Assignment #2 - Matching Design (Non-Equivalent Control Group Design)

Assignment: Estimate the average treatment effect for the treated (ATT) for the vocabulary training. vm is the group indicator with the vocabulary group representing the treatment group and the math group representing the control group. The outcome of interest is the vocabulary achievement score (vocaball).

Step 1. Assess whether the set of observed covariates might meet the strong ignorability assumptions.

Shadish et al. (2008)'s dataset includes a large set of variables that cover several confounders. In my opinion, the most important determinants of the selection process and the outcome model are absolutely reliably measured. We can be confident that most of the confounding biases can be removed.

Step 2. Assess the initial imbalance in baseline covariates.

As can be seen in Table 1 and Figure 3, some variables are statistically different in the two groups, treatment and control. For example, preflit, cauc, vocabpre, and likelit. Hence, it is reasonable to believe that they might affect the selection process and the outcome. Therefore, further balancing is needed before we estimate the treatment effect.

Step 3. For different PS and regression estimators, estimate the PS and the ATT.

Part 1. Estimate the ATT using inverse propensity weighting

(1) Propensity Score Estimation. It is a logistic model like the following equation:

$$T_i = \beta_0 + \beta Zs + e_i \tag{1}$$

Where T_i is the treatment variable (vm), Zs are the covariates (*mathpre, vocabpre, actcomp, hsgpaar, collgpaa, numbmath, likemath, likelit, preflit, majormi, mars, cauc, afram, male, pextra, pagree, pconsc, pemot, pintell, beck, age, married, momdegr, daddegr, credit*), and e_i is the error term.

(2) Balance estimation.

The balance of the covariates in the treatment as well as in the control group improved significantly, as can be seen in 2. For the remaining covariates that are still unbalanced, we may consider addressing the issue by adding them as control variables.

(3) Effect estimation (without further covariate adjustments)

$$Y_i = \beta_0 + \beta_1 T + e_i \tag{2}$$

Where Y_i is the outcome variable (*vocaball*), Tt is the treatment variable (*vm*), and we use weights equaling *iptw*. The results of the regression can be seen in Table 3.

(4) Effect estimation (with additional covariate adjustments)

$$Y_i = \beta_0 + \beta_1 T + \beta_n Xs + e_i \tag{3}$$

Where Y_i is the outcome variable (*vocaball*), T is the treatment variable (*vm*), Xs are the covariates (*mathpre, vocabpre, actcomp, hsgpaar, collgpaa, numbmath, likemath, likelit, preflit, majormi, mars, cauc, afram, male, pextra, pagree, pconsc, pemot, pintell, beck, age, married, momdegr, daddegr, credit*), and we use weights equaling *iptw*. The results of the regression can be seen in Table 3.

Part 2. Stratification.

(1) Propensity Score Estimation. It is a logistic model like the following equation:

$$T_i = \beta_0 + \beta Zs + e_i \tag{4}$$

Where T_i is the treatment variable (vm), Zs are the covariates (*mathpre, vocabpre, actcomp, hsgpaar, collgpaa, numbmath, likemath, likelit, preflit, majormi, mars, cauc, afram, male, pextra, pagree, pconsc, pemot, pintell, beck, age, married, momdegr, daddegr, credit*), and e_i is the error term. The sample size and the ATT-weights can be seen in Table 2. The results of the regression can be seen in Table 3.

(2) Balance estimation (with cubic polynomial of PS-logit):

The balance of the covariates in the treatment as well as in the control group improved significantly, as can be seen in 3. For the remaining covariates that are still unbalanced, we may consider addressing the issue by adding them as control variables.

(3) Effect estimation (without further covariate adjustments):

$$Y_i = \beta_0 + \beta_1 T_i + e_i \tag{5}$$

Where Y_i is the outcome variable (*vocaball*), T is the treatment variable (*vm*) for each individual i, and using weights equaling *strwt*. The results of the regression can be seen in Table 3.

(4) Effect estimation (with further covariate adjustments):

Same as Part 1 except that each individual has a weight of *strwt*.

$$Y_i = \beta_0 + \beta_1 Treatment + \beta_n Xs + e_i \tag{6}$$

Where Y_i is the outcome variable, $Treatment$ is the treatment variable (*vm*), Xs are the covariates (*mathpre, vocabpre, actcomp, hsgpaar, collgpaa, numbmath, likemath, likelit, preflit, majormi, mars, cauc, afram, male, pextra, pagree, pconsc, pemot, pintell, beck, age, married, momdegr, daddegr, credit*), and we use weights equaling *strwt*. The results of the regression can be seen in Table 3.

Analysis of the outcomes of the regression

Table 3 summarizes the outcomes of the four regressions. The first two columns have the results for the inverse-propensity weighting, and the last two the stratification. Both cases present the results of the average treatment effect for the treated (ATT), the standard errors, and the t-values, with and without covariates. As the summary shows, the treatment increased between 8.03 to 9 the vocabulary achievement score for the treated on average. The significance holds with the covariates, the standard errors are around 0.48, and the t-values are bigger than 17. Therefore, the p-value is small, indicating that we can reject the null hypotheses with 95 % of confidence. In other words, these results indicate that we might be confident to say that the treatment had a causal effect on the treated.

References

Shadish, W. R., Clark, M. H., and Steiner, P. M. (2008). Can nonrandomized experiments yield accurate answers? a randomized experiment comparing random and nonrandom assignments. *Journal of the American statistical association*, 103(484):1334–1344.

Appendix

Table 1: Initial imbalance in baseline covariates

	Mean.Diff	Std.Error	p-value	Std.Mean.Diff	Var.Ratio
mathpre	-0.508	0.389	0.193	-0.184	0.861
vocabpre	1.814	0.732	0.014	0.346	0.753
actcomp	0.278	0.678	0.682	0.058	0.891
hsgpaar	-0.048	0.080	0.553	-0.084	0.845
collgpaa	-0.037	0.098	0.704	-0.053	0.714
numbmath	-0.383	0.157	0.016	-0.329	0.448
likemath	-1.771	0.323	0.00000	-0.767	0.731
likelit	0.750	0.313	0.017	0.338	0.844
preflit	0.712	0.118	0	0.836	0.676
majormi	-0.159	0.057	0.006	-0.386	0.583
mars	0.126	3.172	0.968	0.006	1.320
cauc	0.183	0.070	0.010	0.371	0.944
afram	-0.145	0.069	0.037	-0.297	0.889
other	-0.038	0.032	0.236	-0.163	0.520
male	-0.057	0.061	0.352	-0.131	0.854
pextra	1.489	1.112	0.182	0.189	0.853
pagree	0.977	0.689	0.158	0.201	0.885
pconsc	-1.551	0.844	0.067	-0.264	1.144
pemot	-0.243	1.105	0.826	-0.031	0.898
pintell	0.557	0.725	0.443	0.111	1.301
beck	-0.835	0.881	0.344	-0.129	0.464
age	0.276	0.775	0.722	0.052	1.253
married	0.0004	0.038	0.992	0.001	1.000
momdegr	0.475	0.327	0.147	0.206	0.939
daddegr	0.047	0.391	0.904	0.017	1.156
credit	0.113	4.780	0.981	0.003	0.876

Figure 1: Imbalance check

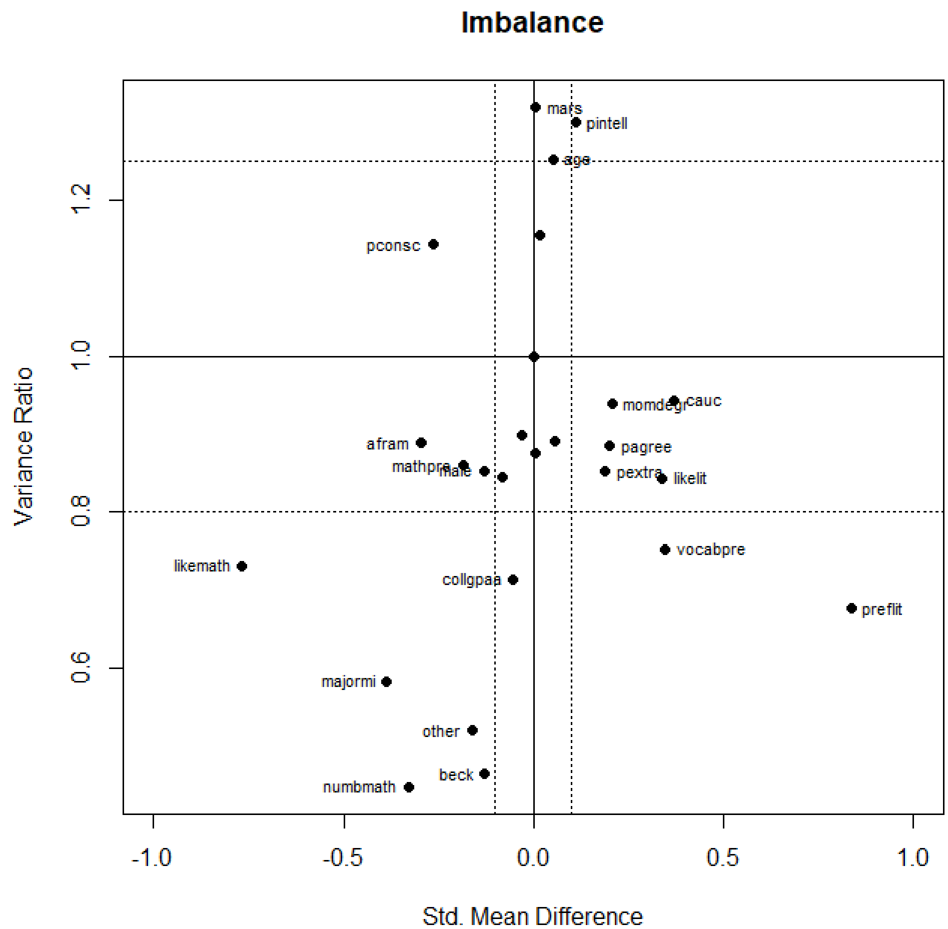

Table 2: Sample size and ATT-weights for stratification

Stratum	q=1	q=2	q=3	q=4	q=5
z=0	33	17	15	9	5
z=1	9	25	27	33	37
Sum	42	42	42	42	42
Weights	0.51	2.77	3.39	6.90	13.92

Table 3: Summary of regressions outcomes

Method	Covariates	ATT	Standard error	t-value
Inverse-Propensity Weighting		8.0307	0.4849	17.06
Inverse-Propensity Weighting	✓	8.1951	0.455	18.04
Stratification		9.00	0.5086	17.70
Stratification	✓	8.211	0.455	18.01

Figure 2: Imbalance check inverse propensity weighting

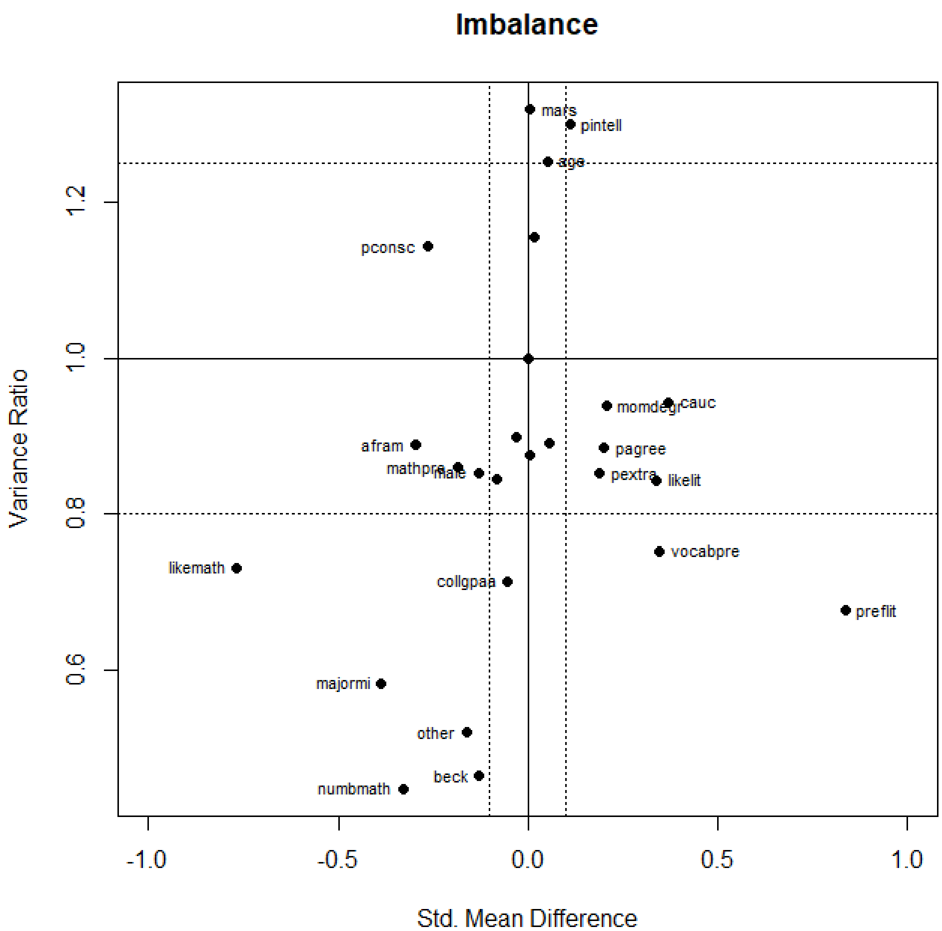

Figure 3: Imbalance check - stratification