Applied Microeconometrics I
Discussion of Problem Set 4

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Summary

- Average grade 79

Exercise 1

Kline (2011) studies the effect of youth curfews on the number of arrests, using a panel data of cities enacting juvenile curfew laws in different years. Let us estimate the impact of juvenile curfew laws on the log of arrests using a DiD strategy which exploits variation in when different cities implemented curfew laws. Note that all cities eventually implement curfew laws, but they do so in different years.

Exercise 1.1

Run the following regression and plot the estimated coefficients on the relative time dummies and their confidence intervals. When you run this regression, cluster your standard errors at the city level. Use the year before the policy implementation as the baseline category.

$$lnarrests_{ct} = \beta_0 + \beta_1 \times time\_to\_treat_c + \beta_2 \times year_t + \beta_3 \times city_c + u_{ct}$$

Exercise 1.1

Code:

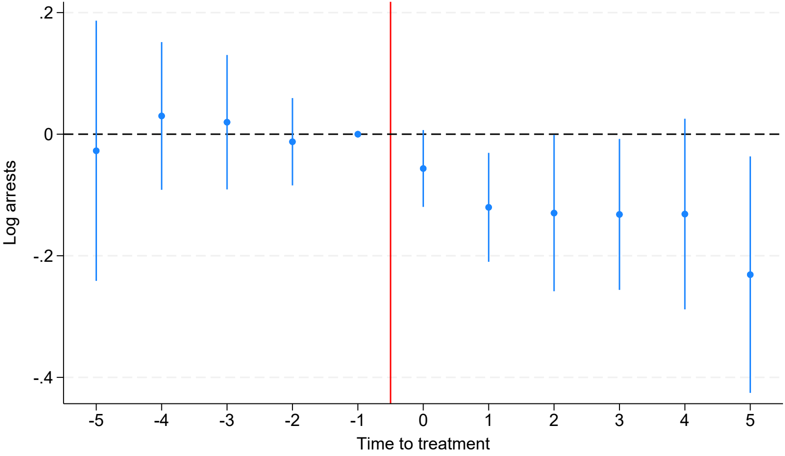
```
// 1.1
gen time_to_treat = year - enacted //event time variable
recode time_to_treat (.=-1) (-1000/-5 = -5) (5/1000 = 5) //assign t=-5 if t<=-5 and t=5 if t>=5
codebook time_to_treat //check range and whether there are empty values: looks OK

replace time_to_treat = time_to_treat + 5 //turn all event times non-negative (from 0 to 10)
encode city, g(cityfe) //turn city into numeric variable

reg lnarrests ib4.time_to_treat i.cityfe i.year, cluster(city) //ib4. states that t=4 is the base category

* create the figure
coefplot, keep(*.time_to_treat) baselevels vertical /// //baselevels = plot base levels
xlab(1 "-5" 2 "-4" 3 "-3" 4 "-2" 5 "-1" 6 "0" 7 "1" 8 "2" 9 "3" 10 "4" 11 "5") ///
xline(5.5, lcolor(red) lstyle(solid)) ///
yline(0, lcolor(black)) ///
xtitle ("Time to treatment") ///
ytitle ("Log arrests") ///
plotregion(fcolor(white)) graphregion(fcolor(white)) bgcolor(white)
```

Event time coefficients:

lnarrests	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
time_to_treat						
0	-.0272704	.1066526	-0.26	0.799	-.2412845	.1867437
1	.0300129	.0605442	0.50	0.622	-.0914779	.1515038
2	.0197496	.0551054	0.36	0.721	-.0908276	.1303267
3	-.0124097	.0357976	-0.35	0.730	-.0842428	.0594234
5	-.0564156	.0314985	-1.79	0.079	-.119622	.0067907
6	-.120307	.044641	-2.69	0.009	-.2098858	-.0307282
7	-.129735	.0640978	-2.02	0.048	-.2583567	-.0011133
8	-.1319668	.0618749	-2.13	0.038	-.2561279	-.0078056
9	-.1313511	.0781446	-1.68	0.099	-.2881598	.0254577
10	-.231023	.0969312	-2.38	0.021	-.4255298	-.0365162

Exercise 1.1

Event time coefficients plotted (including base category $t = -1$):



Exercise 1.2

Based on the plot you've just produced, what can you say about the parallel trends assumption? [Max 30 words]

- Pre-event coefficients are close to zero and statistically insignificant: no evidence against parallel trends assumptions.

Exercise 1.3

Change the number of leads and lags (to 8 instead of 5). Do the coefficients change? Does your answer to 1.2 change? [Max 30 words]

Code:

```
g time_to_treat = year - enacted
recode time_to_treat (.=-1) (-1000/-8 = -8) (8/1000 = 8)
replace time_to_treat = time_to_treat + 8

reg lnarrests ib7.time_to_treat i.cityfe i.year, cluster(city)

coefplot, keep(*.time_to_treat) baselevels vertical ///
xlab(1 "-8" 2 "-7" 3 "-6" 4 "-5" 5 "-4" 6 "-3" 7 "-2" 8 "-1" ///
9 "0" 10 "1" 11 "2" 12 "3" 13 "4" 14 "5" 15 "6" 16 "7" 17 "8" ) ///
xline(8.5, lcolor(red) lstyle(solid)) ///
yline(0, lcolor(black)) ///
xtitle ("Time to treatment") ///
ytitle ("Log arrests") ///
plotregion(fcolor(white)) graphregion(fcolor(white)) bgcolor(white)
```

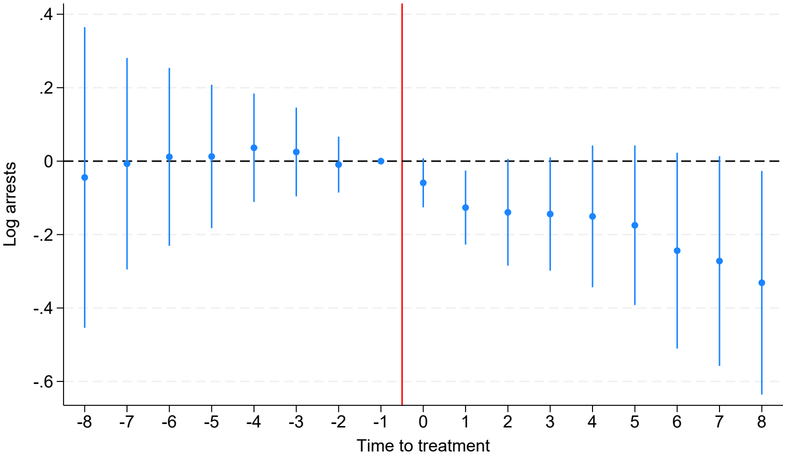
Exercise 1.3

Event time coefficients:

lnarrests	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
time_to_treat						
0	-.0444169	.204049	-0.22	0.829	-.4538712	.3650375
1	-.0068649	.1435637	-0.05	0.962	-.2949466	.2812168
2	.0116183	.1207626	0.10	0.924	-.2307095	.2539461
3	.0127572	.0973296	0.13	0.896	-.1825489	.2080633
4	.0364653	.0735568	0.50	0.622	-.1111373	.1840679
5	.0249647	.0602157	0.41	0.680	-.095867	.1457964
6	-.0093653	.0379312	-0.25	0.806	-.0854799	.0667493
8	-.0590686	.0332796	-1.77	0.082	-.1258489	.0077117
9	-.1264924	.0502357	-2.52	0.015	-.2272977	-.0256871
10	-.1393831	.0723509	-1.93	0.060	-.2845659	.0057996
11	-.1440971	.076781	-1.88	0.066	-.2981695	.0099753
12	-.1504673	.0962153	-1.56	0.124	-.3435375	.0426029
13	-.1746147	.108306	-1.61	0.113	-.3919467	.0427172
14	-.2437689	.132891	-1.83	0.072	-.5104342	.0228964
15	-.2720669	.1422937	-1.91	0.061	-.5576	.0134662
16	-.3312263	.1517186	-2.18	0.034	-.6356719	-.0267808

Exercise 1.3

Event time coefficients plotted (including base category $t = -1$):



- Results appear stable.

Exercise 1.4

Based on the estimates in 1.1, what do you conclude about the impact of the program on arrests? [Max 30 words]

- Post-period event time coefficients are negative and mostly significant: program seems to reduce arrests.

Exercise 1.5

Explain your empirical strategy. What are the key assumptions that you need to make in order to causally interpret β_1? What are the possible threats to the validity of your estimates? [Max 75 words]

- **Dynamic DiD**. Compares outcomes of cities where law changed in a given year, before and after that year, to those cities where the law changed in some other year, controlling for year- and city fixed effects.
- Key assumptions: **parallel trends** (in the absence of the changes, arrest rates would have evolved in parallel on average for all groups of cities that adopted laws in different years) and **no anticipation effects** (a law change doesn't affect outcomes before it actually takes place)
- Threats: for example, simultaneous shocks/policy changes confounding the estimates.

Exercise 1.5 Extra

- Something to keep in mind for the future, but out of the scope of this course: dynamic DiD/TWFE setups, such as this one, are problematic if the treatment effects are heterogeneous: the estimates are, in general, not valid.
- "One strand of the DiD literature has focused on settings where there are more than two time periods and units are treated at different point in times. Multiple authors have noted that the coefficients from standard TWFE models may not represent a straightforward weighted average of unit-level treatment effects when treatment effects are allowed to be heterogeneous. In short, TWFE regressions make both 'clean' comparisons between treated and not-yet-treated units as well as 'forbidden' comparisons between units who are both already-treated. When treatment effects are heterogeneous, these 'forbidden' comparisons potentially lead to severe drawbacks such as TWFE coefficients having the opposite sign of all individual-level treatment effects due to 'negative weighting' problems. Even if all of the weights are positive, the weights 'chosen' by TWFE regressions may not correspond with the most policy-relevant parameter." (Roth et al. 2023)
- **There are estimators that can deal with this!** See e.g., survey articles about the latest DiD advancements by Roth et al. 2023 and de Chaisemartin & D'Haultfœuille (2023).

Exercise 2

The paper by Christian Dustmann et al. (2022) examines the effect of the 2015 introduction of a nation-wide minimum wage (MW) of 8.50 EUR/hour in Germany that affected 15% of all employees. They compare the outcome, the change in establishment quality (as measured by average daily wages paid by the employer), over a two-year period for workers who earned less than the MW and for workers who earned considerably more prior to the introduction of the MW.

Exercise 2.1

Which empirical strategy would you use to study the effect of the introduction of MW on worker reallocation to employers? Answer by using the division of workers described above and the fact that the MW was introduced in 2015. [Max 75 words]

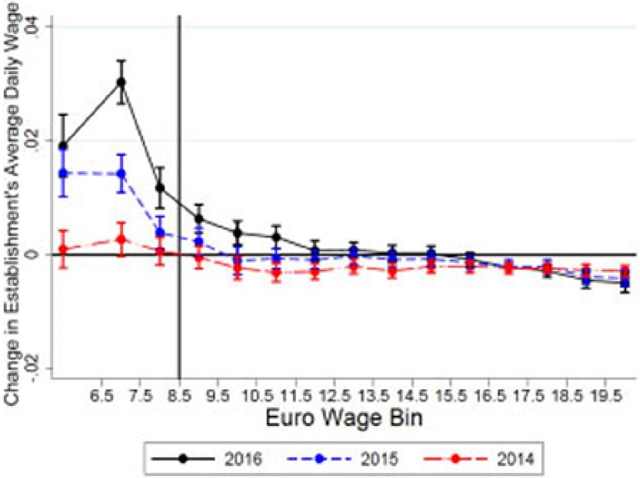
- DiD:
  Treated = employees earning below the MW
  Control = employees earning above the MW
  Compare outcomes between the treated and controls before and after is the 2015 policy change.
  Key assumption: in the absence of the treatment, both groups would follow parallel trends.

Exercise 2.2

The figure below reports the changes in a worker's establishment's average daily log wages between 2012 and 2014 (red line), 2013 and 2015 (blue line) and 2014 and 2016 (black line) relative to the change in average daily log wages between 2011 and 2013 (pre-policy); the x-axis gives the workers' wage distribution at the baseline. The workers to the left of the black line at 8.50 EUR are the workers who were earnings below the MW before the introduction of the MW.

What does each of the three lines tell you about the impact of MW on the reallocation of workers to better firms? [Max 75 words]

Exercise 2.2



(A) Establishment's Average Daily Wage

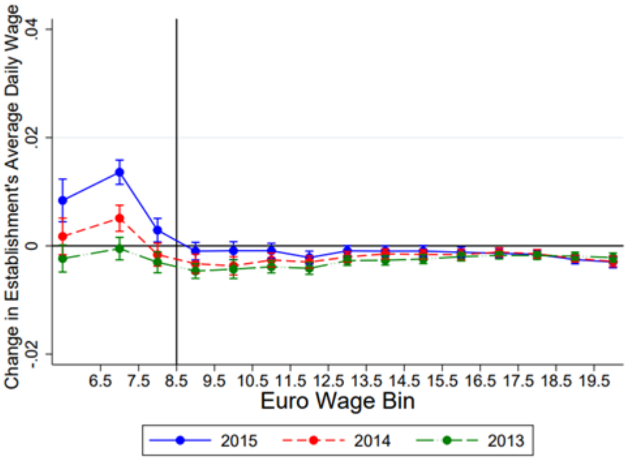
Exercise 2.2

- These are reform effects.
- The red line is placebo because the effect is measured before the reform (these effects should be 0, because the reform has not taken place yet).
- The blue line is the immediate reform effect
- Black line is longer-term effect.
- On LHS of the vertical line we can see large positive effects for those earning considerably less than the MW (for them, we expect the reform to be binding/affect their relatively low wage); basically no effects on the RHS to employees substantially above MW.

Exercise 2.3

The figure below shows one-year (as opposed to two-year) changes in workers' establishment's average daily wages, along the wage distribution of workers at the baseline. The blue line reports the change between 2014 and 2015, relative to the change between 2011 and 2012; the red line reports the change between 2013 and 2014, relative to 2011 and 2012; the green line reports the change between 2012 and 2013, relative to 2011 and 2012.

Exercise 2.3



(a) Establishments' Average Log Daily Wages

Exercise 2.3

- Now that we have one-year changes (as opposed to two-year changes in the past graph), we can see evidence of anticipation effects for employees below the minimum wage (on the LHS of the vertical line).
- We can also see some negative anticipation effects on the RHS.
- Some of the changes for employees below MW appear to happen already before the introduction of the MW.

Exercise 3

In 1980, between May and September, 125,000 Cuban immigrants arrived in Miami, Florida. This increased the size of the Miami labor force by 7% in a very short period of time. For all intents and purposes, this was an exogenous increase in the Miami labor supply. Card (1990) uses this setting to study the labor market effects of immigration.

Here is a table adapted from Card (1990). It shows the log hourly earnings of white workers aged 16-61 in Miami and four comparison cities.

	1979	1981
Miami	1.85	1.85
Comparison cities	1.93	1.91

Exercise 3.1

Suppose you were to compare the hourly earnings of white workers in Miami in 1981 and 1979 in order to draw conclusions about the causal effects of immigration on native wages. What assumptions should you make in order to draw such conclusions and how plausible are they? [Max 50 words]

- No confounding (unobserved) changes over time other than the arrival of the Cuban immigrants.
- Without additional data, we must assume that wages would have remained the same between 1979 and 1981 in the absence of Cuban immigrants.
- Not plausible.

Exercise 3.2

Suppose you were to compare the 1981 hourly earnings of white workers in Miami and comparison cities in order to draw conclusions about the causal effects of immigration on native wages. What assumptions should you make in order to draw such conclusions and how plausible are they? [Max 50 words]

- No confounding (unobserved) city specific differences other than the arrival of the Cuban immigrants.
- Without additional data, we must assume that wages would have been the same in Miami and comparison cities in the absence on Cuban immigrants.
- Not plausible.

Exercise 3.3

How would you use the information in the table above to study the effect of immigration on native wages using a difference-in-differences strategy? What is the DiD estimate you obtain? [Max 50 words]

	1979	1981	Difference
Miami	1.85	1.85	0
Comparison cities	1.93	1.91	-0.02
Difference	0.08	0.06	0.02

Difference in differences

- Calculate the difference over time in both cities (or between cities in both years), and then the difference of those differences. DiD estimate: 0.02
- Hourly wages for white workers increased in Miami compared to control cities due to immigration of the Cubans.
- Key assumption: parallel trends