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A SAS macro to estimate Average Treatment Effects with Matching Estimators

Nicolas Moreau

http://cemoi.univ-reunion.fr/publications/

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Abstract

This paper presents a SAS macro to estimate the Average Treatment Effect (ATE) and the Average Treatment Effect for the Treated (ATET) with nearest-neighbor matching.

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Introduction

In this paper, we present the SAS macro `nn_matching`. `nn_matching` estimates nearest neighbor matching with replacement for the average treatment effect (ATE) and average treatment effect for the treated (ATET). In this respect, we draw heavily on Abadie et al. (2004) and Abadie and Imbens (2002, 2011). We refer the reader to these articles for a clear and comprehensive presentation of the matching estimator.

Following these authors, `nn_matching` provides the simple and bias-corrected matching estimators. Variance estimation is conducted by assuming homoscedasticity of the conditional variance or allowing for heteroscedasticity of the conditional variance. The source code is available at http://cemoi.univ-reunion.fr.

Syntax of `nn_matching`

The syntax is `%nn_matching(data=,y=,w=,x=,M=,scaling=,covarbias=);`

where `data` specifies the data set, `y` the outcome variable, `w` the binary variable treatment indicator, `x` the list of covariates to be used in the matching, and `M` the number of matches to be made per observation. `M` could be any integer between 1 and the minimum of the number of treated units and controls in the sample.

If there are ties and if different matched pairs \((i,j)\) and \((i,l)\) lead to the same distance \(d_{ij} = d_{il}\), then the number of matches per unit is greater than `M`.

`Scaling` specifies the metric for measuring the distance between two vectors of covariates. Following Abadie et al. (2004), the default is the diagonal matrix of the inverses of the sample variances of each covariate in `x` when scaling is not specified by the user. If `scaling=1`, the Mahalanobis metric is used; it is the inverse of the sample covariance matrix of the covariates. If `scaling=2`, the identity matrix is used instead. `Covarbias` specifies the list of covariates to be used to compute the bias-corrected matching estimator. The default list is `x` when `covarbias` is not specified by the user.

Note that all variables in `y`, `x`, `w` and `covarbias` must be numeric.

Results presentation and output data files

ATE and ATET are automatically computed. For each estimated parameter, estimated standard errors that assume homoscedasticity of the conditional variance or allow for heteroscedasticity of the conditional variance are supplied.

The bias-corrected matching estimator developed in Abadie and Imbens (2002, 2011) is automatically computed if the number of “continuous” covariates in `x` is greater than 1. In `nn_matching`, all variables that are not binary are considered as continuous.

The first two output tables summarize the model specification and estimation options. The third table provides summary statistics, such as the number of treated units, the number of controls matched to treated units, and so on. The fourth and final table shows the main results. The “Estimate” column reports the estimated ATE and ATET. The next column shows the corresponding robust standard errors. “z” corresponds to the z-statistics to test whether ATE or ATET are 0; these are computed as the estimated parameters divided by their corresponding standard error. The “P-value” column reports the p-values for the z-statistics for a two-sided test.
The last two columns show the lower and upper bounds of the 95% confidence interval for the z-
statistics.

To assess the validity of the balancing hypothesis, *nn_matching* provides normalized differences
(see Abadie and Imbens, 2011; Austin, 2009) so as box-plots and empirical distribution functions to
compare the covariate distributions between treatment groups before and after matching. Theses
plots are edited for continuous variables alone. For binary variables, contingency tables are
provided.

Two temporary output data files are created, which need to be stored in a specific folder with a
libname statement to become permanent.

*Outdata1* includes an internal identification number for observation *i* created by the program that is
based on the original sort order and called *_id_* . *nbelements* specifies the number of matches for
unit *i* . *count* is the number of times unit *i* is used as a match. *km_i* specifies the number of times unit
*i* is used as a match for any observation *j* of the opposite treatment group weighted by the total
number of matches for the given observation *j* . *Outdata1* also includes the outcome variable *y*,
covariates *x*, and treatment group indicator *w*.

*Outdata2* includes the list of indices for the *M* closest matches for unit *i* . *_id_* is the internal
identification number for observation *i* and *idM* the corresponding identification number of *i* ’s
closest matches in the opposite treatment group. For each *_id_* , there is one row per match. For
instance, if unit 3 is matched with units 5, 6, and 10, there are three rows in *outdata2* that
-correspond to *_id_*=3, the first with *idM*=5, the second with *idM*=6, and the last with *idM*=10. For
each matched pair (*i*,*j*), the distance (as an absolute value) between unit *i* and unit *j* of the opposite
treatment group is stored as unit *j* ’s outcome value.

**An example**

Following Abadie et al. (2004), we use the particular data set constructed by Dehejia and Wahba
(1999) from Lalonde (1986) to examine the effect of participation in a job-training program on
individuals' earnings in 1978.

re78: individual earnings in 1978
treat = 1 if the individual participates to the job-training program, 0 otherwise
educ: years of education
black=1 if Afro-American, 0 otherwise
hisp=1 if Hispanic, 0 otherwise
married=1 if married, 0 otherwise
re74 (re75): individual earnings in 1974 (1975)
u74 (u75)=1 if unemployed in 1974 (1975), 0 otherwise.

The macro statement:

```
%nn_matching(data=lib.lalonde,y=re78,w=treat,x=age educ black hisp married re74 re75 u74 u75,M=4,scaling=,covarbias=);
```

replicate Abadie et al. (2004)'s results apart from the standard error of ATET with bias-correction
under homoscedasticity of the conditional variance which is larger in Abadie et al. (2004). The
results are presented below.

ESTIMATING AVERAGE TREATMENT EFFECTS
Model specification

Outcome variable: re78
Binary treatment: Treat
Matching variables: age educ black hisp married re74 re75 u74 u75

Estimation options

Number of matches requested: 4
Scaling matrix used: Inverse variances
Covariates used for bias correction: age educ black hisp married re74 re75 u74 u75

Summary statistics

Number of observations: 445
Number of control units: 260
Number of treated units: 185
Number of treated units matched to controls: 174
Number of control units matched to treated: 239
Number of times a treated unit is used as a match (MIN): 1
Number of times a treated unit is used as a match (MAX): 21
Number of times a control unit is used as a match (MIN): 1
Number of times a control unit is used as a match (MAX): 11

Estimation results assuming homoscedasticity of the conditional variance

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Std.Error</th>
<th>z</th>
<th>P-value</th>
<th>L. bound 95% CI</th>
<th>U. bound 95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Treatment Effect (ATE)</td>
<td>1903.326</td>
<td>720.215</td>
<td>2.643</td>
<td>0.008</td>
<td>491.731</td>
<td>3314.921</td>
</tr>
<tr>
<td>ATE with bias correction</td>
<td>1717.726</td>
<td>720.341</td>
<td>2.385</td>
<td>0.017</td>
<td>305.883</td>
<td>3178.724</td>
</tr>
<tr>
<td>Average Treatment Effect for the Treated (ATET)</td>
<td>1994.622</td>
<td>712.729</td>
<td>2.799</td>
<td>0.005</td>
<td>597.699</td>
<td>3391.544</td>
</tr>
<tr>
<td>ATET with bias correction</td>
<td>1838.424</td>
<td>712.824</td>
<td>2.579</td>
<td>0.01</td>
<td>441.314</td>
<td>3235.534</td>
</tr>
</tbody>
</table>

Estimation results allowing for heteroscedasticity of the conditional variance

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Std.Error</th>
<th>z</th>
<th>P-value</th>
<th>L. bound 95% CI</th>
<th>U. bound 95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Treatment Effect (ATE)</td>
<td>1903.326</td>
<td>745.421</td>
<td>2.553</td>
<td>0.011</td>
<td>442.328</td>
<td>3364.324</td>
</tr>
<tr>
<td>ATE with bias correction</td>
<td>1717.726</td>
<td>745.421</td>
<td>2.304</td>
<td>0.021</td>
<td>256.729</td>
<td>3178.724</td>
</tr>
</tbody>
</table>
Estimation results allowing for heteroscedasticity of the conditional variance

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Std.Error</th>
<th>z</th>
<th>P-value</th>
<th>L. bound 95% CI</th>
<th>U. bound 95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Treatment Effect</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>for the Treated (ATET)</td>
<td>1994.622</td>
<td>752.634</td>
<td>2.65</td>
<td>0.008</td>
<td>519.486</td>
<td>3469.757</td>
</tr>
<tr>
<td>ATET with bias correction</td>
<td>1838.424</td>
<td>752.634</td>
<td>2.443</td>
<td>0.015</td>
<td>363.289</td>
<td>3313.56</td>
</tr>
</tbody>
</table>

Normalized covariate mean differences are presented in the following table:

**Normalized covariate mean differences between treated and controls**

<table>
<thead>
<tr>
<th></th>
<th>Unmatched Samples</th>
<th>Matched samples (T)</th>
<th>Matched samples (C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>AGE</td>
<td>0.107</td>
<td>0.115</td>
<td>0.06</td>
</tr>
<tr>
<td>EDUC</td>
<td>0.141</td>
<td>0.097</td>
<td>0.105</td>
</tr>
<tr>
<td>BLACK</td>
<td>0.044</td>
<td>-0.029</td>
<td>0.081</td>
</tr>
<tr>
<td>HISP</td>
<td>-0.175</td>
<td>-0.079</td>
<td>-0.16</td>
</tr>
<tr>
<td>MARRIED</td>
<td>0.094</td>
<td>0.091</td>
<td>0.05</td>
</tr>
<tr>
<td>RE74</td>
<td>-0.002</td>
<td>0.057</td>
<td>-0.012</td>
</tr>
<tr>
<td>RE75</td>
<td>0.084</td>
<td>0.095</td>
<td>0.096</td>
</tr>
<tr>
<td>U74</td>
<td>-0.094</td>
<td>-0.092</td>
<td>-0.084</td>
</tr>
<tr>
<td>U75</td>
<td>-0.177</td>
<td>-0.154</td>
<td>-0.182</td>
</tr>
</tbody>
</table>

Note: 'Matched samples (T)' is for normalized mean differences between all sample treated and their matches, 'Matched samples (C)' for normalized mean differences between all sample controls and their matches.

Comparing binary covariate distributions between treatment groups before and after matching

<table>
<thead>
<tr>
<th>SampleType</th>
<th>All treated</th>
<th>All controls</th>
<th>Matched controls</th>
<th>Matched treated</th>
</tr>
</thead>
<tbody>
<tr>
<td>black</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Distribution in %</td>
<td>15.68</td>
<td>17.31</td>
<td>14.37</td>
<td>14.64</td>
</tr>
<tr>
<td>1 Distribution in %</td>
<td>84.32</td>
<td>82.69</td>
<td>85.63</td>
<td>85.36</td>
</tr>
<tr>
<td>hisp</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Distribution in %</td>
<td>94.05</td>
<td>89.23</td>
<td>93.68</td>
<td>92.05</td>
</tr>
<tr>
<td>1 Distribution in %</td>
<td>5.95</td>
<td>10.77</td>
<td>6.32</td>
<td>7.95</td>
</tr>
<tr>
<td>married</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 Distribution in %</td>
<td>81.08</td>
<td>84.62</td>
<td>82.76</td>
<td>84.52</td>
</tr>
<tr>
<td>1 Distribution in %</td>
<td>18.92</td>
<td>15.38</td>
<td>17.24</td>
<td>15.48</td>
</tr>
<tr>
<td>u74</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Visual diagnostic to assess the validity of the balancing hypothesis for continuous variables is then provided:

**Checking balance: visual diagnostic for continuous variables**
References


Austin P. C. (2009), "Balance diagnostics for comparing the distribution of baseline covariates between treatment group in propensity-score matched samples", Statistics in Medicine, vol. 28: 3083–3107.
