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Applying the propensity score approach in studies on consequences of sickness absence.

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Outline

- A question to be addressed*
  (i.e. the motivating example)
- Propensity scores – what, how, and why?
- The answer to the question.

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Partial sick leave associated with disability pension: propensity score approach in a register-based cohort study

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The question we whish to address

Partial or full sick leave → ? → Disability pension

Data:

Setting: Sample from the national sickness insurance registers representative of the Finnish working population (full-time workers) with long-term sickness absence due to musculoskeletal disorders, mental disorders, traumas or tumours.

Outcome measures: A three-category measure and a binary measure for the occurrence of disability pension on the last day of 2008 were computed.

Confounders: gender, age, diagnostic group, insurance district, income, length of sickness absence before treatment assignment.

The randomized study revisited

A randomized study has two key components.

1. The inclusion criterions
   - Define who are eligible to participate in the trial.
   - Thereby they define to which population the obtained results apply.
2. The randomization
   - For each person enrolled in the trial, which treatment they receive is decided by "the flip of a coin".
   - Probability of treatment can depend on baseline characteristics; e.g. sex or age, but the actual treatment choice is completely random.

The randomized trial vs. the observational study

Randomized

50/50 split → Partial / Full

Observational

?/? split will depend on confounders → Partial / Full

Are the full and partial sick leave groups comparable?

	Partial sick leave (n=1 012)	Full sick leave (n=25 247)
Age (years)	47±9	48±11
Women (%)	72%	53%
Gross income (€)	27 128±11 541	23 811±11 764
Sickness absence prior to treatment assignment (days)	93.9±63.8	21.0±41.8
Sickness absence in connection with treatment assignment (days)	27.0±9.4	100.1±84.2
Diagnostic groups of sick leave		
Mental disorders (%)	42.2	26.0
Musculoskeletal disorders (%)	38.8	47.0
Tumours (%)	9.8	8.5
Traumas (%)	9.2	18.4
Occupational group		
Technical and scientific work, etc (%)	12.0	5.7
Social and healthcare (%)	30.7	10.2
Administration and office work (%)	18.4	13.1

Propensity scores

- Definition (Rosenbaum and Rubin (Biometrika, 1983)):
  The propensity score (e(C)) is the probability that an individual would have been treated based on that individual's observed pre-treatment variables:

  $$e(C) = P(A = 1 \mid C)$$

- Idea: In a randomized study, treatment assignment A and pre-treatment variables C are independent.
- The propensity score e(C) has the property that treatment assignment A is independent of pre-treatment variables C for any given value of e(C).
- That is, treated and untreated individuals with the same e(C) have identical distributions of C.

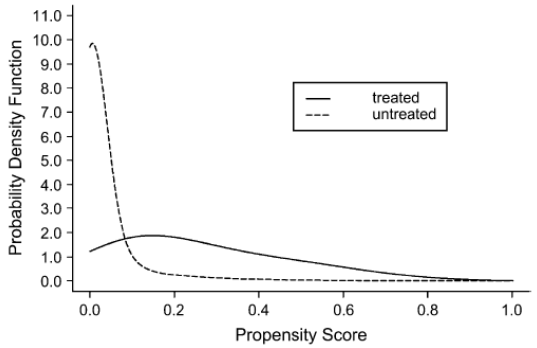
Computing propensity score

- The propensity score is unknown and must be estimated. For a binary A, logistic regression is the obvious choice for e(C).
- Why should one choose a propensity score approach rather than including c in a standard regression model?
  - We can ask the doctor what is important when he or she decides who to treat (A | C) – we cannot ask nature what is important when "she decides" who will die (Y | C)!
  - If P(Y = 1) is small and P(A = 1) is not small then e(C) allows a richer model, e.g. including many interactions.
- It has been argued that over-fitting when developing the model for e(C) may not be a bad thing to do.

Computing propensity score in SAS

- Use proc logistic to fit a logistic regression and save the predicted probabilities in a new dataset.

```
proc logistic data = disAb;
class sickLeaveType (…);
model sickLeaveType(event='1') = age sex (…);
output out=psdataset pred=ps;
run;
```



Uses of propensity scores

Matching

- Match each person in partial sickness leave group with a person in the full sickness leave group with equal values for the propensity score.
- Very easy to communicate.
- Interpretation can be tricky.
- Not optimal usage of data.

Covariate in regression

- Use the value of the propensity score as a covariate in a regression.
- Interpretation as for ordinary multiple regression.
- Not recommended

Weighting

- Weigh each observation in by 1/PS or 1/(1-PS)
- Interpretation as a proper randomized trial.

Using propensity scores: Matching

- If there are no unmeasured confounders the causal effect of treatment can be obtained by comparing individuals from the two treatment arms with the same propensity score.

- The easiest way to do this is for every person on treatment to find the person from the control group, which has the same propensity score (or very close) and match those.

In SAS:

```
/* Load the gmatch macro from:
   http://mayoresearch.mayo.edu/mayo/research/biostat/upload/gmatch.sas  */

%gmatch(data=psdataset, group=sickLeaveType, id=ptID,
              mvars=ps, wts=1, dmaxk=0.05,out=mtch,
              seedca=87877,seedco=987973);
```


Do we have balance after matching?

Covariate	Subjects with PS (n=26 259)		After PS matching (n=2024)	
	Partial sick leave (n=1 012)	Full sick leave (n=25 247)	Partial sick leave (n=1 012)	Full sick leave (n=1 012)
Diagnostic groups of sick leave				
Mental disorders (%)	42.2	26.0	42.2	42.2
Musculoskeletal disorders (%)	38.8	47.0	38.8	38.8
Tumours (%)	9.8	8.5	9.8	9.8
Traumas (%)	9.2	18.4	9.2	9.2

Note that both groups now have the covariate distribution as the partial sick leave group.

Results

	Full disability pension
Full sample	
Crude (n=25 830)	0.3 (0.2 to 0.4)
Adjusted* (n=25 823)	0.6 (0.4 to 0.8)
Adjusted† (n=25 823)	0.6 (0.4 to 0.7)
PS matching‡ (n=2024)	0.6 (0.4 to 0.7)

*Multinomial regression adjusted for: covariates, reference=no disability pension.
†Multinomial regression adjusted for: PS and variables with residual imbalance, reference=no disability pension.
‡GEE-analysis in the matched subsample.
GEE, generalised estimating equation; PS, propensity score.

	Full disability pension				
	ARR (%)	95% CI	RRR (%)	95% CI	NNT
Total	6	3 to 9	41	24 to 55	16

*NNT, number needed to treat to prevent full disability pension.

Conclusion

Does PS matching mimic a randomized trial?

- Yes and no; it mimics a very odd randomized trial.
- By employing weighting instead of matching the traditional randomized trial can be mimicked.

Is it easier to do confounder control using PS?

- Yes, to a certain extent.
- In some situations you will have more power to compute PS than include covariates in multiple regression.

Does PS analysis require fewer assumptions than traditional tools?

- NO!