

Estimation of average treatment effects based on propensity scores

Sascha O. Becker
University of Munich

Andrea Ichino
EUI

Abstract.

In this paper, we give a short overview of some propensity score matching estimators suggested in the evaluation literature and we provide a set of Stata programs which we illustrate using the National Supported Work (NSW) demonstration widely known in labor economics.

Keywords: propensity score, matching, average treatment effect, evaluation

1 Introduction

In the evaluation literature, data often do not come from randomized trials but from (non-randomized) observational studies. In seminal work, Rosenbaum and Rubin (1983) proposed propensity score matching as a method to reduce the bias in the estimation of treatment effects with observational data sets. These methods have become increasingly popular in medical trials and in the evaluation of economic policy interventions.

Since in observational studies assignment of subjects to the treatment and control groups is not random, the estimation of the effect of treatment may be biased by the existence of confounding factors. Propensity score matching is a way to “correct” the estimation of treatment effects controlling for the existence of these confounding factors based on the idea that the bias is reduced when the comparison of outcomes is performed using treated and control subjects who are as similar as possible. Since matching subjects on an n -dimensional vector of characteristics is typically unfeasible for large n , this method proposes to summarize pre-treatment characteristics of each subject into a single-index variable (the propensity score) which makes the matching feasible.

In this paper, we give a short overview of some propensity score matching estimators suggested in the evaluation literature and we provide a set of Stata programs which we illustrate using the National Supported Work (NSW) demonstration widely known in labor economics. In using these programs, it should be kept in mind that they only allow to reduce, and not to eliminate, the bias generated by unobservable confounding factors. The extent to which this bias is reduced depends crucially on the richness and quality of the control variables on which the propensity score is computed and the matching performed. To be more precise, the bias is eliminated only if the exposure to treatment can be considered to be purely random among individuals who have the same value of the propensity score.

2 The propensity score

The propensity score is defined by Rosenbaum and Rubin (1983) as the conditional probability of receiving a treatment given pre-treatment characteristics:

$$p(X) \equiv Pr\{D = 1|X\} = E\{D|X\}. \quad (1)$$

where $D = \{0, 1\}$ is the indicator of exposure to treatment and X is the multidimensional vector of pre-treatment characteristics. Rosenbaum and Rubin (1983) show that if the exposure to treatment is random within cells defined by X , it is also random within cells defined by the values of the mono-dimensional variable $p(X)$. As a result, given a population of units denoted by i , if the propensity score $p(X_i)$ is known the Average effect of Treatment on the Treated (ATT) can be estimated as follows:

$$\begin{aligned} \tau &\equiv E\{Y_{1i} - Y_{0i}|D_i = 1\} \\ &= E\{E\{Y_{1i} - Y_{0i}|D_i = 1, p(X_i)\}\} \\ &= E\{E\{Y_{1i}|D_i = 1, p(X_i)\} - E\{Y_{0i}|D_i = 0, p(X_i)\}|D_i = 1\} \end{aligned} \quad (2)$$

where the outer expectation is over the distribution of $(p(X_i)|D_i = 1)$ and Y_{1i} and Y_{0i} are the potential outcomes in the two counterfactual situations of (respectively) treatment and no treatment.

Formally, the following two hypotheses are needed to derive (2) given (1).¹

Lemma 1. Balancing of pre-treatment variables given the propensity score.
If $p(X)$ is the propensity score, then

$$D \perp X \mid p(X). \quad (3)$$

Lemma 2. Unconfoundedness given the propensity score.
Suppose that assignment to treatment is unconfounded, i.e.

$$Y_1, Y_0 \perp D \mid X. \quad (4)$$

Then assignment to treatment is unconfounded given the propensity score, i.e.

$$Y_1, Y_0 \perp D \mid p(X). \quad (5)$$

If the Balancing Hypothesis of Lemma 1 is satisfied, observations with the same propensity score must have the same distribution of observable (and unobservable) characteristics independently of treatment status. In other words, for a given propensity score, exposure to treatment is random and therefore treated and control units should be on average observationally identical. Any standard probability model can be used to estimate the propensity score. For example, $Pr\{D_i = 1|X_i\} = F(h(X_i))$, where $F(\cdot)$ is the normal or the logistic cumulative distribution and $h(X_i)$ is a function of covariates with linear and higher order terms. The choice of which higher order terms to include

¹See Rosenbaum and Rubin (1983) or Imbens (2000) for a proof.

is determined solely by the need to obtain an estimate of the propensity score that satisfies the Balancing Hypothesis. Inasmuch as the specification of $h(X_i)$ which satisfies the Balancing Hypothesis is more parsimonious than the full set of interactions needed to match cases and controls on the basis of observables, the propensity score reduces the dimensionality problem of matching treated and control units on the basis of the multidimensional vector X .²

The program *pscore.ado* estimates the propensity score and tests the Balancing Hypothesis (Lemma 1) according to the following algorithm:³

1. Estimate the probit (or logit) model:

$$Pr\{D_i = 1|X_i\} = \Phi(h(X_i)) \quad (6)$$

where Φ denotes the normal (logistic) c.d.f. and $h(X_i)$ is a starting specification which includes all the covariates as linear terms without interactions or higher order terms.

2. Split the sample in k equally spaced intervals of the propensity score, where k is determined by the user and the default is 5.
3. Within each interval test that the average propensity score of treated and control units do not differ.
4. If the test fails in one interval, split the interval in halves and test again.
5. Continue until, in all intervals, the average propensity score of treated and control units do not differ.
6. Within each interval, test that the means of each characteristic do not differ between treated and control units. This is a necessary condition for the Balancing Hypothesis.⁴
7. If the means of one or more characteristics differ, inform the user that the balancing properties is not satisfied and that a less parsimonious specification of $h(X_i)$ is needed.

Steps 2-7 of the algorithm can be restricted to the common support. This restriction implies that the test of the balancing property is performed only on the observations whose propensity score belongs to the intersection of the supports of the propensity score of treated and controls. Imposing the common support condition in the estimation of the propensity score may improve the quality of the matches used to estimate the ATT.⁵

²It is important to note that the outcome plays no role in the algorithm for the estimation of the propensity score. This is equivalent, in this context, to what happens in controlled experiments in which the design of the experiment has to be specified independently of the outcome.

³Note that the Unconfoundedness Hypothesis of Lemma 2 cannot be tested.

⁴Note that it is not sufficient in the sense that the balancing may not hold for higher order moments of the distribution of characteristics. So, to be precise, the program does not test the Balancing Hypothesis, but only one of its implications. In future versions of the program we plan to add tests for higher moments of the distribution of characteristics.

⁵See the next section for a further discussion of the common support condition.

3 Matching estimators of the ATT based on the Propensity Score

An estimate of the propensity score is not enough to estimate the ATT of interest using equation (2). The reason is that the probability of observing two units with exactly the same value of the propensity score is in principle zero since $p(X)$ is a continuous variable. Various methods have been proposed in the literature to overcome this problem and four of the most widely used are *Nearest Neighbor Matching*, *Radius Matching*, *Kernel Matching* and *Stratification Matching*.

Beginning with the latter, the *Stratification* method consists of dividing the range of variation of the propensity score in intervals such that within each interval treated and control units have on average the same propensity score. For practical purposes the same blocks identified by the algorithm that estimates the propensity score can be used. Then, within each interval in which both treated and control units are present, the difference between the average outcomes of the treated and the controls is computed. The ATT of interest is finally obtained as an average of the ATT of each block with weights given by the distribution of treated units across blocks.

One of the pitfalls of the Stratification method is that it discards observations in blocks where either treated or control units are absent. This observation suggests an alternative way to match treated and control units, which consists of taking each treated unit and searching for the control unit with the closest propensity score, i.e. the *Nearest Neighbor*. Although it is not necessary, the method is usually applied *with replacement*, in the sense that a control unit can be a best match for more than one treated unit. Once each treated unit is matched with a control unit, the difference between the outcome of the treated units and the outcome of the matched control units is computed. The ATT of interest is then obtained by averaging these differences.

While in the case of the Stratification method there may be treated units which are discarded because no control is available in their block, in the case of the Nearest Neighbor method all treated units find a match. However, it is obvious that some of these matches are fairly poor because for some treated units the nearest neighbor may have a very different propensity score and nevertheless he would contribute to the estimation of the treatment effect independently of this difference. The *Radius Matching* and *Kernel Matching* methods offer a solution to this problem. With *Radius Matching* each treated unit is matched only with the control units whose propensity score falls in a predefined neighborhood of the propensity score of the treated unit. If the dimension of the neighborhood (i.e. the radius) is set to be very small it is possible that some treated units are not matched because the neighborhood does not contain control units. On the other hand, the smaller the size of the neighborhood the better is the quality of the matches. With *Kernel Matching* all treated are matched with a weighted average of *all* controls with weights that are inversely proportional to the distance between the propensity scores of treated and controls.

It is clear from the above considerations that these four methods reach different points on the frontier of the tradeoff between quality and quantity of the matches and

none of them is a priori superior to the others. Their joint consideration, however, offers a way to assess the robustness of the estimates.

It should also be noted that with all these methods the quality of the matches may be improved by imposing the common support restriction. Note, however, that in this way high quality matches may be lost at the boundaries of the common support and the sample may be considerably reduced. So imposing the common support restriction is not necessarily better (see Lechner (2001a)). All of our programs allow for the common support option as discussed below.

We now proceed to a more detailed and formal description of these estimators. We start with the joint analysis of *Nearest Neighbor Matching* and *Radius Matching* which can be described in a common framework, moving next to *Kernel Matching* and *Stratification Matching*.

Nearest Neighbor Matching (attnd.ado and attnw.ado) and Radius Matching (attr.ado)

Let T be the set of treated units and C the set of control units, and Y_i^T and Y_j^C be the observed outcomes of the treated and control units, respectively. Denote by $C(i)$ the set of control units matched to the treated unit i with an estimated value of the propensity score of p_i . Nearest neighbor matching sets

$$C(i) = \min_j \| p_i - p_j \| \quad (7)$$

which is a singleton set unless there are multiple nearest neighbors. In practice, the case of multiple nearest neighbors should be very rare, in particular if the set of characteristics X contains continuous variables; the likelihood of multiple nearest neighbors is further reduced if the propensity score is estimated and saved in double precision.

In radius matching,

$$C(i) = \{p_j \mid \| p_i - p_j \| < r\}, \quad (8)$$

i.e. all the control units with estimated propensity scores falling within a radius r from p_i are matched to the treated unit i .

In both nearest neighbor and radius matching, denote the number of controls matched with observation $i \in T$ by N_i^C and define the weights $w_{ij} = \frac{1}{N_i^C}$ if $j \in C(i)$ and $w_{ij} = 0$ otherwise. Then, the formula for both types of matching estimators can be written as follows (where M stands for either nearest neighbor matching or radius matching and the number of units in the treated group is denoted by N^T):

$$\begin{aligned} \tau^M &= \frac{1}{N^T} \sum_{i \in T} \left[Y_i^T - \sum_{j \in C(i)} w_{ij} Y_j^C \right] \\ &= \frac{1}{N^T} \left[\sum_{i \in T} Y_i^T - \sum_{i \in T} \sum_{j \in C(i)} w_{ij} Y_j^C \right] \end{aligned} \quad (9)$$

$$= \frac{1}{N^T} \sum_{i \in T} Y_i^T - \frac{1}{N^T} \sum_{j \in C} w_j Y_j^C$$

where the weights w_j are defined by $w_j = \sum_i w_{ij}$.

To derive the variances of these estimators the weights are assumed to be fixed and the outcomes are assumed to be independent across units.

$$\begin{aligned} \text{Var}(\tau^M) &= \frac{1}{(N^T)^2} \left[\sum_{i \in T} \text{Var}(Y_i^T) + \sum_{j \in C} (w_j)^2 \text{Var}(Y_j^C) \right] \\ &= \frac{1}{(N^T)^2} \left[N^T \text{Var}(Y_i^T) + \sum_{j \in C} (w_j)^2 \text{Var}(Y_j^C) \right] \\ &= \frac{1}{N^T} \text{Var}(Y_i^T) + \frac{1}{(N^T)^2} \sum_{j \in C} (w_j)^2 \text{Var}(Y_j^C). \end{aligned} \quad (10)$$

In the programs *attn.d.ado*, *attnw.ado*, and *attr.ado*, standard errors are obtained analytically using the above formula, or by bootstrapping using the *bootstrap* option.

As far as the difference between *attn.d.ado* and *attnw.ado* is concerned, it is most easily understood by briefly describing the way nearest neighbors are computationally determined in the two programs. To save on computing time, nearest neighbors are not determined by comparing treated observations to every single control, but by first sorting all records by the estimated propensity score and then searching forward and backward for the closest control unit(s). If for a treated unit forward and backward matches happen to be equally good, there are two computationally feasible options to obtain analytical standard errors while at the same time exploiting the very fast forward and backward search strategy: *attnw.ado* gives equal weight (hence the letters “nw” for nearest neighbor and equal weight) to the groups of forward and backward matches; *attn.d.ado* randomly draws either the forward or backward matches (hence the letters “nd” for nearest neighbor and random draw). In practice, the case of multiple nearest neighbors should be very rare, in particular if the set of X’s contains continuous variables, in which case both *attnw.ado* and *attn.d.ado* should give equal results. The likelihood of multiple nearest neighbors is further reduced if the propensity score is estimated and saved in double precision, which is what *pscore.ado* does by default.

Kernel matching method (atnk.ado)

The kernel matching estimator is given by

$$\tau^K = \frac{1}{N^T} \sum_{i \in T} \left\{ Y_i^T - \frac{\sum_{j \in C} Y_j^C G\left(\frac{p_j - p_i}{h_n}\right)}{\sum_{k \in C} G\left(\frac{p_k - p_i}{h_n}\right)} \right\} \quad (11)$$

where $G(\cdot)$ is a kernel function and h_n is a bandwidth parameter. Under standard conditions on the bandwidth and kernel ,

$$\frac{\sum_{j \in C} Y_j^C G\left(\frac{p_i - p_j}{h_n}\right)}{\sum_{k \in C} G\left(\frac{p_k - p_i}{h_n}\right)} \quad (12)$$

is a consistent estimator of the counterfactual outcome Y_{0i} . In the program *atrk.ado*, standard errors are obtained by bootstrapping using the *bootstrap* option. Users can choose between the default Gaussian kernel or the Epanechnikov kernel.

Stratification method (*atts.ado*)

This method is based on the same stratification procedure used for estimating the propensity score. Note that by construction, in each block defined by this procedure the covariates are balanced and the assignment to treatment can be considered random. Hence, letting q index the blocks defined over intervals of the propensity score, within each block the program computes

$$\tau_q^S = \frac{\sum_{i \in I(q)} Y_i^T}{N_q^T} - \frac{\sum_{j \in I(q)} Y_j^C}{N_q^C} \quad (13)$$

where $I(q)$ is the set of units in block q while N_q^T and N_q^C are the numbers of treated and control units in block q .

The estimator of the *ATT* in equation 2 based on the Stratification method is then computed with the following formula:

$$\tau^S = \sum_{q=1}^Q \tau_q^S \frac{\sum_{i \in I(q)} D_i}{\sum_{\forall i} D_i} \quad (14)$$

where the weight for each block is given by the corresponding fraction of treated units and Q is the number of blocks.

Assuming independence of outcomes across units, the variance of τ^S is computed by

$$Var(\tau^S) = \frac{1}{N^T} \left[Var(Y_i^T) + \sum_{q=1}^Q \frac{N_q^T}{N^T} \frac{N_q^T}{N_q^C} Var(Y_j^C) \right] \quad (15)$$

In the program *atts.ado*, standard errors are obtained analytically using the above formula, or by bootstrapping using the *bootstrap* option.

4 Syntax

`pscore` and `att*` are regression-like commands

```

pscore treatment [varlist] [weight] [if exp] [in range] , pscore(newvar) [
    blockid(newvar) detail logit comsup level(#) numblo(#) ]

attnd outcome treatment [varlist] [weight] [if exp] [in range] [ ,
    pscore(scorevar) logit index comsup detail bootstrap reps(#) noisily
    dots ]

attnw outcome treatment [varlist] [weight] [if exp] [in range] [ ,
    pscore(scorevar) logit index comsup detail bootstrap reps(#) noisily
    dots ]

attr outcome treatment [varlist] [weight] [if exp] [in range] [ ,
    pscore(scorevar) logit index radius(#) comsup detail bootstrap
    reps(#) noisily dots ]

attk outcome treatment [varlist] [weight] [if exp] [in range] [ ,
    pscore(scorevar) logit index epan bwidth(#) comsup detail bootstrap
    reps(#) noisily dots ]

atts outcome treatment [varlist] [if exp] [in range] , pscore(scorevar)
    blockid(blockvar) [ comsup detail bootstrap reps(#) noisily dots ]

```

5 Options

Note the following points:

- It is important to clean up your dataset before running this suite of Stata programs, in particular to delete observations with missing values.
- In `pscore`, the option `pscore(newvar)` is compulsory.
- `pscore` and the `att*` programs are closely related in that users will typically first run `pscore` to estimate the propensity score and test whether the balancing property holds, and then proceed to estimating the ATT with one or more of the `att*` programs.
- Note, however, that all `att*` programs are stand-alone programs, i.e. if users prefer to estimate the propensity score with their own procedure, they can do so, specifying the name of the estimated propensity score as an input variable in the `att*` programs.
- If users are confident about the “correct” specification for the propensity score, that specification can be used directly in the `att*` programs to estimate the

propensity score without first running `pscore`. This is actually advisable if bootstrapped standard errors are requested because, when users do not specify their own previously estimated propensity score, the bootstrap encompasses the estimation of the propensity score based on the specification given by `varlist`. Re-estimating the propensity score at each replication of the bootstrap procedure is recommended to account for the uncertainty associated with the estimation of the propensity score. Even more so when the `comsup` option is specified because in this case the region of common support changes with every bootstrap sample, and bootstrapped standard errors pick up this uncertainty as well. So, typically, users would first identify a specification satisfying the balancing property - using e.g. `pscore` - and then provide exactly this specification in `varlist` and use bootstrapped standard errors.

- For `atts`, in addition to the estimated propensity score, users must provide a variable containing the block identifier for the estimated propensity score. Therefore, in the case of `atts` it is most convenient to rely on `pscore` because it nicely generates both the estimated propensity score variable and the block identifier.

5.1 Options for `pscore`

`pscore(newvar)` is a compulsory option and asks users to specify the variable name for the estimated propensity score.

`blockid(newvar)` allows users to specify the variable name for the block number of the estimated propensity score.

`detail` displays more detailed output documenting the steps performed to obtain the final results.

`logit` uses a logit model to estimate the propensity score instead of the default probit model.

`comsup` restricts the analysis of the balancing property to all treated plus those controls in the region of common support. A dummy variable named `it:comsup` is added to the dataset to identify the observations in the common support.

`level(#)` allows to set the significance level of the tests of the balancing property. The default is 0.01. Note that this significance level applies to the test of each single variable of the vector X of pre-treatment characteristics, i.e. the balancing property is not rejected only in case it holds for every single X . This is a relatively conservative approach because of the following argument. Assume that the significance level is set to 0.05, that X consists of 20 variables, and that the tests of the balancing property are mutually independent. Then, with probability $\binom{20}{1} (0.05)^1 (0.95)^{19} = 0.37$, one of the tests rejects the balancing property although it actually holds true.

`numblo(#)` allows to set the number of blocks of equal score range to be used at the beginning of the test of the balancing hypothesis. The default is set to 5 blocks.

5.2 Options common to all `att*` commands

`comsup` restricts the computation of the ATT to the region of common support.

`detail` displays more detailed output documenting the steps performed to obtain the final results.

`bootstrap` bootstraps the standard error of the treatment effect.

`reps(integer)` specifies the number of bootstrap replications to be performed. The default is 50. This option produces an effect only if the `bootstrap` option is specified.

`noisily` requests that any output from the bootstrap replications be displayed. This option produces an effect only if the `bootstrap` option is specified.

`dots` requests that a dot be placed on the screen at the beginning of each bootstrap replication. This option produces an effect only if the `bootstrap` option is specified.

5.3 Options for `attnd` and `attnw`

`pscore(scorevar)` specifies the name of the user-provided variable containing the estimated propensity score; if this option is not specified, `attnd` and `attnw` will estimate the propensity score with the specification provided in `varlist` using a probit.

`logit` allows a logit estimation of the propensity score instead of the default probit model when the option `pscore(scorevar)` is not specified by the user.

`index` requires the use of the linear index as the propensity score when the option `pscore(scorevar)` is not specified by the user.

5.4 Options for `attr`

`pscore(scorevar)` specifies the name of the user-provided variable containing the estimated propensity score; if this option is not specified, `attr` will estimate the propensity score with the specification provided in `varlist` using a probit.

`logit` allows a logit estimation of the propensity score instead of the default probit model when the option `pscore(scorevar)` is not specified by the user.

`index` requires the use of the linear index as the propensity score when the option `pscore(scorevar)` is not specified by the user.

`radius(#)` specifies the size of the radius. The default is 0.1.

5.5 Options for `atrk`

`pscore(scorevar)` specifies the name of the user-provided variable containing the estimated propensity score; if this option is not specified, `atrk` will estimate the propensity score with the specification provided in `varlist` using a probit.

`logit` allows a logit estimation of the propensity score instead of the default probit model when the option `pscore(scorevar)` is not specified by the user.

`index` requires the use of the linear index as the propensity score when the option `pscore(scorevar)` is not specified by the user.

`epan` specifies that the Epanechnikov kernel be used by kernel rather than the default Gaussian one.

`bwidth(#)` specifies the bandwidth to be used when choosing the `epan` option. Default is 0.06. This option produces an effect only if the Epanechnikov kernel is requested.

5.6 Options for `atts`

`pscore(scorevar)` is a compulsory option which specifies the name of the user-provided variable containing the estimated propensity score.

`blockid(blockvar)` is a compulsory option and specifies the name of the user-provided variable containing the block identifier of the estimated propensity score.

6 Example: NSW - PSID data

We use data from Dehejia and Wahba (1999), DW for short, which is based on Lalonde's (1986) seminal study on the comparison between *experimental* and *non-experimental* methods for the evaluation of causal effects. The data combine the treated units from a randomized evaluation of the National Supported Work (NSW) demonstration with nonexperimental comparison units drawn from survey data. For the purpose of this section, we restrict our analysis to the so-called NSW-PSID-1 subsample, consisting of the male NSW treatment units and the largest of the three PSID subsamples (see DW99 for more detail). We use this dataset for two reasons: first, it is widely known in labor economics (starting with Lalonde, 1986, re-analysed by Dehejia and Wahba, 1999 and 2002, and by Smith and Todd, 2003) to illustrate the working of propensity score and matching techniques. Second, the data are publicly available at Rajeev Dehejia's website under the following address: <http://www.columbia.edu/~rd247/nswdata.html>. We tried to replicate the results produced by Dehejia and Wahba (1999) but - similar to Smith and Todd (2003) - have not been able to numerically replicate all of their estimates because of lack of detailed information in some crucial instances (e.g. number of blocks used in stratification, significance levels, exact procedure for testing the balancing property). However, we get qualitatively similar results. The outcome of interest is RE78 (real earnings in 1978); the treatment T is participation in the NSW treatment group. Control variables are age, education, Black (1 if black, 0 otherwise), Hispanic (1 if Hispanic, 0 otherwise), married (1 if married, 0 otherwise), nodegree (1 if no degree, 0 otherwise), RE75 (earnings in 1975), and RE74 (earnings in 1974). The treatment group contains 185 observations, the control group 2490 observations, so the total number of observations is 2675.

6.1 Output from pscore

The output from running pscore using the DW99 specification is as follows:⁶⁷

```
. pscore T age age2 educ educ2 marr black hisp RE74 RE75 RE742 RE752 blackU74
> , pscore(mypscore) blockid(myblock) comsup numblo(5) level(0.005) logit;

*****
Algorithm to estimate the propensity score
*****

The treatment is T

      T |          Freq.      Percent      Cum.
-----+-----
      0 |          2490       93.08       93.08
      1 |           185        6.92      100.00
-----+-----
    Total |          2675      100.00

Estimation of the propensity score
Iteration 0:  log likelihood = -672.64954
              (output omitted)
Iteration 9:  log likelihood = -204.97537

Logit estimates
Number of obs   =      2675
LR chi2(12)     =      935.35
Prob > chi2     =      0.0000
Pseudo R2      =      0.6953

Log likelihood = -204.97537
```

T	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
age	.3316904	.1203295	2.76	0.006	.0958489 .5675318
age2	-.0063668	.0018554	-3.43	0.001	-.0100033 -.0027303
educ	.8492683	.3477041	2.44	0.015	.1677807 1.530756
educ2	-.0506202	.0172492	-2.93	0.003	-.084428 -.0168124
marr	-1.885542	.2993282	-6.30	0.000	-2.472214 -1.298869
black	1.135973	.3517793	3.23	0.001	.446498 1.825447
hisp	1.96902	.5668567	3.47	0.001	.8580017 3.080039
RE74	-.0001059	.0000353	-3.00	0.003	-.000175 -.0000368
RE75	-.0002169	.0000414	-5.24	0.000	-.000298 -.0001357
RE742	2.39e-09	6.43e-10	3.72	0.000	1.13e-09 3.65e-09
RE752	1.36e-10	6.55e-10	0.21	0.836	-1.15e-09 1.42e-09
blackU74	2.144129	.4268089	5.02	0.000	1.307599 2.980659
_cons	-7.474742	2.443502	-3.06	0.002	-12.26392 -2.685566

note: 22 failures and 0 successes completely determined.

Note: the common support option has been selected
The region of common support is [.00061067, .9752541]

Description of the estimated propensity score
in region of common support

⁶educ2 denotes squared education, RE742 and RE752 denote the square of RE74 and RE75, respectively, and blackU74 is the interaction of black and a dummy for non-employment (i.e. zero earnings) in 1974

⁷Note that when specifying the detail option, (even) more detailed output is displayed documenting the steps performed to obtain the final results.

Estimated propensity score

Percentiles		Smallest		
1%	.0006426	.0006107		
5%	.0008025	.0006149		
10%	.0010932	.0006159	Obs	1342
25%	.0023546	.000618	Sum of Wgt.	1342
50%	.0106667		Mean	.1377463
		Largest	Std. Dev.	.2746627
75%	.0757115	.974804		
90%	.6250823	.9749805	Variance	.0754396
95%	.949302	.9752244	Skewness	2.185182
99%	.970598	.9752541	Kurtosis	6.360726

 Step 1: Identification of the optimal number of blocks
 Use option detail if you want more detailed output

The final number of blocks is 7
 This number of blocks ensures that the mean propensity score
 is not different for treated and controls in each blocks

Following the algorithm described in Section 2, blocks for which the average propensity scores of treated and controls differ are split in half. The algorithm continues until, in all blocks, the average propensity score of treated and controls does not differ. In our case, this happens for a number of seven blocks. Thereafter `pscore` proceeds to the test of the balancing property for each covariate.

 Step 2: Test of balancing property of the propensity score
 Use option detail if you want more detailed output

The balancing property is satisfied

When the `detail` option is not specified, the only output produced by `pscore` is a statement saying whether the balancing property is satisfied (which is the case for the DW data with $p=0.005$) or not. In the latter case the user is informed for which variable(s) in which block(s) the balancing property failed and a message is issued suggesting to try a different specification of the propensity score.

In case the balancing property holds, the final distribution of treated and controls across blocks is tabulated together with the inferior of each block:

This table shows the inferior bound, the number of treated and the number of controls for each block

Inferior of block of pscore	T		Total
	0	1	
.0006107	924	7	931
.05	102	4	106

.1	56	7	63
.2	41	28	69
.4	14	21	35
.6	13	20	33
.8	7	98	105
Total	1157	185	1342

Note: the common support option has been selected

```
*****
End of the algorithm to estimate the pscore
*****
```

Note that we imposed the common support condition in this example using the `comsup` option. Consequently, block identifiers are missing for control observations outside the common support and the number of observations in the table is 1342 instead of 2675.

After running `pscore`, users can proceed to estimate average treatment effects using one of the `att*` programs.

6.2 Output from `attnd` and `attnw`

The typical output from `attnd` or `attnw`⁸ is

```
. attnd RE78 T age age2 educ educ2 marr black hisp RE74 RE75 RE742 RE752 blackU
> 74, comsup boot reps(100) dots logit;
```

```
The program is searching the nearest neighbor of each treated unit.
This operation may take a while.
```

```
ATT estimation with Nearest Neighbor Matching method
(random draw version)
Analytical standard errors
```

n. treat.	n. contr.	ATT	Std. Err.	t
185	57	1667.644	2113.592	0.789

Note: the numbers of treated and controls refer to actual nearest neighbour matches

Bootstrapping of standard errors

```
command: attnd RE78 T age age2 educ educ2 marr black hisp RE74 RE75 RE742 R
> E752 blackU74 , pscore() logit comsup
statistic: r(attnd)
(obs=2675)
.....
> .....
```

⁸Remember that `attnd` and `attnw` will generally give the same results (except for bootstrapped standard errors) unless there are only discrete covariates and multiple nearest neighbors. This is not the case in our example, and therefore to save space we report here only the output of `attnd`.

Bootstrap statistics

Variable	Reps	Observed	Bias	Std. Err.	[95% Conf. Interval]	
bs1	100	1667.644	-85.68572	1211.026	-735.2937	4070.582 (N)
					-839.9554	3643.178 (P)
					-394.5013	4064.472 (BC)

N = normal, P = percentile, BC = bias-corrected

ATT estimation with Nearest Neighbor Matching method
(random draw version)
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
185	57	1667.644	1211.026	1.377

Note: the numbers of treated and controls refer to actual nearest neighbour matches

Note that in this example, only 57 different controls have been matched to the 185 treated. These results are very close to the ones obtained by Dehejia and Wahba (1999).

6.3 Output from attr

For attr with radius $r = 0.0001$ we obtain

```
. attr RE78 T age age2 educ educ2 marr black hisp RE74 RE75 RE742 RE752 blackU7
> 4, comsup boot reps(100) dots logit radius(0.0001);
```

The program is searching for matches of treated units within radius.
This operation may take a while.

ATT estimation with the Radius Matching method
Analytical standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
23	66	-5546.140	2388.723	-2.322

Note: the numbers of treated and controls refer to actual matches within radius

Bootstrapping of standard errors

```
command: attr RE78 T age age2 educ educ2 marr black hisp RE74 RE75 RE742 RE
> 752 blackU74 , pscore() logit comsup radius(.0001)
```

statistic: r(attr)
(obs=2675)

```
.....
> .....
```

Bootstrap statistics

Variable	Reps	Observed	Bias	Std. Err.	[95% Conf. Interval]
----------	------	----------	------	-----------	----------------------

bs1	100	-5546.14	425.988	4657.081	-14786.8	3694.519	(N)
					-13867.87	5668.455	(P)
					-13867.87	5668.455	(BC)

N = normal, P = percentile, BC = bias-corrected

ATT estimation with the Radius Matching method
Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
23	66	-5546.140	4657.081	-1.191

Note: the numbers of treated and controls refer to actual matches within radius

The large difference with respect to the caliper matching results of Dehejia and Wahba (2002) comes from the fact that caliper matching differs from radius matching in that the nearest control is used as a match if a treated unit has no control units within radius r . While caliper matching uses all treated units, our method only uses those treated that have control matches within radius r (here, 23 out of 185 treated). This example illustrates the sensitivity of the results to extreme assumptions used in the matching procedure. If the radius is chosen to be very small, many treated units are not matched and the results are no longer representative of the population of treated. For a more detailed discussion of this issue see Smith and Todd (2003).

6.4 Output from `attk`

For `attk` the results are as follows:⁹

```
. attk RE78 T age age2 educ educ2 marr black hisp RE74 RE75 RE742 RE752 blackU7
> 4, comsup boot reps(100) dots logit;
```

```
The program is searching for matches of each treated unit.
This operation may take a while.
```

ATT estimation with the Kernel Matching method

n. treat.	n. contr.	ATT	Std. Err.	t
185	1157	1537.943	.	.

Note: Analytical standard errors cannot be computed. Use the bootstrap option to get bootstrapped standard errors.

Bootstrapping of standard errors

```
command: attk RE78 T age age2 educ educ2 marr black hisp RE74 RE75 RE742 RE
> 752 blackU74 , pscore() comsup logit bwidth(.06)
statistic: r(attk)
```

⁹Note that Dehejia and Wahba do not present results for kernel matching.

```
(obs=2675)
.....
> .....
```

Bootstrap statistics

Variable	Reps	Observed	Bias	Std. Err.	[95% Conf. Interval]		
bs1	100	1537.943	-51.50918	1016.874	-479.755	3555.642	(N)
					-439.9654	3601.629	(P)
					-343.8961	3826.322	(BC)

N = normal, P = percentile, BC = bias-corrected

ATT estimation with the Kernel Matching method
 Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
185	1157	1537.943	1016.874	1.512

In kernel matching, all treated as well as all controls (in the common support which has been imposed here) are used. The estimate of the ATT is quite close to the one obtained with nearest neighbor matching.

6.5 Output from atts

Finally, for atts with the blocks obtained in pscore:¹⁰

```
. atts RE78 T, pscore(mypscore) blockid(myblock) comsup boot reps(100) dots;
```

ATT estimation with the Stratification method
 Analytical standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
185	1157	2208.600	777.866	2.839

Bootstrapping of standard errors

```
command: atts RE78 T , pscore(mypscore) blockid(myblock) comsup
statistic: r(atts)
(obs=2675)
.....
> .....
```

¹⁰Note that there are two special cases as concerns the computation of the ATT and its analytical standard error. First, if there is no treated and/or no control unit in one (or more) of the blocks, the ATT is computed on the remaining blocks which practically amounts to imposing a (block-based) common support condition. Second, if there is exactly one treated and/or one control in one (or more) of the blocks, the ATT in that block can still be computed but the standard error cannot. In this case, atts will produce missing values for the standard error. However, bootstrapped standard errors can still be computed.

Bootstrap statistics

Variable	Reps	Observed	Bias	Std. Err.	[95% Conf. Interval]	
bs1	100	2208.6	96.6845	850.9957	520.0395	3897.16 (N)
					570.5178	4012.478 (P)
					778.2358	4184.918 (BC)

N = normal, P = percentile, BC = bias-corrected

ATT estimation with the Stratification method

Bootstrapped standard errors

n. treat.	n. contr.	ATT	Std. Err.	t
185	1157	2208.600	850.996	2.595

Here, the difference with respect to the DW99 results is slightly bigger than for nearest neighbor matching. This might be explained by a different number of blocks used in stratification, different significance levels, or a different procedure for testing the balancing property (see general remark at the beginning of the section 6). But overall, the results obtained by `attnw`, `attk`, and `atts` are quite close to each other, and taken together give evidence of a positive ATT in the range of 1500-2200 \$ associated with the NSW demonstration (when evaluated with non-experimental comparison groups) which is close to the experimental estimates of about 1700 \$.

7 Saved Results

The the `att*` commands save in `r()`

Scalars

<code>r(nt*)</code>	number of treated used in the computation of <code>att*</code>
<code>r(nc*)</code>	number of controls used in the computation of <code>att*</code>
<code>r(att*)</code>	ATT obtained by <code>att*</code>
<code>r(seatt*)</code>	analytical s.e. for <code>att*</code>
<code>r(tsatt*)</code>	analytical t-stat for <code>att*</code>
<code>r(bseatt*)</code>	bootstrapped s.e. for <code>att*</code>
<code>r(btsatt*)</code>	bootstrapped t-stat. for <code>att*</code>
<code>r(mean1)</code>	mean outcome of matched treated for <code>attk</code>
<code>r(mean0)</code>	mean outcome of matched controls for <code>attk</code>

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9 References

- Cochran, W. and Rubin, D.B. (1973), "Controlling Bias in Observational Studies", *Sankhya* 35, 417-446.
- Dehejia, R.H. and S. Wahba (1999), "Causal Effects in Nonexperimental Studies: Reevaluation of the Evaluation of Training Programs", *Journal of the American Statistical Association* 94, 1053-1062.
- Dehejia, R.H. and S. Wahba (2002) "Propensity Score Matching Methods for Non-Experimental Causal Studies", *Review of Economics and Statistics*, 84(1), 151-161.
- Heckman, James, Hidehiko Ichimura, Jeffrey Smith and Petra Todd (1998): "Characterizing Selection Bias Using Experimental Data," *Econometrica*, 66(5), 1017-1098.
- Heckman, James, Hidehiko Ichimura and Petra Todd (1997): "Matching As An Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Program," *Review of Economic Studies*, 64(4), 605-654.
- Heckman, James, Hidehiko Ichimura and Petra Todd (1998), "Matching As An Econometric Evaluation Estimator," *Review of Economic Studies*, 65(2), 261-294.
- Heckman, James., LaLonde, Robert, Smith, Jeffrey. (1999), "The Economics and Econometrics of Active Labour Market Programme", in Ashenfelter, O. and Card, D. (eds.), *The Handbook of Labor Economics*, Volume III.
- Imbens, G.W. (2000), "The Role of Propensity Score in Estimating Dose-Response Functions", *Biometrika*, 87(3), 706-710.
- Lechner, Michael (2001a). "A note on the common support problem in applied evaluation studies", Discussion Paper 2001-01, Department of Economics, University of St. Gallen.
- Lechner, M. (2001b), "Identification and Estimation of Causal Effects of Multiple Treatments under the Conditional Independence Assumption", in: Lechner, M., Pfeiffer, F. (eds), *Econometric Evaluation of Labour Market Policies*, Heidelberg: Physica/Springer, p. 43-58.
- Jones, M. C., Marron, J. S. and Sheather, S. J. (1996): "A Brief Survey of Bandwidth Selection for Density Estimation", *Journal of the American Statistical Association*, Vol. 91, No. 433, 401-407.

Rosenbaum, P.R., and D.B. Rubin (1983) “The Central Role of the Propensity Score in Observational Studies for Causal Effects”, *Biometrika* 70(1), 41-55.

Rosenbaum, P.R., and D.B. Rubin (1984) “Reducing Bias in Observational Studies using Subclassification on the Propensity Score”, *Journal of the American Statistical Association* 79, 516-524.

Rubin, D.B. (1974), “Estimating Causal Effects of Treatments in Randomised and Non-Randomised Studies”, *Journal of Educational Psychology*, 66, 688-701.

Smith, Jeffrey and Petra Todd (2003), “Does Matching Overcome Lalonde’s Critique of Non Experimental Estimators?”, forthcoming: *Journal of Econometrics*.

Silverman, B.W. (1986) *Density Estimation for Statistics and Data Analysis* (London: Chapman and Hall).

About the Authors

Sascha O. Becker is assistant professor of Economics at the University of Munich, Germany. He is also affiliated with CESifo and IZA.

Andrea Ichino is professor of Economics at the European University Institute, Florence, Italy. He is also affiliated with CESifo, CEPR and IZA.

Please address any correspondence to Sascha O. Becker (so.b@gmx.net) or Andrea Ichino (andrea.ichino@iue.it).