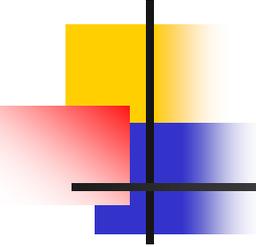
- Logit (Ross Procedure) = intercept + preoperative LVESD + preoperative creatinin + age + concomitant CABG + mixed valve disease + gender + ...
- Included 23 predictors



Building the propensity score model

- $\text{Logit (Rehabilitation)} = \text{intercept} + \text{age} + \text{medicaid insurance} + \text{vision score} + \text{mood score} + \text{activities of daily living score} + \text{use of assistive devices} + \dots$
- They used 112 predictors!



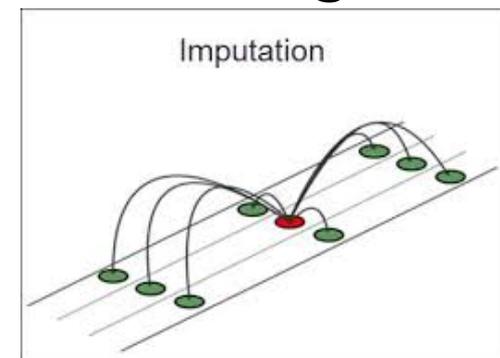


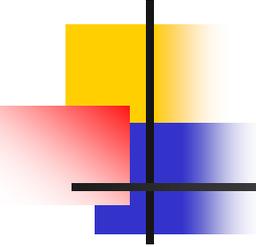
Building the propensity score model, steps

- 1. Identify potential confounders (related both to treatment and outcome).
- 2. Impute missing data.
- 3. Build a non-parsimonious model, potentially including quadratics and interactions.
- 4. Stratify or match on the resulting propensity scores; assess the balance of covariates in the treatment groups.
- 5. If balance is poor, refit the model including additional confounders or higher order terms.

Building the propensity score model: missing data

- If an individual is missing one datapoint for one covariate, they will be omitted from the logistic regression.
- Must impute missing data!
- For example, in the rehabilitation study, 7 of the 112 predictors were missing values for 0.5% to 5.5% of the sample. The authors appropriately replaced these missing values with the mean values from the non-missing data.





Building the propensity score model: fit the model

- Normal rules of model building don't apply!
 - Don't worry about parsimony
 - Don't worry about overfitting
 - Try multiple interactions and quadratic terms
- But... do consider omitting variables that are unrelated to outcomes (which cannot be confounders):
 - simulations show that including these does not improve balance or reduce bias, but may make it harder to find matches

Building the propensity score model: evaluate the model

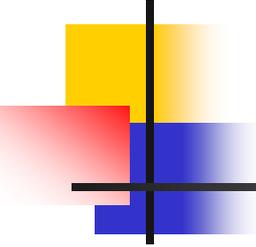
- The model is a success if it balances the treatment groups with respect to covariates!
- If balance is not achieved, refit the logistic model.



Evaluating the propensity score model

- Evaluate balance with “standardized differences” in lieu of p-value tests.
 - P-value tests depend highly on sample size.
 - A non-significant p-value does not guarantee that the groups are balanced.
- Standardized difference is the mean difference between groups expressed as the percent of 1 standard deviation.
- Standardized differences $< 10\%$ are considered balanced.





Standardized differences

- Standardized difference =
$$\frac{\bar{x}_1 - \bar{x}_2}{\left(\frac{s_1 + s_2}{2}\right)} \times 100$$

- Example, Ross study, unmatched cohort:

- Mean (SD) of age for Ross patients = 41.6 (11.0) years

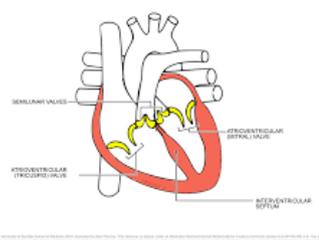
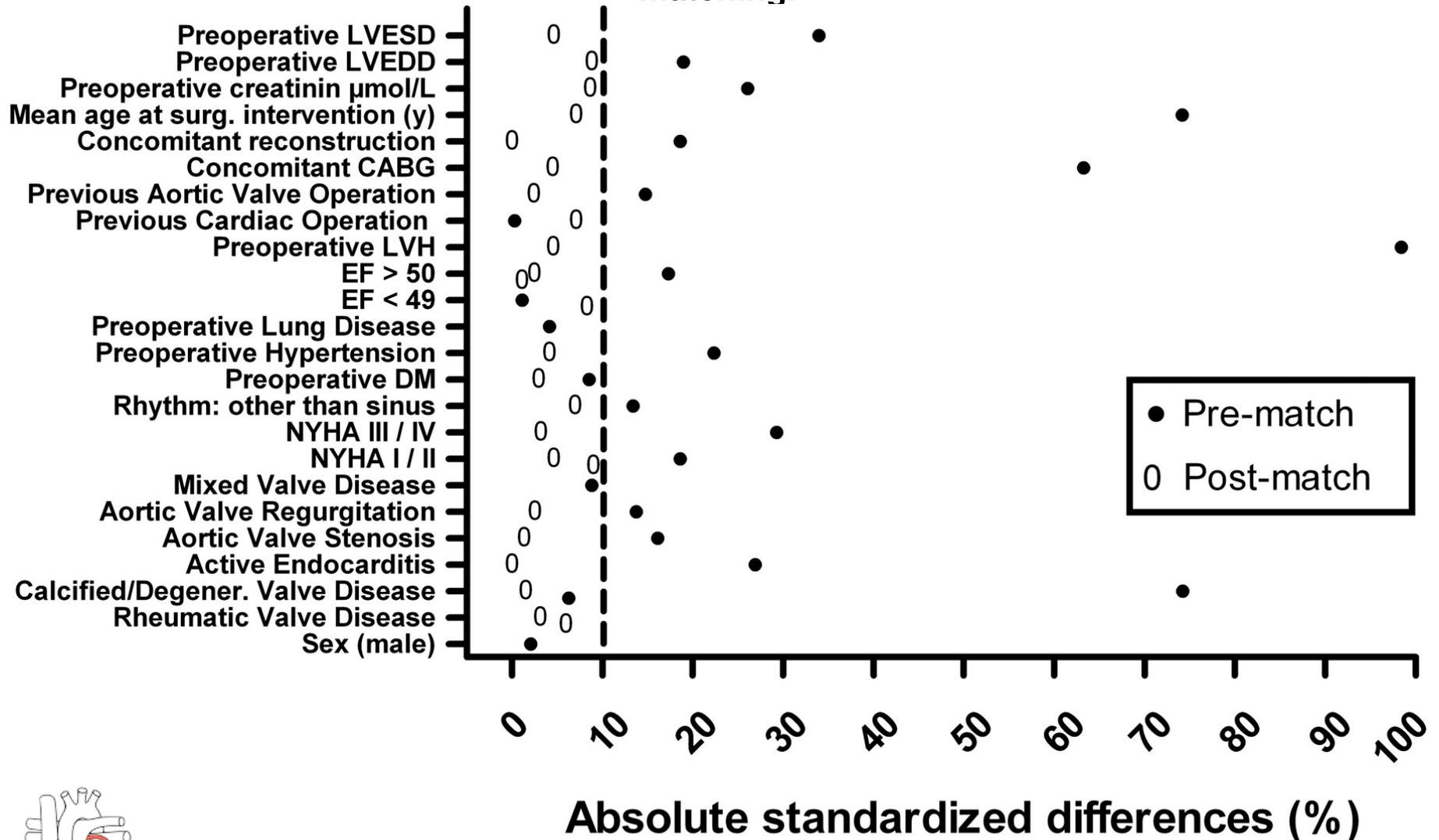
- Mean (SD) of age for mechanical valve patients = 49.5 (10.3) years

- Average SD = 10.65 years

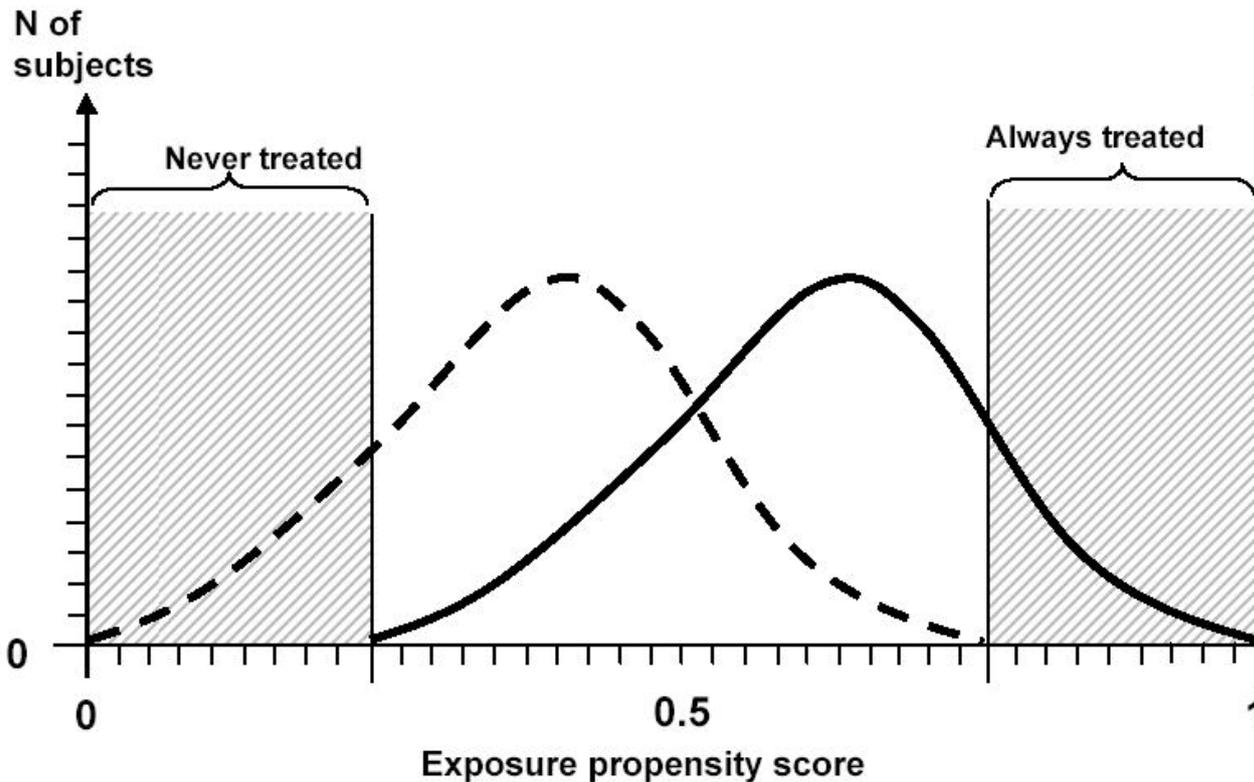
- Standardized difference =

$$\frac{49.5 - 41.6}{10.65} \times 100 = 75\%$$

Love plots for absolute standardized differences for baseline covariates between patients with mechanical valve and patients with the Ross procedure, before and after propensity score matching.



Use of propensity scores: Evaluating overlap



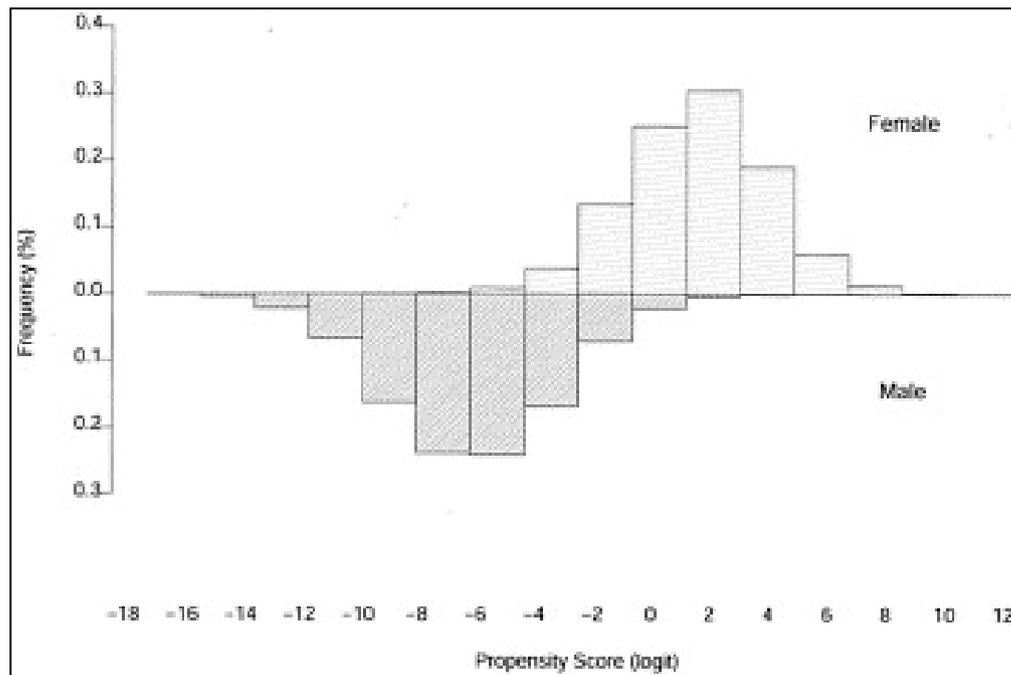
— = Treated subjects
- - - = Untreated subjects

Comparing the distributions of propensity scores in different treatment groups may reveal:

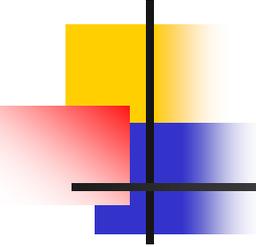
-Certain subjects for whom there are no good comparators. These subjects should be excluded from the analysis.

Evaluating overlap

- Propensity score distributions may reveal when patient populations are too divergent to make meaningful comparisons, e.g.:

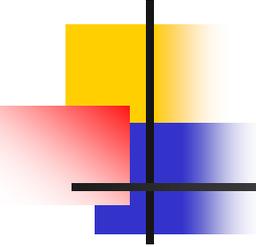


Gorman Koch C, Khandwala F, Nussmeier N, Blackstone EH. Gender and outcomes after coronary artery bypass grafting: a propensity-matched comparison. *The Journal of Thoracic and Cardiovascular Surgery* 2003; 126: 2032-2043.



Use of propensity scores

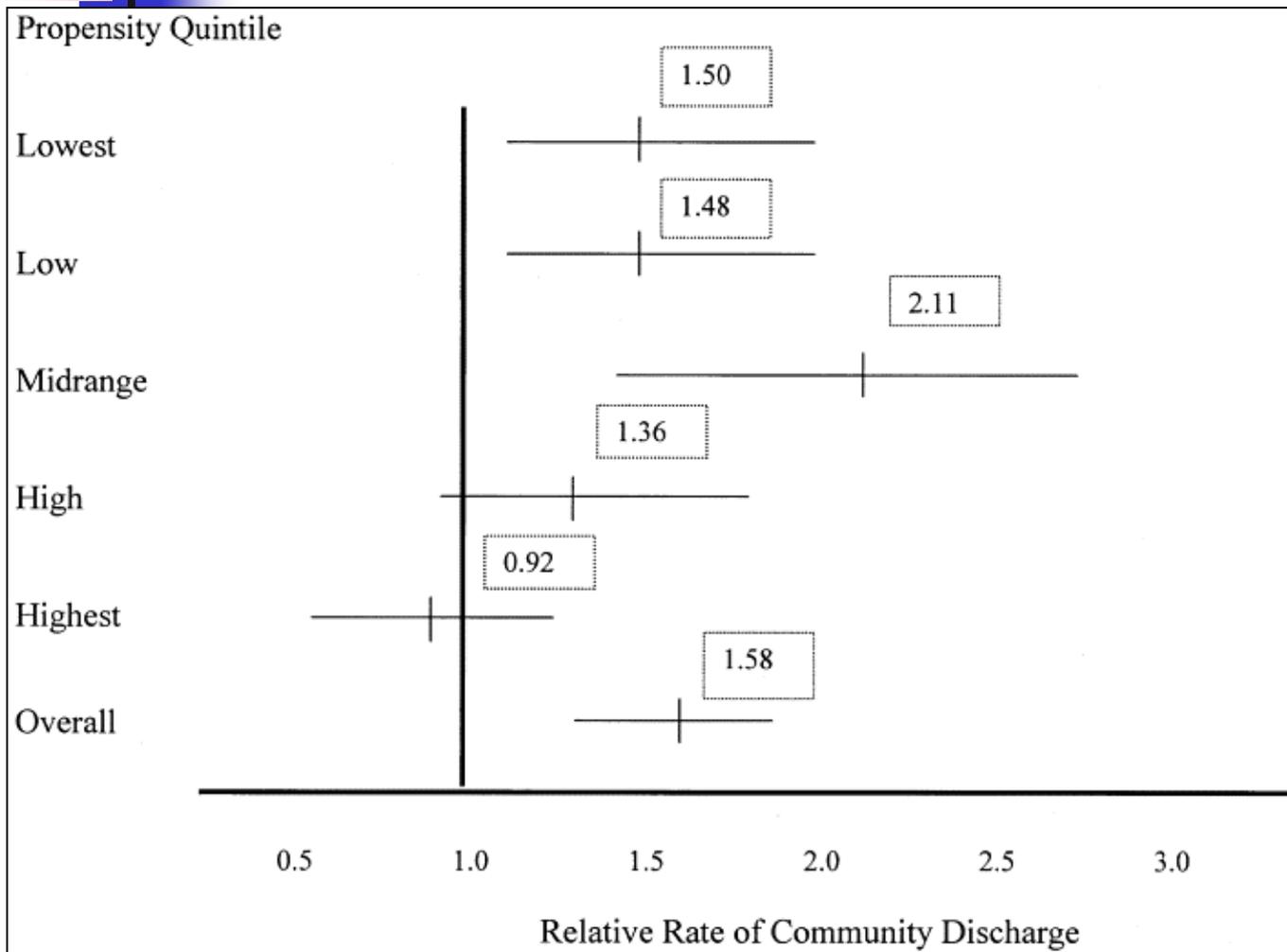
- 1. Stratification
- 2. Matching
- 3. Statistical adjustment



1. Propensity score stratification

- Stratify on propensity score.
- E.g., in the rehabilitation study, authors stratified on quintiles of propensity score.
- Data are analyzed with Mantel-Haenzel methods for stratified data.

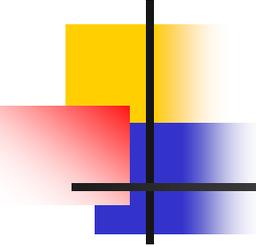
Propensity score stratification



Their analysis revealed a significant interaction between propensity score and treatment effect!

The summary relative rate is 1.58, but the relative rate varies significantly by propensity for treatment.



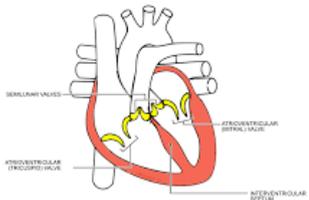


2. Propensity score matching

- Matching on the propensity score optimizes matching.
- Many algorithms for propensity score matching:
 - Nearest-neighbor
 - Caliper matching
 - Mahalanobis metric matching in conjunction with propensity score
 - Others...

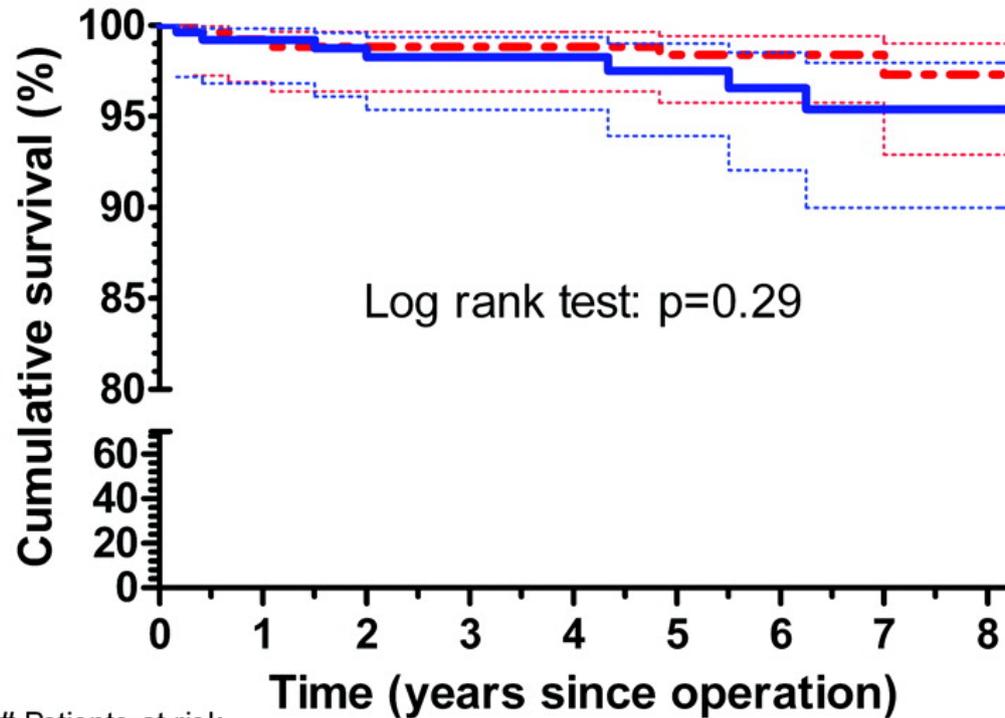
Propensity score matching

- Nearest-neighbor method:
 - In the Ross study, authors randomly ordered the mechanical valve patients and then sequentially matched each one to the Ross patient with the closest propensity score. If no Ross patients had a propensity score within 25%, the patient was left unmatched and excluded.
 - In fact, matches could be found only for 253 of 406 mechanical valve patients.



Results, matched cohort (n=253 pairs)

Cumulative Survival

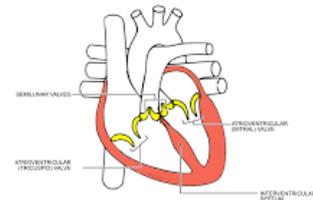


- - - Mechanical AVR
with optimal anticoagulation therapy
- Ross-procedure

Survival at 7 years:
Mechanical AVR: 97%
Ross procedure: 95%

Patients at risk

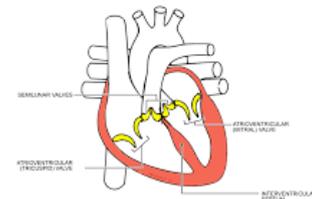
M. AVR	252	251	251	250	226	176	95	21
Ross	236	206	177	147	114	95	74	50

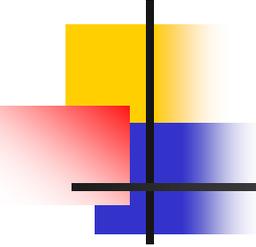


Results, matched cohort (n=253 pairs)

Table 3.
Association of Procedure With Late Mortality

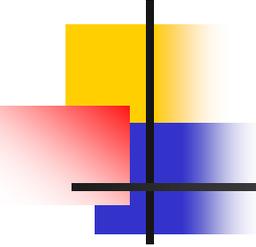
	Events, n/Total Follow-Up, y		Hazard Ratio (95% Confidence Interval)	P
	Mechanical Valve	Ross Procedure		
After matching, n	253	253		
All-cause mortality	5/1682	7/1310	1.86 (0.58–5.91)	0.29
Valve-related mortality	0	4/1310		
Non-valve-related cardiac mortality	3/1682	1/1310		
Non-valve-related noncardiac mortality	1/1682	2/1310		
Unknown	1/1682	0		





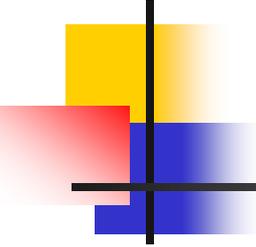
Propensity score matching

- Tradeoff between inexact matching and incomplete matching.
 - Inexact matching increases residual confounding.
 - Incomplete matching decreases statistical power and generalizability of results.



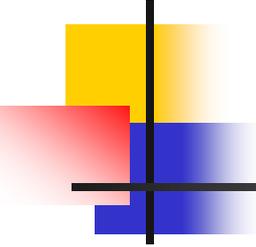
Propensity score matching

- Matched data may be correlated and should be analyzed as matched pairs.
- There is some ongoing debate on this issue.



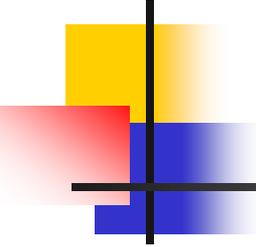
3. Statistical adjustment with propensity scores

- Outcome = intercept + treatment + propensity scores (+ other covariates?)



Assumptions!

- Assumes a certain relationship between the propensity score and outcome (e.g., linear in the logit)
- Assumes no interaction between propensity score and treatment (unless you add an interaction term between PS and tx).

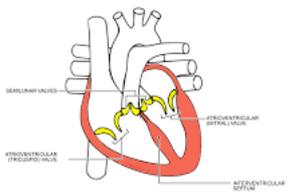


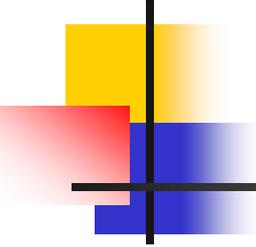
Statistical adjustment with propensity scores

- Is similar to adjusting for all the covariates used to calculate the propensity score.
- But...is beneficial compared with traditional adjustment when the ratio of events: confounders < 10

Cox regression for mortality, Ross study (unmatched cohort)

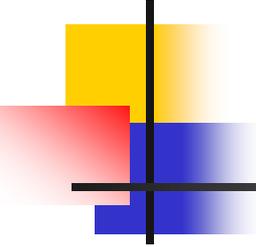
- $\ln(\text{rate of death}) = \text{Ross (vs. mechanical valve)} + \text{propensity score}$
- HR = 3.64 (95% CI: 1.22 – 10.88)
- Could be driven by extreme skewness of the propensity scores in the Ross group...





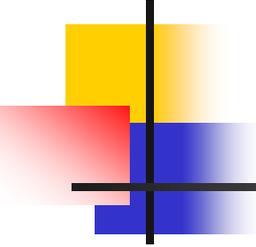
Ways to address unmeasured confounding...

- Propensity score calibration
 - Collect more detailed confounder information in a subset of the sample.
 - Use this information to adjust or “calibrate” the propensity score estimates in the full set of data.
 - Use the corrected, or calibrated, propensity score for analyses of outcomes.



Summary: Advantages of propensity scores

- Focus the researcher on the problem of confounding by indication.
- Reduce a large set of confounders to a single, intuitive variable.
- Reveal subjects that cannot be compared or instances when whole groups cannot be compared.
- Make statistical adjustment possible when the number of confounders is large relative to the number of outcome events.



Summary: Disadvantages of propensity scores

- Are inferior to randomization.
- Do not solve the problems of residual and unmeasured confounding.
- May give the researcher/reader a false sense of security.
- Offer little benefit over traditional statistical adjustment when the ratio of outcomes/sample size:confounders is large.
- Are the subject of ongoing statistical debate, e.g.:
“Why Propensity Scores Should Not Be Used for Matching” King and Neilson, November 2018 preprint.