POLS 5385: Causal Inference - Homework 1

João Pedro Bastos

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1. Regress FTE on an intercept, T, treat, and DID. What does the coefficient on DID tell you?

Table 1: Initial Results

FTE	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
T	-2.490	1.472	-1.69	0.091	-5.380	0.400
Treat	-2.944	1.160	-2.54	0.011	-5.221	-0.667
DiD	2.939	1.641	1.79	0.074	-0.281	6.159
Constant	20.013	1.041	19.23	0.000	17.970	22.057

Table 1 reports the results of our differences-in-differences regression that replicates Card and Krueger (1994). Assuming that without treatment, the gap between the treated (New Jersey) and the control (Pennsylvania) would remain the same, the coefficient suggest that average full time employment (FTE) rose by 2.94 jobs per store in New Jersey following the minimum wage increase. The result is statistically significant at the 10% level.

2. Now compute the standard errors and p-values using the Wild Cluster Bootstrap. What changes?

Table 2 repeats the exercise but clusters standard errors at the state level. Of course, all coefficients are the same, but the standard errors (and associated p-values for the t-tests) are artificially low relative to Table 1. I then recalculate the p-values using the clustered wild bootstrap-t standard errors using the `boottest` package.

Table 2: Results with Clustered Standard Errors

FTE	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
T	-2.490	0.000	-6.9e+12	0.000	-2.490	-2.490
Treat	-2.944	0.000	-9.4e+12	0.000	-2.943	-2.943
DiD	2.939	0.000	7.9e+12	0.000	2.939	2.939
Constant	20.013	0.000	6.6e+13	0.000	20.013	20.013

Table 3 compares the p-values obtained from the original clustered standard errors to the ones obtained by clustered wild bootstrapping. The bootstrapped p-values are noticeably larger, to the extent that T and $Treat$ cease to be significant. Our coefficient of interest, DiD, remains significant, though only at the 10% level.

Table 3: Comparison of p-values from different methods

	Original Clustered Standard Errors (p-value)	Clustered Wild Bootstrap Standard Errors (p-value)
T	0.000	0.171
Treat	0.000	0.230
DiD	0.000	0.060

3. Create a simple, non regression DID where you compute the average FTE in PA and NJ before and after the treatment (4 averages). Use them to compute the difference in difference estimate of the treatment effect and compare it to the coefficient on DID in the regression. Explain your results.

Table 4 summarizes the four states of average full time employment (FTE): Pennsylvania pre-treatment, New Jersey pre-treatment, Pennsylvania post-treatment, and New Jersey post-treatment. From the first row, it can be seen that mean FTE was slightly higher in PA prior to the treatment (February 1992). This difference, -2.94, is captured by the coefficient for the $Treat$ in our regression DiD. Our identifying assumption is that this gap would have remained the same if not for the treatment – a minimum wage increase in New Jersey.

Table 4: Results from Non-Regression Differences-in-Differences

	Employment by State		
	PA	NJ	NJ - PA
FTE before	20.013	17.069	-2.944
FTE after	17.523	17.518	-0.005
ΔFTE	-2.49	0.449	2.94

The second row show the average FTE in each state following the minimum wage increase in New Jersey. While in Pennsylvania FTE diminished, it remained roughly the same in New Jersey. The difference (NJ - PA) in FTE following the treatment was -0.005.

To arrive at our coefficient of interest DiD, we just need to take the difference between the pre- and post-treatment differences. That is:

$$\begin{aligned} DiD &= (NJ_{Post} - PA_{Post}) - (NJ_{Pre} - PA_{Pre}) \\ DiD &= (17.069 - 20.013) - (17.518 - 17.523) \\ DiD &= -0.005 - (-2.94) = 2.94 \end{aligned} \tag{1}$$

Intuitively, our parallel trends assumption that the initial gap between PA and NJ would have remained the same implies that, without treatment, FTE in NJ would have fallen to 14.129. We can subtract this number (the projected value for the NJ, assuming a parallel trend) from the observed value (17.518) to arrive at 2.94. Thus, since in NJ it actually rose, we attribute 2.94 increase in employment to the treatment.

4. Re-run the regression model above but only for Burger King stores. Explain and interpret your results.

Table 5 reports the results for the DiD regression when we consider only Burger King stores (column 1), around 42% of the original sample. The results are remarkably stronger than in the full sample, suggesting that full time employment increased by 4.62 jobs per store, on average. Not only the coefficient is larger (4.629 vs. 2.94), but it is also significant at the 5% level. For the sake of comparison, I also report the results for the three other fast-food chains. Interestingly, although the coefficient is positive for three out of four chains (it is negative for KFC), it is only significant for Burger King stores.

Table 5: Results by Fast Food Chain

	BK stores only (1)	KFC stores only (2)	Roy Rogers stores only (3)	Wendy's stores only (4)
T	-3.368	2.042	-3.868	-2.577
	(2.070)	(1.964)	(3.106)	(3.472)
Treat	-7.005***	2.065	3.085	-1.910
	(1.645)	(1.506)	(2.424)	(2.835)
DID	4.629**	-1.273	2.422	3.571
	(2.326)	(2.130)	(3.428)	(4.009)
Constant	25.65***	7.792***	16.74***	20.83***
	(1.463)	(1.389)	(2.197)	(2.455)
N	326	160	190	104
R^2	0.059	0.023	0.045	0.008

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

References

Card, D. and Krueger, A. B. (1994). Minimum wages and employment: A case study of the fast-food industry in new jersey and pennsylvania. *The American Economic Review*, 84(4):772–793.