41903 Pset 3

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May 12, 2022

Question 2

(a)

```
#setwd("C:/Users/17036/OneDrive/Documents/GitHub/metrics3-zombie-boards/Psets/3")
murder <- read.delim("PS3Data/MURDER_RAW.txt", header=FALSE)

colnames(murder) <- c('id','state','year','mrdrte','exec','unem','d90','d93',
                      'cmrdrte','cexec','cunem','cexec1','cunem1')

# Use only data for 1990 and 1993
data <- murder %>%
  filter(year==90 | year==93)

reg_pooled <- lm(mrdrte~d93+exec+unem, data=data)
### calculate standard errors
# standard homoskedastic standard errors
se.homo_pooled <- sqrt(diag(vcov(reg_pooled)))
# robust standard errors
HCV.coef_pooled <- vcovHC(reg_pooled, type = 'HC1')
se.robust_pooled <- sqrt(diag(HCV.coef_pooled))
# clustered standard errors
CLCV.coef_pooled <- cluster.vcov(reg_pooled,data$state)
se.cluster_pooled <- sqrt(diag(CLCV.coef_pooled))
```

In the table below we report the IID standard errors, heteroskedasticity-robust standard errors, and clustered standard errors. Robust SEs were calculated as follows:

$$\hat{\Omega} = \left(\frac{1}{NT}\sum_{i,t} x_{it}x_{it}'\right)^{-1}\left(\frac{1}{NT}\sum_{i,t} x_{it}x_{it}'\hat{\epsilon}_{it}^2\right)\left(\frac{1}{NT}\sum_{i,t} x_{it}x_{it}'\right)^{-1}$$

Where $\hat{\epsilon}$ is the POLS residual. We also include clustered standard errors; however, if we suspect the observations are serially correlated (as would be implied by the use of clustered SEs) we should not be using POLS anyway. Nevertheless, clustered SEs were calculated as follows:

$$\hat{\Omega} = \left(\frac{1}{NT}\sum_{i,t} x_{it}x_{it}'\right)^{-1}\left(\frac{1}{NT}\sum_{i,t} x_{it}x_{i,90}'\hat{\epsilon}_{it}\hat{\epsilon}_{i,90} + x_{it}x_{i,93}'\hat{\epsilon}_{it}\hat{\epsilon}_{i,93}\right)\left(\frac{1}{NT}\sum_{i,t} x_{it}x_{it}'\right)^{-1}$$

Table 1: Pooled OLS

	IID	Robust	Clustered
(Intercept)	-5.2780	-5.2780	-5.2780
	(4.4278)	(5.3868)	(6.6760)
d93	-2.0674	-2.0674	-2.0674
	(2.1446)	(1.9981)	(1.3066)
exec	0.1277	0.1277	0.1277
	(0.2632)	(0.1342)	(0.1678)
unem	2.5289^{**}	2.5289^{**}	2.5289^{**}
	(0.7817)	(1.1076)	(1.5047)
R^2	0.1016	0.1016	0.1016
Adj. R^2	0.0741	0.0741	0.0741
Num. obs.	102	102	102

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

```
texreg(list(reg_pooled, reg_pooled, reg_pooled), digits=4, caption.above=TRUE,
       override.se = list(se.homo_pooled, se.robust_pooled, se.cluster_pooled),
       custom.model.names=c("IID", "Robust", "Clustered"),
       caption = "Pooled OLS")
```

(b)

In this setting FE and FD are numerically identical because there are only two time periods, 1990 and 1993. To see this, recall the fixed effect model:

$$
\begin{aligned}
y_{i1} - \bar{y}_i &= (x_{i1} - \bar{x}_i)'\beta + \epsilon_{i1} - \bar{\epsilon}_i \\
y_{i1} - \left(\frac{y_{i1} + y_{i0}}{2}\right) &= \left(x_{i1} - \frac{x_{i1} + x_{i0}}{2}\right)'\beta + \epsilon_{i1} - \left(\frac{\epsilon_{i1} + \epsilon_{i0}}{2}\right) \\
\frac{y_{i1} - y_{i0}}{2} &= \left(\frac{x_{i1} - x_{i0}}{2}\right)'\beta + \frac{\epsilon_{i1} - \epsilon_{i0}}{2} \\
y_{i1} - y_{i0} &= (x_{i1} - x_{i0})'\beta + \epsilon_{i1} - \epsilon_{i0}
\end{aligned}
$$

Which is exactly the first differences model.

In the table below we report only the results for FD. We chose FD because it reduces the procedure down to a cross-sectional dataset and only requires heterskedasticity-robust standard errors, rather than maintaining the panel data structure and requiring clustered standard errors. Clustered standard errors are reported in the table below, but only to illustrate that they are identical to robust in the first differences method when we only have two periods.

There does not appear to be any deterrant effect of capital punishment; based on these results we fail to reject the null hypothesis that the coefficient on *exec* is equal to zero.

(c)

First Differences

```
data_90 <- data %>%
  filter(year==90)
data_93 <- data %>%
  filter(year==93)
```

```r
data_fd <- left_join(data_90,data_93,by=c("id"))
data_fd$delta_mrdrte <- data_fd$mrdrte.y-data_fd$mrdrte.x
data_fd$delta_exec <- data_fd$exec.y-data_fd$exec.x
data_fd$delta_unem <- data_fd$unem.y-data_fd$unem.x
reg_fd <- lm(delta_mrdrte~delta_exec+delta_unem, data=data_fd)
### calculate standard errors
# standard homoskedastic standard errors
se.homo_fd <- sqrt(diag(vcov(reg_fd)))
# robust standard errors
HCV.coef_fd <- vcovHC(reg_fd, type = 'HC1')
se.robust_fd <- sqrt(diag(HCV.coef_fd))
# clustered standard errors
CLCV.coef_fd <- cluster.vcov(reg_fd,data_fd$state.x)
se.cluster_fd <- sqrt(diag(CLCV.coef_fd))
```

Table 2: First Differences

	IID	Robust	Clustered
(Intercept)	0.4133	0.4133	0.4133
	(0.2094)	(0.2000)	(0.2000)
delta_exec	-0.1038^{*}	-0.1038^{*}	-0.1038^{*}
	(0.0434)	(0.0170)	(0.0170)
delta_unem	-0.0666	-0.0666	-0.0666
	(0.1587)	(0.1469)	(0.1469)
R^2	0.1097	0.1097	0.1097
Adj. R^2	0.0727	0.0727	0.0727
Num. obs.	51	51	51

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

```
texreg(list(reg_fd, reg_fd, reg_fd), digits=4, caption.above=TRUE,
       override.se = list(se.homo_fd,se.robust_fd,se.cluster_fd),
       custom.model.names=c("IID", "Robust", "Clustered"),
       caption = "First Differences")
```

As explained above, we used heteroskedasticity-robust SEs because the assumptions required for IID standard errors are too strong, and in a first differences model with only two periods, clustered and robust SEs are identical (as demonstrated in the table above).

From these results the coefficient on *exec* is negative and statistically significant, so it does appear that there is a deterrant effect of capital punishment.

(d)

FD is preferred in this context because POLS requires the assumption that there is no serial correlation between observations. This is an unrealistic assumption in this setting because there could be many persistent features of states that are correlated both with executions and with the murder rate.

Question 4

(a)

Assumption: after controlling for *Log of state nonfarm employment*, *state fixed effect* (all the non-observable state-level factors influencing both outcome and the implication of policy, and don't change over time) and *year fixed effect* (all the non-observable year-level macroeconomics factors influencing both outcome and the implication of policy), implication of policy is independent on the error term.

Implication: the policy increases THS employment by 12.8%, while this is not statistically significant - essentially, the policy has no causal effect.

```r
df <- read.table("PS3Data/autor_out2.txt", header = TRUE,
                 quote="\"", comment.char="")

a <- feols(lnths ~ mico + lnemp | s + t, cluster = 's', df)
out <- etable(a, tex = TRUE)
```

```r
knitr::asis_output(c("\\begin{center}", out, "\\end{center}"))
```

Dependent Variable:	lnths
Model:	(1)
Variables	
mico	0.1280
	(0.0888)
lnemp	2.014***
	(0.4236)
Fixed-effects	
s	Yes
t	Yes
Fit statistics	
Observations	850
R^2	0.97270
Within R^2	0.13857

Clustered (s) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

(b)

Assumption: after controlling for *Log of state nonfarm employment*, *state fixed effect* (all the non-observable state-level factors influencing both outcome and the implication of policy, and don't change over time), *year fixed effect* (all the non-observable year-level macroeconomics factors influencing both outcome and the implication of policy) and *state-level time trends* (states can have their own linear time trends over the years), implication of policy is independent on the error term.

Implication: the policy increases THS employement by 14.5%, which is statistically significant.

```r
b <- feols(lnths ~ mico + lnemp | s + t + s[t], cluster = 's', df)
out <- etable(b, tex = TRUE)
```

```r
knitr::asis_output(c("\\begin{center}", out, "\\end{center}"))
```

Dependent Variable:	lnths
Model:	(1)
Variables	
mico	0.1451**
	(0.0566)
lnemp	1.500***
	(0.4139)
Fixed-effects	
s	Yes
t	Yes
Varying Slopes	
t (s)	Yes
Fit statistics	
Observations	850
R^2	0.98848
Within R^2	0.08042

Clustered (s) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

(c)

Assumption: 1) After controlling for *state fixed effect* (all the non-observable state-level factors influencing both outcome and the implication of policy, and don't change over time), *year fixed effect* (all the non-observable year-level macroeconomics factors influencing both outcome and the implication of policy), *lnemp* is not correlated with other omitted variables and only influences the outcome through implication of the policy. 2) *lnemp* is correlated with implication of the policy. 3) The labor market law cannot have a direct effect until it is passed.

Implication: the policy decreases THS employment by 10.18%, while this is not statistically significant - essentially, the policy has no causal effect.

```
c <- feols(lnths ~ 1 | s + t | mico ~ lnemp, cluster = 's', df)
out <- etable(c, tex = TRUE)
```

```
knitr::asis_output(c("\\begin{center}", out, "\\end{center}"))
```

Dependent Variable:	lnths
Model:	(1)
Variables	
mico	-10.18
	(23.04)
Fixed-effects	
s	Yes
t	Yes
Fit statistics	
Observations	850
R^2	-1.6737
Within R^2	-83.358

Clustered (s) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

(d)

The results for model *a* and *b* are quite similar: lead terms are close to zero and not significant, which validates the assumptions behind them, since there's no pre-trend, or anticipatory response.

According to the contemporaneous and lag terms, the treatment effect is stronger in first two years (especially in the second year), and relatively weaker after the third year. Need to mention, even though the magtitude of coefficients make sence, they are not statistically significant.

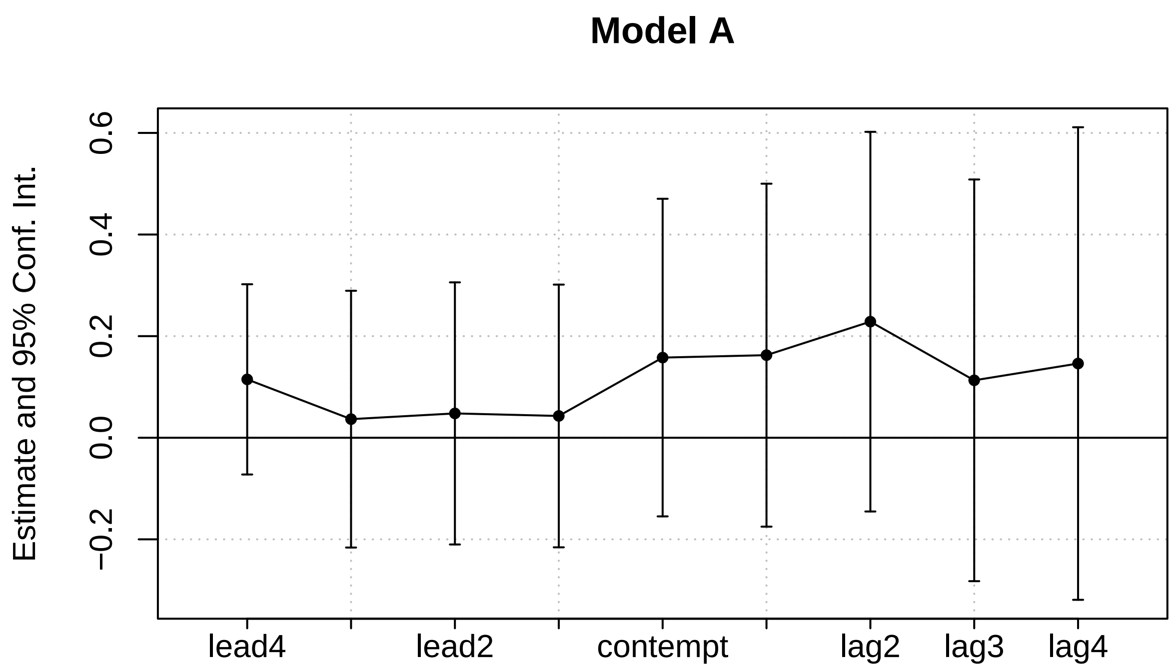
```
df_d <- df %>%
  group_by(s) %>%
  mutate(first.treat = min(
    if_else(mico==1, t, NA_integer_),
    na.rm = TRUE
  )) %>%
  ungroup() %>%
  mutate(
    lead1 = ifelse(t == first.treat - 1, 1, 0),
    lead2 = ifelse(t == first.treat - 2, 1, 0),
    lead3 = ifelse(t == first.treat - 3, 1, 0),
    lead4 = ifelse(t == first.treat - 4, 1, 0),
    contempt = ifelse(t == first.treat, 1, 0),
    lag1 = ifelse(t == first.treat + 1, 1, 0),
    lag2 = ifelse(t == first.treat + 2, 1, 0),
    lag3 = ifelse(t == first.treat + 3, 1, 0),
    lag4 = ifelse(t >= first.treat + 4, 1, 0)
    )

d_a <- feols(lnths ~ contempt + lnemp +
               lead1 + lead2 + lead3 + lead4 +
               lag1 + lag2 + lag3 + lag4
               | s + t, cluster = 's', df_d)
d_b <- feols(lnths ~ contempt + lnemp +
               lead1 + lead2 + lead3 + lead4 +
               lag1 + lag2 + lag3 + lag4
               | s + t + s[t], cluster = 's', df_d)
out <- etable(d_a, d_b, tex = TRUE)
```

```r
knitr::asis_output(c("\\begin{center}", out, "\\end{center}"))
```

Dependent Variable:	lnths	
Model:	(1)	(2)
Variables		
contempt	0.1578	0.1493
	(0.1595)	(0.1379)
lnemp	2.028***	1.526***
	(0.4303)	(0.4067)
lead1	0.0429	0.0093
	(0.1319)	(0.1149)
lead2	0.0479	-0.0064
	(0.1316)	(0.1170)
lead3	0.0366	-0.0348
	(0.1290)	(0.1134)
lead4	0.1149	0.0494
	(0.0955)	(0.0802)
lag1	0.1625	0.1616
	(0.1722)	(0.1422)
lag2	0.2285	0.2344
	(0.1906)	(0.1587)
lag3	0.1130	0.1270
	(0.2017)	(0.1688)
lag4	0.1461	0.2084
	(0.2373)	(0.1857)
Fixed-effects		
s	Yes	Yes
t	Yes	Yes
Varying Slopes		
t (s)		Yes
Fit statistics		
Observations	850	850
R^2	0.97282	0.98868
Within R^2	0.14253	0.09646

Clustered (s) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

```r
coefplot(d_a, drop = 'lnemp',
         order = c("lead4", "lead3", "lead2", "lead1", 'contempt',
                   "lag1", "lag2", "lag3", "lag4"),
         main = "Model A",
         pt.join = TRUE)
```




```
coefplot(d_b, drop = 'lnemp',
         order = c("lead4", "lead3", "lead2", "lead1", 'contempt',
                   "lag1", "lag2", "lag3", "lag4"),
         main = "Model B",
         pt.join = TRUE)
```