Assignment 6

Foundations of Econometrics

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This is short document attached to the do-file submitted for Assignment 6 with brief comments about what has been done.

0: Prepare variables

- wages: Transformed into logs
- Birth decades: Dummies for i) born between 1950-1959, ii) 1960-1669, iii) born after (and incl.) 1970 (to incl those few born in 1980 & 1981)
- 1995 earnings deciles: 10 dummies for whether in 1995-earning decile 1, 2, 3, ..., 10
- 1995 earnings deciles × gender: 10 interactions between earnings decile and gender dummy.

1: Propensity Scores and Balancing Property

The `pscore` command computes the propensity scores, that is the probability that an individual is assigned treatment (displaced by separation or mass-layoff, respectively) given the set of covariates.

The instructions mention to run the command for an arbitrarily chosen year, so I do it for 1996.

The command also test whether the balancing property is satisfied, that is whether the distribution of covariates is similar across levels of treatment. Figures 1 and 2 show that the balancing property is satisfied for the treatments separation and mass-layoff, respectively. So, we can be more confident that individuals in treatment and control groups are comparable and that mean differences then are treatment effects.

```
The balancing property is satisfied


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

Inferior of block of pscore	separation 0	1	Total
0	291	30	321
.1	3,116	406	3,522
.125	3,125	458	3,583
.1375	5,203	882	6,085
.15	6,226	1,257	7,483
Total	17,961	3,033	20,994

Figure 1: Balancing Property where Treatment is Separation

```
The balancing property is satisfied


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

Inferior of block of pscore	mass_layoff 0	1	Total
0	3,644	34	3,678
.0125	9,815	156	9,971
.01875	5,247	119	5,366
.025	1,925	54	1,979
Total	20,631	363	20,994

Figure 2: Balancing Property where Treatment is Mass-Layoff

2: Average Treatment Effect on the Treated Estimates

The ATT is estimated by matching for treatments 'separation' and 'mass-layoff' in each year 1996, 1997, ..., 2001, respectively. Estimation using nearest-neighbor matching method yields the results presented in Figure 3. Using kernel matching method, these results are presented in Figure 4. In general, the estimates from the nearest neighbor matching method are higher than the estimates from the kernel matching method. The reason is that the kernel method uses all the observations (weighted) to estimate the counterfactual.

t	attnd_sep	attnd_mass
-3	-.0025247	-.0369748
-2	-.0043594	-.0424737
-1	-.021595	-.0297548
0	-.0708061	-.0989407
1	-.0988392	-.1068058
2	-.0361865	-.0526519

Figure 3: Estimation of ATT with Nearest Neighbor matching method for treatments Separation and Mass-Layoff, respectively

t	attk_sep	attk_mass
-3	-.0090796	-.0726539
-2	-.0087606	-.0778302
-1	-.0221157	-.0677952
0	-.0680253	-.1407512
1	-.0944275	-.1535287
2	-.0308388	-.1042137

Figure 4: Estimation of ATT with Kernel matching method for treatments Separation and Mass-Layoff, respectively

3: Differenced Average Treatment Effect on the Treated Estimates

The DATT is estimated very similarly to the ATT. The results are presented in Figure 5 (for the nearest neighbor method) and Figure 6 (for the kernel matching method). It is seen again, that the estimates using nearest neighbor matching methods are higher than those using the kernel. The explanation herefore is that same as mentioned in qc. 2.

t	dattnd_sep	dattnd_mass
-3	-.0028304	-.0486283
-2	-.0046651	-.0541272
-1	-.0219007	-.0414082
0	-.0711117	-.1105941
1	-.0991449	-.1184592
2	-.0364922	-.0643054

Figure 5: Estimation of Differenced ATT with Nearest Neighbor matching method for treatments Separation and Mass-Layoff, respectively

t	dattk_sep	dattk_mass
-3	-.0018045	-.0181775
-2	-.0014854	-.0233538
-1	-.0148405	-.0133188
0	-.0607501	-.0862748
1	-.0871523	-.0990523
2	-.0235635	-.0497373

Figure 6: Estimation of Differenfed ATT with Kernel matching method for treatments Separation and Mass-Layoff, respectively

4: Visualizing Results

The results from Point 2 and 3 are visualized graphically in Figure 7. The earnings loss can be seen by inspecting the log wages at time $t = -1$ (i.e. before displacement) and $t = 1$ (i.e. a year after displacement – for the displacement to have time to take full effect). Then from Figure 7, regardless of which estimator and which matching method, we find earnings losses to be between 10–15% compared to those that did not get displaced. This is lower than the estimate of 25% in Jacobson et al. (1993). It can be seen how earnings losses are partially recovered 2 years after displacement, although there is still a gap.

The estimates are not directly comparable to the Figure 1 in the instructions (which uses the model from Jacobson et al. (1993) on the same data as this assignment deals with), as this figure is in levels and Figure 7 is in relative changes. It would be useful to know whether the model from Jacobson et al. (1993) also measures $\approx$ 25% earnings losses on the VWH data. It can be concluded however, that utilizing the model from Couch and Placzek (2010) (as this assignment has done) estimates 10-15% earnings losses. Therefore, I would argue that Couch and Placzek (2010) are right and that the estimates in Jacobson et al. (1993) are overestimated.

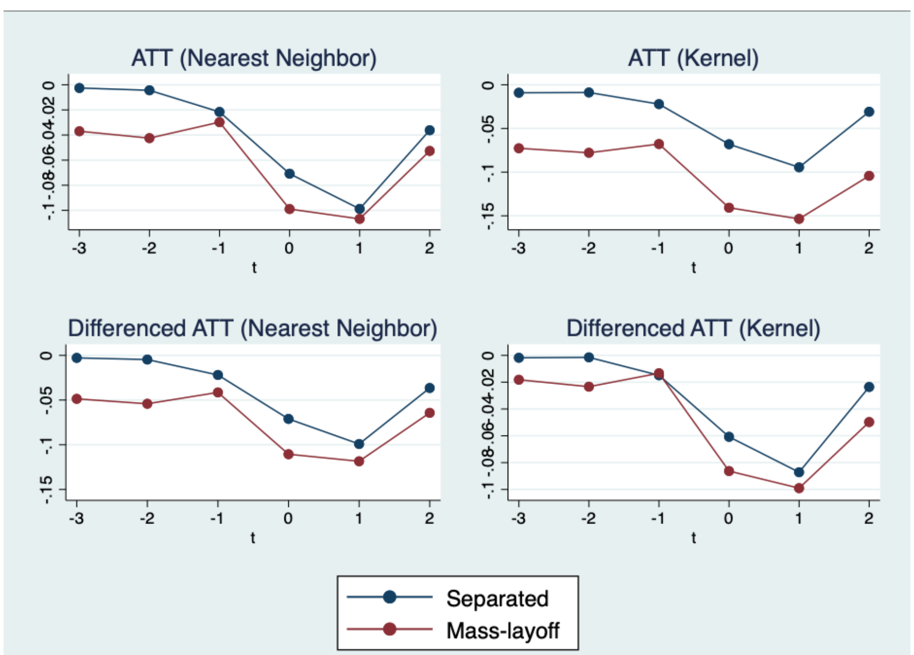

Figure 7: Results from Point 2 and 3

References

Couch, K. A. and D. W. Placzek (2010): "Earnings Losses of Displaced Workers Revisited," *American Economic Review*, 100, 572–89.

Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan (1993): "Earnings Losses of Displaced Workers," *The American Economic Review*, 83, 685–709.