Assignment 5

Group name: Foodies with hoodies

Contents

1 Question 1 **2**

1.1 (i) 2

1.2 (ii) 3

2 Question 2 **3**

2.1 (i) 3

2.2 (ii) 5

2.3 (iii) 6

2.4 (iv) 7

2.5 (v) 7

2.6 (vi) 9

2.7 (vii) 11

```
# load packages
if(!require(pacman)){install.packages("pacman")}

p_load(devtools,tidyverse,dplyr,ggplot2,latex2exp,stargazer, fixest,
 ↪  modelsummary, knitr)
```

1 Question 1

1.1 (i)

Suppose the differences in outcomes between the treatment and the control group is:

$$Y_{g1} - Y_{g0} = (\alpha_1 - \alpha_0) + \delta D_g + (U_{g1} - U_{g0}), \tag{1}$$

in which: δ is the estimated treatment effect.

The parallel trends assumption state that without the intervention of the treatment $(\delta = 0)$, the difference of between the control and treatment group ($\alpha_1 - \alpha_0$) remain constant over time. Since in this example, they only look at the pre-treatment period, the parallel trends assumption could be violated due to the fact that after the treatment period, the differences in outcomes of control and treatment groups are not constant over time anymore unrelated to the treatment.

When parallel trend is violated, it means that $\alpha_1 - \alpha_0$ changes over time and this means it is no longer possible to estimate Equation 1 using OLS. If we continue estimating it using OLS, we will have a biased and inconsistent estimator.

One example for violation of this assumption could be that the there exists autocorrelation in the treatment group after getting treated. Specifically, the outcome of the next time lag is influenced by the outcome of the previous lag. Prior to the treatment, both the control and the treatment group have the same time trend because both experience no treatment. However, after receiving the treatment but not due to this, the treated group has a steeper slope in their outcomes due to autocorrelation and is no longer parallel to the control group. Suppose for example that one wishes to investigate the treatment effects on savings among the poorest income bracket, where treatment is giving them a fixed amount of monthly stipend. However, the pre-treatment period was during a crisis, where the poorest income bracket savings were stagnating. After the treatment, there was a booming economic period, where savings were autocorrelated. Then one group turns out to experience a divergent trend in savings not due to the stipend but simply because the economic situation changed the dependent variable's properties.

1.2 (ii)

The difference-in-difference estimator is an OLS estimator Equation 1, which can be written in the form below:

$$Y_{g1} - Y_{g0} = \beta_0 + \delta D_g + U_g. \tag{2}$$

Now suppose that $Corr(D_g, \beta_0) \neq 0$. The main problem with applying the OLS estimator in this case is that the estimator will be biased and inconsistent due to endogeneity issues. This is because the estimator treats the time trend β_0 as a constant, however, in this case, the parallel trends assumption is not satisfied and thus β_0 is not constant. This makes the error term change over time and is correlated with the treatment variable D_g. This implies that the treatment was probably not assigned time-group conditional randomly and this causes the endogeneity of the treatment to the error term, which in turn causes the previously mentioned biasedness and inconsistency.

2 Question 2

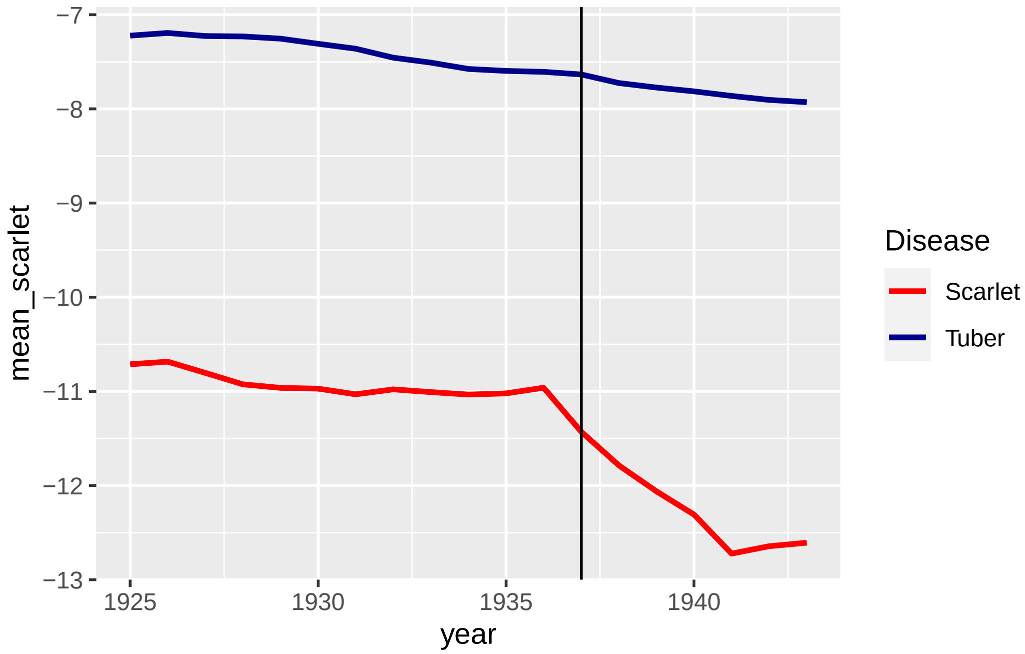
```
dfData = read.csv("assignment5.csv")
attach(dfData)
```

2.1 (i)

```
# Get subgroups and mean per year
df_scarlet = dfData[dfData$treated==1,]
mean_scarlet = df_scarlet %>% group_by(year) %>%
  summarise(mean_rate=mean(lnm_rate),
            .groups = 'drop')
df_tuber = dfData[dfData$treated==0,]
mean_tuber = df_tuber %>% group_by(year) %>%
  summarise(mean_rate=mean(lnm_rate),
            .groups = 'drop')

# reformat into dataframe
df_grouped =
 ↪  data.frame(mean_tuber$year,mean_scarlet$mean_rate,mean_tuber$mean_rate)
names(df_grouped) = c("year","mean_scarlet","mean_tuber")
```

```
# Plot
ggplot() +
  geom_line(data=df_grouped,aes(y=mean_scarlet,x=
  ↪  year,colour="Scarlet"),size=1 )+
  geom_line(data=df_grouped,aes(y=mean_tuber,x=
  ↪  year,colour="Tuber"),size=1) +
  scale_color_manual(name = "Disease", values = c("Tuber" = "darkblue",
  ↪  "Scarlet" = "red")) +
  geom_vline(xintercept = 1937) #add a vertical line indicating
  ↪  treatment year
```



From our graph, we can observe that while both diseases had a relatively slight downwards trend (so at first glance, we may assume parallel trends), the treatment appearance seems to affect the scarlet fever with a strong drop-off in means. This might imply that the drop in the scarlet fever against the tuberculosis is due to the treatment (the appearance of the drug is the treatment for fever but not a treatment for tuberculosis). However, we have to make a lot of assumptions for this to indeed hold true.

2.2 (ii)

```r
# get mean effects
mean_treated_1936 = as.numeric(df_scarlet[df_scarlet$year==1936,] %>%
  summarise(mean_rate=mean(lnm_rate),
            .groups = 'drop'))
mean_treated_1937 = as.numeric(df_scarlet[df_scarlet$year==1937,] %>%
  summarise(mean_rate=mean(lnm_rate),
            .groups = 'drop'))

mean_control_1936 = as.numeric(df_tuber[df_tuber$year==1936,] %>%
  summarise(mean_rate=mean(lnm_rate),
            .groups = 'drop'))
mean_control_1937 = as.numeric(df_tuber[df_tuber$year==1937,] %>%
  summarise(mean_rate=mean(lnm_rate),
            .groups = 'drop'))

Before_Treatment_1936 <- c(mean_treated_1936, mean_control_1936,
 ↪  (mean_treated_1936-mean_control_1936))
After_Treatment_1937 <- c(mean_treated_1937, mean_control_1937,
 ↪  (mean_treated_1937-mean_control_1937))
Difference <- c((mean_treated_1936 - mean_treated_1937),
 ↪  (mean_control_1936 - mean_control_1937), ((mean_treated_1936 -
 ↪  mean_treated_1937) - (mean_control_1936 - mean_control_1937)))

dfTable <- data.frame(Before_Treatment_1936, After_Treatment_1937,
 ↪  Difference)
rownames(dfTable) <- c("Treatment", "Control", "Difference")

kable(dfTable, caption="Treatment and time differences of treatment and
 ↪  control groups", digits=3, label = "tab_did")
```

Table 1: Treatment and time differences of treatment and control groups

	Before_Treatment_1936	After_Treatment_1937	Difference
Treatment	-10.962	-11.429	0.467
Control	-7.607	-7.635	0.028
Difference	-3.355	-3.794	0.439

From Table 1, we can see that the difference-in-differences estimator is 0.439. This DiD estimator is obtained by the differences in means, for treatment group pre-treatment, treatment group post-treatment, control group pre-treatment and control group post-treatment.

2.3 (iii)

```
# Create indicator variable
dfData$indicator <- ifelse(dfData$year >=1937, 1, 0)

# Get subdata for the year 1936 and 1937
dfSub = dfData[dfData$year==1936 | dfData$year==1937,]

# DiD model
DiD1 = feols(lnm_rate ~ indicator*treated| year + treated, data = dfSub,
 ↪  se="standard")
summary(DiD1)
```

```
OLS estimation, Dep. Var.: lnm_rate
Observations: 192
Fixed-effects: year: 2,  treated: 2
Standard-errors: IID
                   Estimate Std. Error  t value Pr(>|t|)
indicator:treated -0.439008   0.218887 -2.00564 0.046329 *
... 2 variables were removed because of collinearity (indicator and treated)
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
RMSE: 0.750306     Adj. R2: 0.848869
                 Within R2: 0.020948
```

We estimated a differences-in-differences model for only a subset of the data for 1936-37 excluding the group and time fixed effects. We also find that the cross-term variable of treatment with the indicator is significant at a 5% level, suggesting that the post-event mortality rate significantly decreased thanks to the treatment. However, this only looks at t and $t-1$ periods and does not take any other in effect, as well as does not investigate the parallel trends assumption. Hence based on only this regression model, one should be careful to claim that the treatment leads to significant reduction in mortality rates.

	(1)	(2)
indicator × treated	−0.439**	−0.867***
	(0.219)	(0.060)
Num.Obs.	192	1721
R2	0.851	0.916
R2 Adj.	0.849	0.915
R2 Within	0.021	0.108
R2 Within Adj.	0.016	0.107
AIC	442.6	3200.1
BIC	455.6	3314.5
RMSE	0.75	0.61
Std.Errors	IID	IID
FE: year	X	X
FE: treated	X	X

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

2.4 (iv)

```r
DiD2= feols(lnm_rate ~ indicator*treated| year + treated, data = dfData,
 ↪   se="standard")
msummary(list(DiD1,DiD2), stars = c('*' = .1, '**' = .05, '***' = .01))
```

From the second model (2), in comparison with the first (1) from Section 2.3, we can observe an even stronger estimated effect of the treatment in a DiD model between before and after the treatment. The coefficient nearly doubles for the entire time horizon estimation, increasing its significance as well. The interpretation of the coefficient means that the treatment decreases the average log mortality of scarlet fever from the pre-treatment period to the post-treatment period by 0.867. This would imply that the appearance of the sulfa drugs helped reducing the log mortality of scarlet fever across states. However, we can also voice the same concerns as before about the parallel trends, namely what if the mortality of scarlet fever has been on a stronger downtrend than tuberculosis prior to the treatment already.

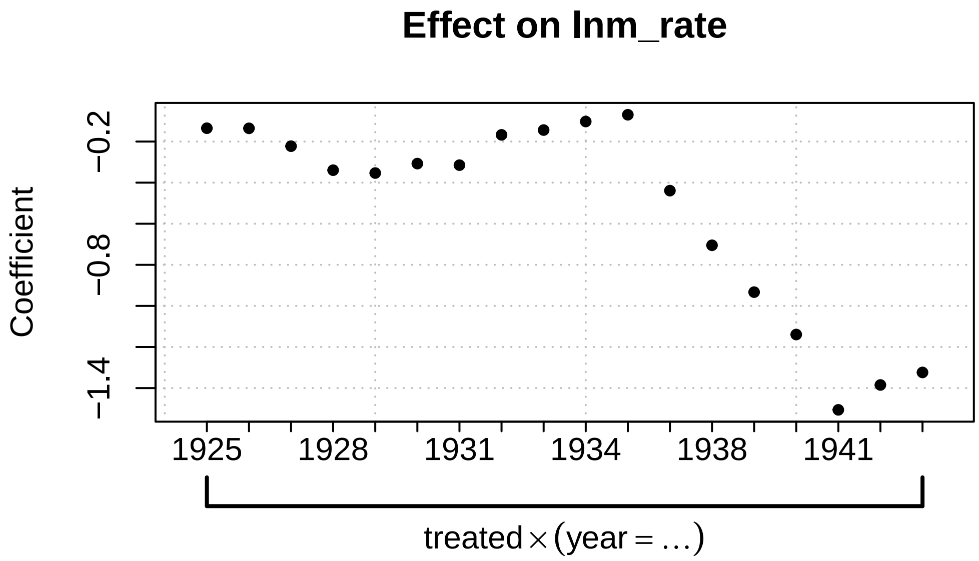
2.5 (v)

For this question, we can take out the two-way fixed effect of group and year and create an interaction variable of year and treated group, making the year 1936 the reference year and thus normalize its coefficients to 0. This way, we estimate the effect of the treatment before and after the event with considering the different periods around the particular year.

```r
es <- feols(lnm_rate ~ i(year, treated, ref = 1936)|year+treated, data =
 ↪  dfData)
summary(es)
```

```
OLS estimation, Dep. Var.: lnm_rate
Observations: 1,721
Fixed-effects: year: 19,  treated: 2
Standard-errors: Clustered (year)
                     Estimate Std. Error       t value  Pr(>|t|)
year::1925:treated -0.135176   5.59e-13 -2.420236e+11 < 2.2e-16 ***
year::1926:treated -0.135567   5.58e-13 -2.428443e+11 < 2.2e-16 ***
year::1927:treated -0.222575   5.60e-13 -3.975258e+11 < 2.2e-16 ***
year::1928:treated -0.339383   5.62e-13 -6.038792e+11 < 2.2e-16 ***
year::1929:treated -0.353351   5.59e-13 -6.319386e+11 < 2.2e-16 ***
year::1930:treated -0.307318   5.60e-13 -5.490184e+11 < 2.2e-16 ***
year::1931:treated -0.314916   5.60e-13 -5.626043e+11 < 2.2e-16 ***
year::1932:treated -0.167430   5.60e-13 -2.987636e+11 < 2.2e-16 ***
year::1933:treated -0.144043   5.62e-13 -2.565318e+11 < 2.2e-16 ***
year::1934:treated -0.102580   5.60e-13 -1.831545e+11 < 2.2e-16 ***
year::1935:treated -0.069522   5.62e-13 -1.237185e+11 < 2.2e-16 ***
year::1937:treated -0.439008   5.58e-13 -7.861498e+11 < 2.2e-16 ***
year::1938:treated -0.704925   5.54e-13 -1.272684e+12 < 2.2e-16 ***
year::1939:treated -0.932996   5.51e-13 -1.692804e+12 < 2.2e-16 ***
year::1940:treated -1.139170   5.48e-13 -2.077248e+12 < 2.2e-16 ***
year::1941:treated -1.505930   5.78e-13 -2.604525e+12 < 2.2e-16 ***
year::1942:treated -1.384778   5.44e-13 -2.545701e+12 < 2.2e-16 ***
year::1943:treated -1.323763   5.86e-13 -2.258105e+12 < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
RMSE: 0.593665     Adj. R2: 0.917231
                 Within R2: 0.142828
```

```r
coefplot(es, ylab = "Coefficient", innerCI=5, outerCI=7, lwdInner=5,
 ↪  lwdOuter=7)
```



From the plot and the regression results we can see that across the groups (states), before the treatment the scarlet fever mortality was significantly lower in each year (year-treatment cross-term), around 0.2 coefficient before the treatment. However, around and after the treatment year, this effect increased in magnitude, reaching up to -1.5 decrease in log mortality in 1941 compared to tuberculosis.

2.6 (vi)

We need to cluster standard errors at the fixed effect levels: namely time and group fixed effects, year and treated variables.

```
DiD3= feols(lnm_rate ~ indicator*treated, data = dfData, se="cluster",
 ↪  cluster=c("year", "treated"))
msummary(list(DiD1,DiD2,DiD3), stars = c('*' = .1, '**' = .05, '***' =
 ↪  .01))
```

In this

	(1)	(2)	(3)
indicator × treated	-0.439^{**}	-0.867^{***}	-0.861^{**}
	(0.219)	(0.060)	(0.029)
(Intercept)			-7.391^{***}
			(0.025)
indicator			-0.416
			(0.070)
treated			-3.545^{***}
			(0.010)
Num.Obs.	192	1721	1721
R2	0.851	0.916	0.907
R2 Adj.	0.849	0.915	0.907
R2 Within	0.021	0.108	
R2 Within Adj.	0.016	0.107	
AIC	442.6	3200.1	3331.7
BIC	455.6	3314.5	3353.5
RMSE	0.75	0.61	0.64
Std.Errors	IID	IID	by: year & treated
FE: year	X	X	
FE: treated	X	X	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

2.7 (vii)

For this, we can use the Wald test to check on the pre-trends from the event study model before the actual treatment period.

```
wald(es,
 ↪  keep=c("year::1925:treated","year::1926:treated","year::1927:treated","year::1928:trea
```

```
Wald test, H0: joint nullity of year::1925:treated, year::1926:treated, year::1927:treated, y
 stat = 8.527e+22, p-value < 2.2e-16, on 11 and 1,683 DoF, VCOV: Clustered (year).
```

We reject the null hypothesis, which means that there is enough evidence which suggests that the parallel trends condition is not satisfied. This means that the decreasing trend in scarlet fever was stronger anyway compared to the tuberculosis and regardless of the treatment (the appearance of a drug effective for the former but not for the latter). Then we can use the placebo test, in which we pick fake treatment periods before the actual treatment period and see if there is a significant effect. In theory, if the common trends assumption was satisfied, the placebo (fake) treatment should not be significant, only the real treatment effect should yield a significant effect.

```
# Create fake indicator variables
dfData$D_fake1 <- ifelse(dfData$year >=1928, 1, 0)
dfData$D_fake2 <- ifelse(dfData$year >=1930, 1, 0)
dfData$D_fake3 <- ifelse(dfData$year >=1932, 1, 0)
dfData$D_fake4 <- ifelse(dfData$year >=1934, 1, 0)

# Test fake models
DiD1_fake = feols(lnm_rate ~ D_fake1*treated|year + treated, data =
 ↪  dfData, cluster = "treated^year")
DiD2_fake = feols(lnm_rate ~ D_fake2*treated|year + treated, data =
 ↪  dfData, cluster = "treated^year")
DiD3_fake = feols(lnm_rate ~ D_fake3*treated|year + treated, data =
 ↪  dfData, cluster = "treated^year")
DiD4_fake = feols(lnm_rate ~ D_fake4*treated|year + treated, data =
 ↪  dfData, cluster = "treated^year")
msummary(list(DiD1_fake,DiD2_fake,DiD3_fake,DiD4_fake), stars = c('*' =
 ↪  .1, '**' = .05, '***' = .01))
```

Using the placebo test, we also find that the parallel trend pre-treatment period is not satisfied, because the fake treatment periods yield significant treatment effects as well. Therefore using

	(1)	(2)	(3)	(4)
D_fake1 × treated	-0.407***			
	(0.092)			
D_fake2 × treated		-0.358***		
		(0.105)		
D_fake3 × treated			-0.386***	
			(0.116)	
D_fake4 × treated				-0.513***
				(0.127)
Num.Obs.	1721	1721	1721	1721
R2	0.907	0.907	0.907	0.909
R2 Adj.	0.905	0.906	0.906	0.908
R2 Within	0.011	0.014	0.020	0.040
R2 Within Adj.	0.011	0.013	0.020	0.039
AIC	3376.8	3372.3	3361.1	3326.8
BIC	3491.3	3486.7	3475.6	3441.2
RMSE	0.64	0.64	0.63	0.63
Std.Errors	by: treated^year	by: treated^year	by: treated^year	by: treated^year
FE: year	X	X	X	X
FE: treated	X	X	X	X

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

event studies alone is not warranted and one should consider differences-in-differences or differences-in-differences-in-differences instead.