

AN INTRODUCTION TO MATCHING METHODS FOR CAUSAL INFERENCE AND THEIR IMPLEMENTATION IN STATA

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Stata Users' Group Meeting

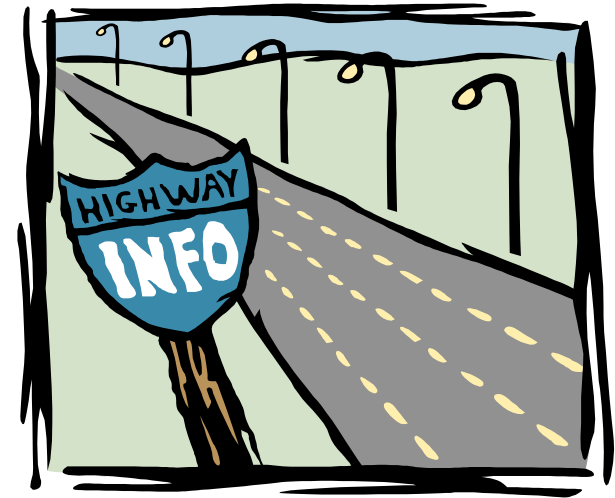
London, September 10, 2010

(PS)MATCHING IS EXTREMELY POPULAR...

- 240,000 entries by googling: propensity score matching
- >8,300 downloads of `-psmatch2-`
among the top 1‰ research items by number of citations, discounted by citation age of the RePEc/IDEA database
- >1,340 support emails
 - Europe, US, Canada, Central + South America, former SU, Australia, Asia, Africa and the Middle East
 - epidemiology, sociology, economics, statistics, criminology, agricultural economics, health economics, transport economics, public health, nutrition, paediatrics, biostatistics, finance, urban planning, geography and geosciences

Roadmap

1. The counterfactual concept of causality
2. What is matching?
3. Should we use it?
4. How do we use it?
 - a. Matching estimators
 - b. Practical Stata example using `psmatch2`



THE EVALUATION PROBLEM

Y_{0i}, Y_{1i} → Outcome of i under treatment 0 and under treatment 1

$D_i \in \{0, 1\}$ → Treatment indicator

$Y_i = D_i Y_{1i} + (1 - D_i) Y_{0i}$ → Observed outcome of i

$$Y_i = Y_{0i} + (Y_{1i} - Y_{0i}) D_i$$

Causal effect on Y
of treatment 1 relative
to treatment 0 for i

X_i → Set of observed characteristics of i

Which parameter?

□ ATT = $E(Y_1 - Y_0 \mid D=1) = E(Y_1 \mid D=1) - E(Y_0 \mid D=1)$

□ ATNT = $E(Y_1 - Y_0 \mid D=0) = E(Y_1 \mid D=0) - E(Y_0 \mid D=0)$

□ ATE = $E(Y_1 - Y_0) = \text{ATT} \cdot P(D=1) + \text{ATNT} \cdot P(D=0)$

Need to invoke (untestable) assumptions to identify average unobserved counterfactuals.

MATCHING METHODS

1. Identifying assumption: **Selection on Observables**
(all the relevant differences between treated and non-treated are captured in X):

$$\text{ATT: } Y_0 \perp D \mid X \rightarrow E(Y_0 \mid X, D=1) = E(Y_0 \mid X, D=0)$$

$$\text{ATNT: } Y_1 \perp D \mid X \rightarrow E(Y_1 \mid X, D=1) = E(Y_1 \mid X, D=0)$$

$$\text{ATE: } Y_0, Y_1 \perp D \mid X$$

2. To give it empirical content: **Common Support**
(we observe participants and non-participants with the same characteristics):

$$\text{ATT: } P(D=1 \mid X) < 1$$

$$\text{ATNT: } 0 < P(D=1 \mid X)$$

$$\text{ATE: } 0 < P(D=1 \mid X) < 1$$

⇒ can use the (observed) mean outcome of the non-treated to estimate the mean (counterfactual) outcome the treated would have had they not been treated.

Matching vs OLS

Matching makes the *same* identifying assumption as OLS but avoids any additional ones:

COMMON SUPPORT → effectively compares only comparable individuals

NON-PARAMETRIC → avoids potential misspecification of $E(Y_0 | X)$

→ allows for arbitrary X -heterogeneity in impacts $E(Y_1 - Y_0 | X)$

But: if OLS is correctly specified, it is more efficient.

Bias decomposition

B_1 difference in the supports of X

Eliminated by performing matching only over Sup_{10}

NB: might recover a different causal impact: $\text{ATT}(\text{Sup}_{10}) \neq \text{ATT}(\text{Sup}_1)$ (external validity)

B_2 difference of the distribution of X over Sup_{10}

Eliminated since matching reweighs $D=0$ data to equate the distribution of X in the $D=1$ sample

B_3 difference in unobservables

Matching just as biased as OLS (internal validity)

⇒ Matching focuses on comparability in terms of observables,
i.e. on constructing a suitable comparison group by carefully matching treated and non-treated on X
/ reweighting the non-treated to realign their X

BUT we don't need matching to make OLS less parametric...

FULLY INTERACTED OLS

film or margins, `dydx(treated) over(treated)`

$$Y = m_0(X_1, X_2) + \delta D + \delta_1(X_1 D) + \delta_2(X_2 D) + \delta_{12}(X_1 X_2 D) + e$$

$$\beta_{ATT} = \delta + \delta_1 \bar{X}_{1|D=1} + \delta_2 \bar{X}_{2|D=1} + \delta_{12} (\overline{X_1 X_2})_{|D=1}$$

$$\beta_{ATNT} = \delta + \delta_1 \bar{X}_{1|D=0} + \delta_2 \bar{X}_{2|D=0} + \delta_{12} (\overline{X_1 X_2})_{|D=0}$$

$$\beta_{ATE} = \delta + \delta_1 \bar{X}_1 + \delta_2 \bar{X}_2 + \delta_{12} (\overline{X_1 X_2})$$

Can F-test for presence of heterogeneous effects.

STILL, matching ($\neq$ OLS) highlights comparability of groups

Check matching quality

Propensity score

- more ‘structural’ model
- more flexible specification
- probit/logit
- probability/index/odds ratio

Matching

- metric: X , $\hat{p}(X)$ or $\{X, \hat{p}(X)\}$
- type of matching
- smoothing parameters
- common support

Assessment of matching quality

CAN we get the two groups balanced?

STRENGTHS AND WEAKNESSES

😊 Advantages 😊

controls for selection on observables and on observably heterogeneous impacts

non-(or semi-) parametric:

no specific form for outcome equation, decision process or either unobservable term

Sup₁₀: compare only comparable people and help in determining which results most reliable

flexible and easy

😞 Disadvantages 😞

selection on observables: matching as good as its X's

Sup₁₀: if impact differs across treated, restricting to Sup₁₀ may change parameter being estimated

→ unable to identify ATT

data hungry

OPERATIONALISING MATCHING METHODS

Curse of dimensionality

- impose linearity in the parameters (regression analysis)
- choose a distance metric
 - ❖ Euclidean, Mahalanobis, etc.

❖ **Propensity Score** $e(x) \equiv P(D=1 | X=x)$

$$X \perp D \mid e(X)$$

$$(Y_1, Y_0) \perp D \mid X \quad \text{and} \quad 0 < e(X) < 1 \\ \Rightarrow (Y_1, Y_0) \perp D \mid e(X)$$

Overview of Matching Estimators

1. pair to each treated i some group of ‘comparable’ non-treated individuals
2. associate to the outcome y_i of treated i , a matched outcome $\hat{y}_i$ given by the (weighted) outcomes of his ‘neighbours’ in the comparison group:

$$\hat{y}_i = \sum_{j \in C^0(p_i)} w_{ij} y_j$$

$C^0(p_i)$ = set of neighbours of treated i in the $D=0$ group

w_{ij} = weight on non-treated j in forming a comparison with treated i , where $\sum_{j \in C^0(p_i)} w_{ij} = 1$

General form of the matching estimator for ATT (within S_{10}):

$$\hat{ATT} = \frac{1}{\#(D=1 \cap S_{10})} \sum_{i \in \{D_i=1 \cap S_{10}\}} \{y_i - \hat{y}_i\} = E(Y \mid \text{treated on } S_{10}) - E(Y \mid \text{matched non-treated})$$

TRADITIONAL MATCHING ESTIMATORS

One-to-one matching

- with or without replacement
- nearest neighbour or within caliper

SIMPLE SMOOTHED MATCHING ESTIMATORS

K -nearest neighbours

- with or without replacement
- nearest neighbour or within caliper
radius matching

WEIGHTED SMOOTHED MATCHING ESTIMATORS

kernel-based matching

local linear regression-based matching

- bandwidth choice
- kernel choice

MAHALANOBIS-METRIC MATCHING

combine the W 's into a distance measure and then match on the resulting scalar:

$$d(i,j) = (W_i - W_j)' V^{-1} (W_i - W_j)$$

Implementing the Common Support requirement

- caliper
- at the boundaries
- trimming

Checking matching quality

Check (and possibly improve on) balancing of observables

- for each variable
- overall measures

$$D \perp X \mid \hat{p}(X)$$

Inference

- naïve variance
- bootstrapping
- Abadie-Imbens standard errors

Leuven and Sianesi (2003) psmatch2 suite

```
psmatch2 depvar [indepvars] [if exp] [in range] [,  
    outcome(varlist)  
    pscore(varname) logit odds index  
    neighbor(integer) ties  
    noreplacement descending  
    caliper(real)  
    radius  
    kernel  
    llr  
    kerneltype(type) bwidth(real)  
    spline nknots(integer)  
    mahalanobis(varlist) add pcaliper(real)  
    common trim(real)  
    ate  
    ai]
```

psgraph

pstest

THE IMPACT OF THE NSW DEMONSTRATION

Very famous data in the evaluation literature,
combining treatment and controls from a randomised evaluation of the NSW Demonstration
with non-experimental individuals drawn from various sources.

LaLonde (1986), Dehejia, R.H. and Wahba, S. (1999), Smith, J. and Todd, P. (2005) with
response, rejoinder, final thoughts.

Also used by Ichino and Becker (2002) and Abadie, Drukker, Leber Herr and Imbens (2001) to
illustrate their respective Stata matching programs.

Here we use the NSW male treated with male comparisons drawn from the PSID.

To keep in mind: experimental impact estimate on real earnings is **+\$886***

WRAPPING UP...

SELECTION ON UNOBSERVABLES

Set of conditioning X matters

⇒ **better data help a lot!**

SELECTION ON OBSERVABLES

avoid use of functional forms in constructing counterfactual

⇒ **(matching $\approx$ fully interacted OLS) $>$ simple OLS**

Matching *versus* simple OLS:

no mis-specification bias; ATT *versus* ATNT

compare comparable people

⇒ **matching $>$ fully interacted OLS**

Matching *versus* fully interacted OLS:

highlights actual comparability of groups, hence reliability (& relevance) of estimates

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