Practical: Difference-in-Differences

Ting Ye and Qingyuan Zhao

July 2022

This practice is to apply methods of DID to study the effect of the minimum wage on teen employment. The dataset is available in the did R package and can be loaded by

```
library(did)
data("mpdta")
```

This dataset includes a time period from 2003-2007 where the federal minimum wage was flat at $ 5.15 per hour. We focus on county level teen employment in states whose minimum wage was equal to the federal minimum wage at the beginning of the period. Some of these states increased their minimum wage over this period – these become treated group. Other did not increase their minimum wage – these are the control group.

We use county level data on teen employment and other county characteristics. The only available pre-treatment county characteristic is the county population.

1. Using static TWFE model to estimate the effect of state minimum wage laws, where the standard errors are clustered by county. Sample code is below.

```
library(tidyverse)
library(clubSandwich)
mpdta<-mpdta %>% mutate(after.ind=1*(year>=first.treat))
fit.twfe<-lm(lemp~after.ind+as.factor(year)+as.factor(countyreal),data=mpdta)

# cluster-robust standard error with CR2 small-sample correction
coeftest.twfe <- coef_test(fit.twfe, vcov = "CR2", cluster = mpdta$countyreal)
coeftest.twfe[2,]
```

2. Repeat the static TWFE model adjusting for the pre-treatment county population lpop. Is your result different from the result in Q1?

3. Using dynamic TWFE model to estimate the effect of state minimum wage laws, where the standard errors are clustered by county. Do the results indicate any violation of the parallel trends assumption from looking at the "pre-trends" before adopting the treatment? Sample code is below.

```
mpdta<- mpdta %>%
mutate(eff_pre_3 = ifelse(year == first.treat - 3, 1, 0),
eff_pre_2 = ifelse(year == first.treat - 2, 1, 0),
eff_pre_1 = ifelse(year == first.treat - 1, 1, 0),
eff_0 = ifelse(year == first.treat, 1, 0),
eff_post_1 = ifelse(year == first.treat + 1, 1, 0),
eff_post_2 = ifelse(year == first.treat + 2, 1, 0),
eff_post_3 = ifelse(year == first.treat + 3, 1, 0))
```

```
fit.twfe.dynamic<-lm(lemp~eff_pre_3+eff_pre_2+eff_pre_1+
eff_0+eff_post_1+eff_post_2+eff_post_3+
as.factor(year)+as.factor(countyreal),data=mpdta)

# cluster-robust standard error with CR2 small-sample correction
coeftest.twfe.dynamic <- coef_test(fit.twfe.dynamic, vcov = "CR2", cluster = mpdta$countyreal)
coeftest.twfe.dynamic[2:8,]
```

4. (Bonus) Using the results from the dynamic TWFE model to make an event plot similar to Page 20 of Lecture 6.

5. Using the "heterogeneity-robust" method by Callaway andSant'Anna (2021) to estimate the effect of state minimum wage laws for each group (group is defined by the year of initiating the treatment), using the did R package.

```
library(did)

## unadjusted
out <- att_gt(yname="lemp",
tname="year",
idname="countyreal",
gname="first.treat",
xformla=NULL,
data=mpdta)

ggdid(out) # group-specific treatment effect

# average effect of treatment 0/1/2/3 time periods after adopting the treatment
agg_dyn <- aggte(out, type = "dynamic")
ggdid(agg_dyn)

## using covariates
out2 <- att_gt(yname="lemp",
tname="year",
idname="countyreal",
gname="first.treat",
xformla=~lpop,
data=mpdta)

ggdid(out2) # group-specific treatment effect

# average effect of treatment 0/1/2/3 time periods after adopting the treatment
agg_dyn2 <- aggte(out2, type = "dynamic")
ggdid(agg_dyn2)
```