ARE 213 PS 2b

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Contents

Problem 1

We first estimate an event study specification.

Part (a)

First determine the minimum and maximum event time values that you can estimate in this data set. Code up a separate event time indicator for each possible value of event time in the data set. Estimate an event study regression using all the event time indicators. What happens?

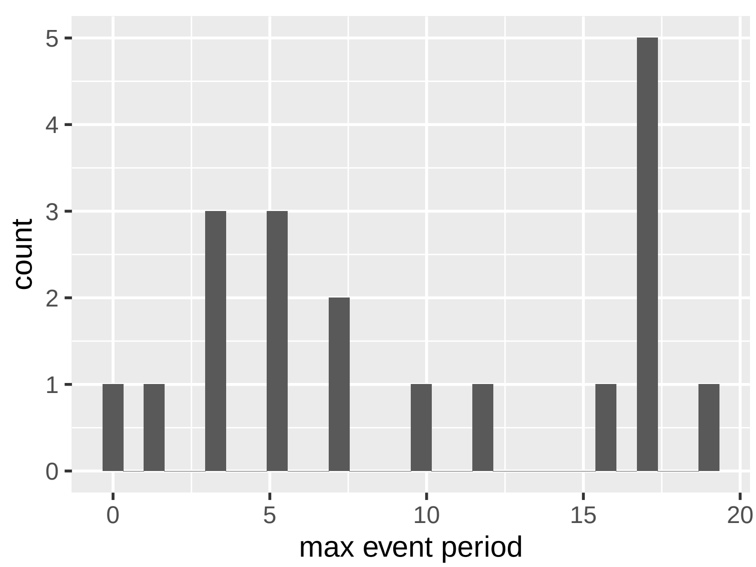
Table 1 lists the minimum and maximum event times that exist in the data for states that enacted a primary seat belt law in our study period (1981-2003).

Table 1: Maximum & Minimum Event Time Values

Max j	Min j
19	-22

Notice from Figure 1 that we have a wide range of maximum event times across our panel of states. One state even has a maximum event time of 0 – meaning they only added primary seat belt laws in the last year of our panel (2003). This means we will have an unbalanced panel if we run a regression on all possible event time dummies. In fact, we will still have an unbalance panel if we create max and min event time bins to aggregate early and late periods (an indicator for a event times greater than 5 and an indicator for all event times less than -5), we will still have an unbalanced panel.

Figure 1: Treated States, maximum event time histogram



To estimate the event study treatment effects, corresponding regression equation is:

$$Y_{st} = \alpha + \sum_{j=min\_t}^{max\_t} \tau_j D_{jst} + \gamma_s + \delta_t + \varepsilon_{st} + u_{st}$$

Note that we are estimating the regression with state and year fixed effects. In practice, we would want to omit a specific event time indicator so all our treatment effects are measured with respect to that event time. If we keep all our indicators, then R will implicitly choose which to event time indicator to omit for us because the event time dummies, along with state and year fixed effects, are colinear.

We can see column (1) of Table 2 that the indicator for event time +19 was omitted for the regression. However, for interpretability, we'd rather have the treatment effects relative to a period closer to the year of initial treatment.

Part (b)

Estimate another event study regression using all the event time indicators save one that you choose to omit. Generate a plot of the event study coefficients.

We have chosen to omit the event time -1 from the regression so the other event time inidicator coefficients can be interpreted as relative to the year immediately before the passage of the primary seat belt law. Column (2) of Table 2 shows that the -1 event time period was omitted, and we we see that all of the treatment effects occuring before event time -1 are not significantly different from zero, whereas all the event time coefficient estimates for after event time -1 are negative and all are signficantly less than zero starting with event period 5.

Table 2: Event Study Regressions

	Log(Fatality per Population)	
	Event Study a	Event Study b
	(1)	(2)
‘-22_ET‘	0.1385 (0.1578)	−0.1545 (0.1137)
‘-21_ET‘	0.4172*** (0.1372)	0.1242 (0.0828)
‘-20_ET‘	0.3697*** (0.1371)	0.0767 (0.0826)
‘-19_ET‘	0.3091** (0.1231)	0.0162 (0.0568)
‘-18_ET‘	0.2851** (0.1231)	−0.0079 (0.0567)
‘-17_ET‘	0.3460*** (0.1191)	0.0531 (0.0475)
‘-16_ET‘	0.3543*** (0.1191)	0.0613 (0.0477)
‘-15_ET‘	0.3526*** (0.1176)	0.0597 (0.0436)
‘-14_ET‘	0.3113*** (0.1175)	0.0184 (0.0440)
‘-13_ET‘	0.3412*** (0.1175)	0.0482 (0.0435)
‘-12_ET‘	0.3161*** (0.1169)	0.0231 (0.0425)
‘-11_ET‘	0.3235*** (0.1168)	0.0305 (0.0423)
‘-10_ET‘	0.3105*** (0.1163)	0.0176 (0.0411)
‘-9_ET‘	0.2946** (0.1162)	0.0017 (0.0412)
‘-8_ET‘	0.3096*** (0.1162)	0.0166 (0.0408)
‘-7_ET‘	0.3313*** (0.1161)	0.0383 (0.0411)
‘-6_ET‘	0.3385*** (0.1156)	0.0455 (0.0397)
‘-5_ET‘	0.3155*** (0.1144)	0.0225 (0.0368)
‘-4_ET‘	0.3268*** (0.1143)	0.0338 (0.0369)
‘-3_ET‘	0.3225*** (0.1138)	0.0295 (0.0359)
‘-2_ET‘	0.2981*** (0.1137)	0.0051 (0.0363)
‘-1_ET‘	0.2929** (0.1137)	
‘0_ET‘	0.2623** (0.1135)	−0.0306 (0.0363)
‘1_ET‘	0.2484** (0.1136)	−0.0445 (0.0365)
‘2_ET‘	0.2464** (0.1139)	−0.0466 (0.0375)
‘3_ET‘	0.2466** (0.1134)	−0.0463 (0.0375)
‘4_ET‘	0.2278** (0.1144)	−0.0651 (0.0397)
‘5_ET‘	0.2127* (0.1138)	−0.0803** (0.0401)
‘6_ET‘	0.1965* (0.1154)	−0.0965** (0.0432)
‘7_ET‘	0.2173* (0.1149)	−0.0756* (0.0438)
‘8_ET‘	0.1612 (0.1165)	−0.1317*** (0.0471)
‘9_ET‘	0.1790 (0.1165)	−0.1140** (0.0471)
‘10_ET‘	0.1772 (0.1162)	−0.1157** (0.0474)
‘11_ET‘	0.1594 (0.1174)	−0.1336*** (0.0494)
‘12_ET‘	0.1443 (0.1170)	−0.1487*** (0.0500)
‘13_ET‘	0.1522 (0.1185)	−0.1408*** (0.0526)
‘14_ET‘	0.1574 (0.1185)	−0.1355** (0.0533)
‘15_ET‘	0.1504 (0.1184)	−0.1425*** (0.0531)
‘16_ET‘	0.0973 (0.1181)	−0.1956*** (0.0533)
‘17_ET‘	0.0842 (0.1183)	−0.2087*** (0.0576)
‘18_ET‘	0.0144 (0.1520)	−0.2785** (0.1135)
‘19_ET‘		−0.2929** (0.1137)
Constant	−1.4815*** (0.1158)	−1.1885*** (0.0387)
Chose dummy to omit	No	Yes
Observations	1,104	1,104
R^2	0.9111	0.9111
Adjusted R^2	0.9013	0.9013
Note:		*p<0.1; **p<0.05; ***p<0.01

Part (c)

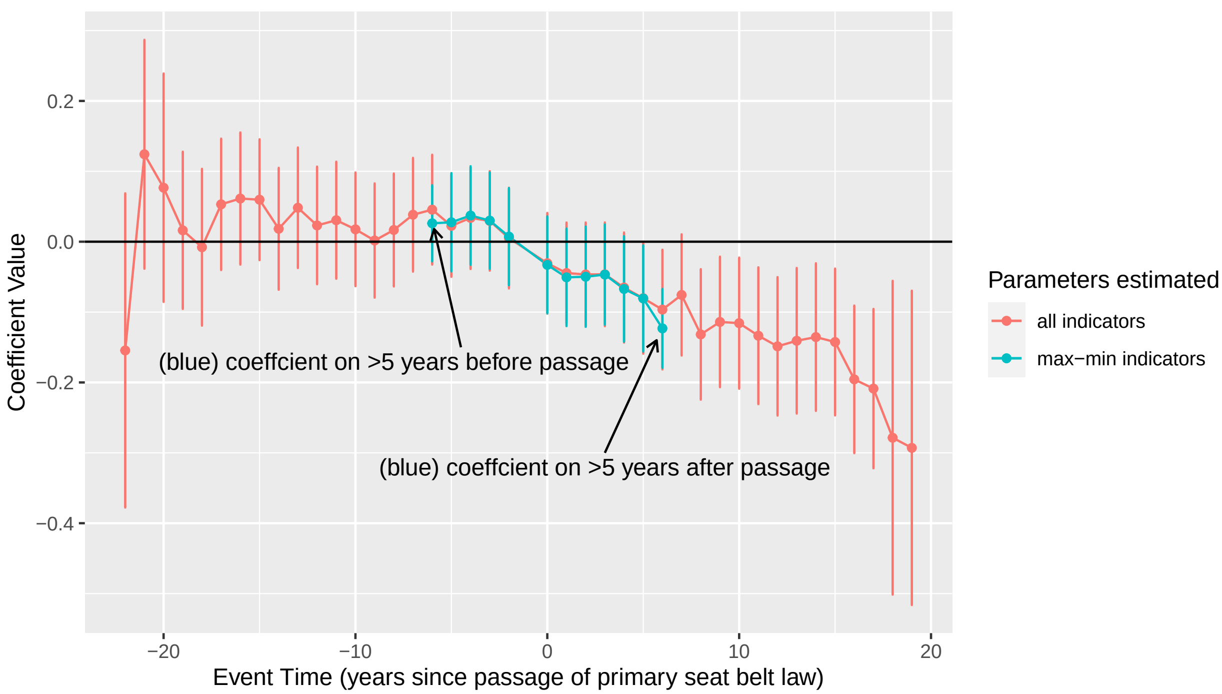
Create minimum and maximum event time indicators that correspond to bins of event time < -5 and event time > 5 respectively. Appropriately specify and estimate an event study regression using these min and max event time indicators. Generate a plot of the event study coefficients. Explain which specification you prefer, this one or the one in part (b).

Table 3: Event Study Regression with Threshold Indicators

	Log(Fatality per Population)
	Event Study c
below_ET	0.0261 (0.0275)
‘-5_ET‘	0.0276 (0.0355)
‘-4_ET‘	0.0372 (0.0356)
‘-3_ET‘	0.0300 (0.0347)
‘-2_ET‘	0.0073 (0.0350)
‘0_ET‘	−0.0329 (0.0350)
‘1_ET‘	−0.0506 (0.0352)
‘2_ET‘	−0.0498 (0.0362)
‘3_ET‘	−0.0467 (0.0361)
‘4_ET‘	−0.0671* (0.0381)
‘5_ET‘	−0.0806** (0.0384)
above_ET	−0.1232*** (0.0285)
Constant	−1.1828*** (0.0373)
Chose dummy to omit	Yes
Agg. Threshold Indicators	Yes
Observations	1,127
R^2	0.9090
Adjusted R^2	0.9019

Note: *p<0.1; **p<0.05; ***p<0.01
below_ and above_ variables are aggregate indicators for all event times that are below -5 and above 5, respectively.

Figure 2: (red) Plot of all possible event-time coefficients and 95% confidence intervals from Table 2; (blue) plot of event-time coefficients and 95% confidence intervals for event-times from years before the passage of the primary seat belt law to 5 years after and coefficents for aggregate event-time indicators of more than 5 years before and more than 5 years after the law passed, plotted at x-values of -6 and 6, respectively (from Table 3)



Part (d)

What happens to your estimates from part (b) if you exclude the "pure control" states from your sample? What about if you exclude the pure controls in part (c)?

Table 4: Event Study Regressions with and without Pure Control States

	Log(Fatality per Population)			
	All indicators	All indicators	Min-max indicators	Min-max indicators
	(1)	(2)	(3)	(4)
‘-22_ET‘	−0.1545 (0.1137)	−0.4460*** (0.1608)		
‘-21_ET‘	0.1242 (0.0828)	−0.1641 (0.1383)		
‘-20_ET‘	0.0767 (0.0826)	−0.1925 (0.1333)		
‘-19_ET‘	0.0162 (0.0568)	−0.2338** (0.1165)		
‘-18_ET‘	−0.0079 (0.0567)	−0.2606** (0.1117)		
‘-17_ET‘	0.0531 (0.0475)	−0.1681 (0.1023)		
‘-16_ET‘	0.0613 (0.0477)	−0.1639* (0.0985)		
‘-15_ET‘	0.0597 (0.0436)	−0.1401 (0.0905)		
‘-14_ET‘	0.0184 (0.0440)	−0.1808** (0.0872)		
‘-13_ET‘	0.0482 (0.0435)	−0.1329 (0.0811)		
‘-12_ET‘	0.0231 (0.0425)	−0.1496* (0.0768)		
‘-11_ET‘	0.0305 (0.0423)	−0.1295* (0.0720)		
‘-10_ET‘	0.0176 (0.0411)	−0.1295* (0.0667)		
‘-9_ET‘	0.0017 (0.0412)	−0.1296** (0.0635)		
‘-8_ET‘	0.0166 (0.0408)	−0.1028* (0.0577)		
‘-7_ET‘	0.0383 (0.0411)	−0.0643 (0.0553)		
‘-6_ET‘	0.0455 (0.0397)	−0.0442 (0.0495)		
below_ET			0.0261 (0.0275)	−0.0165 (0.0311)
‘-5_ET‘	0.0225 (0.0368)	−0.0422 (0.0447)	0.0276 (0.0355)	0.0114 (0.0342)
‘-4_ET‘	0.0338 (0.0369)	−0.0222 (0.0420)	0.0372 (0.0356)	0.0180 (0.0343)
‘-3_ET‘	0.0295 (0.0359)	−0.0014 (0.0375)	0.0300 (0.0347)	0.0222 (0.0326)
‘-2_ET‘	0.0051 (0.0363)	−0.0183 (0.0372)	0.0073 (0.0350)	−0.0015 (0.0336)
‘0_ET‘	−0.0306 (0.0363)	−0.0184 (0.0353)	−0.0329 (0.0350)	−0.0296 (0.0336)
‘1_ET‘	−0.0445 (0.0365)	−0.0219 (0.0346)	−0.0506 (0.0352)	−0.0487 (0.0331)
‘2_ET‘	−0.0466 (0.0375)	−0.0061 (0.0378)	−0.0498 (0.0362)	−0.0416 (0.0348)
‘3_ET‘	−0.0463 (0.0375)	0.0002 (0.0385)	−0.0467 (0.0361)	−0.0406 (0.0347)
‘4_ET‘	−0.0651 (0.0397)	0.0018 (0.0436)	−0.0671* (0.0381)	−0.0555 (0.0367)
‘5_ET‘	−0.0803** (0.0401)	−0.0022 (0.0456)	−0.0806** (0.0384)	−0.0638* (0.0376)
‘6_ET‘	−0.0965** (0.0432)	0.0028 (0.0520)		
‘7_ET‘	−0.0756* (0.0438)	0.0349 (0.0549)		
‘8_ET‘	−0.1317*** (0.0471)	−0.0104 (0.0618)		
‘9_ET‘	−0.1140** (0.0471)	0.0231 (0.0658)		
‘10_ET‘	−0.1157** (0.0474)	0.0219 (0.0689)		
‘11_ET‘	−0.1336*** (0.0494)	0.0361 (0.0753)		
‘12_ET‘	−0.1487*** (0.0500)	0.0449 (0.0787)		
‘13_ET‘	−0.1408*** (0.0526)	0.0874 (0.0858)		
‘14_ET‘	−0.1355** (0.0533)	0.0965 (0.0904)		
‘15_ET‘	−0.1425*** (0.0531)	0.0924 (0.0944)		
‘16_ET‘	−0.1956*** (0.0533)	0.0714 (0.0984)		
‘17_ET‘	−0.2087*** (0.0576)	0.0512 (0.1007)		
‘18_ET‘	−0.2785** (0.1135)	0.0239 (0.1414)		
‘19_ET‘	−0.2929** (0.1137)			
above_ET			−0.1232*** (0.0285)	−0.0820** (0.0326)
Constant	−1.1885*** (0.0387)	−0.9387*** (0.1113)	−1.1828*** (0.0373)	−1.1331*** (0.0463)
Agg. Threshold Indicators	No	No	Yes	Yes
Include Pure Controls	Yes	No	Yes	No
Observations	1,104	414	1,127	437
R^2	0.9111	0.9273	0.9090	0.9224
Adjusted R^2	0.9013	0.9102	0.9019	0.9119
Note:				*p<0.1; **p<0.05; ***p<0.01

For the all-event-times-indicators regressions from part (b), we can see in Table 4 that for event-time indicators after the primary seat belt law is passed (event times ≥ 0), the coefficients change from being all negative and mostly significant to being all insignificant at the 0.1 level and mixed signs. Interestingly, the coefficients on the event-time indicators for times before the passage of the law become significantly negative – indicating that the passage of the law might have caused an increase in traffic fatalities in states in the treatment group (i.e., the effect of treatment on the treated might be the opposite sign we expect). However, we also should note that the coefficient on event time 19 (19 years after the passage of the law) is dropped by the regression because of colinearity – without pure control states, the combination of state and year fixed effects with indicators for all but one event times becomes colinear.

Because we have omitted the coefficient on event time 19 and event time 0, we cannot readily interpret the coefficients in column (2) of Table 4.

If we focus on columns (3) and (4) from Table 4, we can see removing the pure control states (column 4) reduces the significance and magnitude of all our coefficients, but the last two coeffcients for event time 5 ('5_ET') and the aggregate of all event times greater than 5 (above_ET) are still signficant and negative. One way to interpret this is that the treatment effect on the treated is smaller than that of the average treatment effect. We also could hypothesize that the states that passed the primary seat belt laws during our study period were doing something other than passing the primary law and something different from the pure control states to reduce traffic fatalities, so our comparison within the treatment states (column 4) estimates a smaller effect than when we compare our treated states to the pure control states.

Part (e)

Overall, does the event study regression make you more confident or less confident that seat belt laws reduce fatalities (relative to the fixed effects results that you estimated on the last problem set)? Briefly explain.

Part (f*)

Building off the event study regression from part (c), estimate the interaction weighted event study estimator from Sun and Abraham (2020). As a reminder, the interacted event study regression takes the standard event time indicators (without any binning) and interacts each one with a cohort indicator (a cohort refers to a group of states that share the same date on which they were first treated). You then form the estimate for event time coefficient τ_j by averaging the estimates of the cohort-specific τ_j using the weights described in Sun and Abraham (2020).

Problem 2

We now apply the synthetic control methods from Abadie et al (2010).

Part (a)

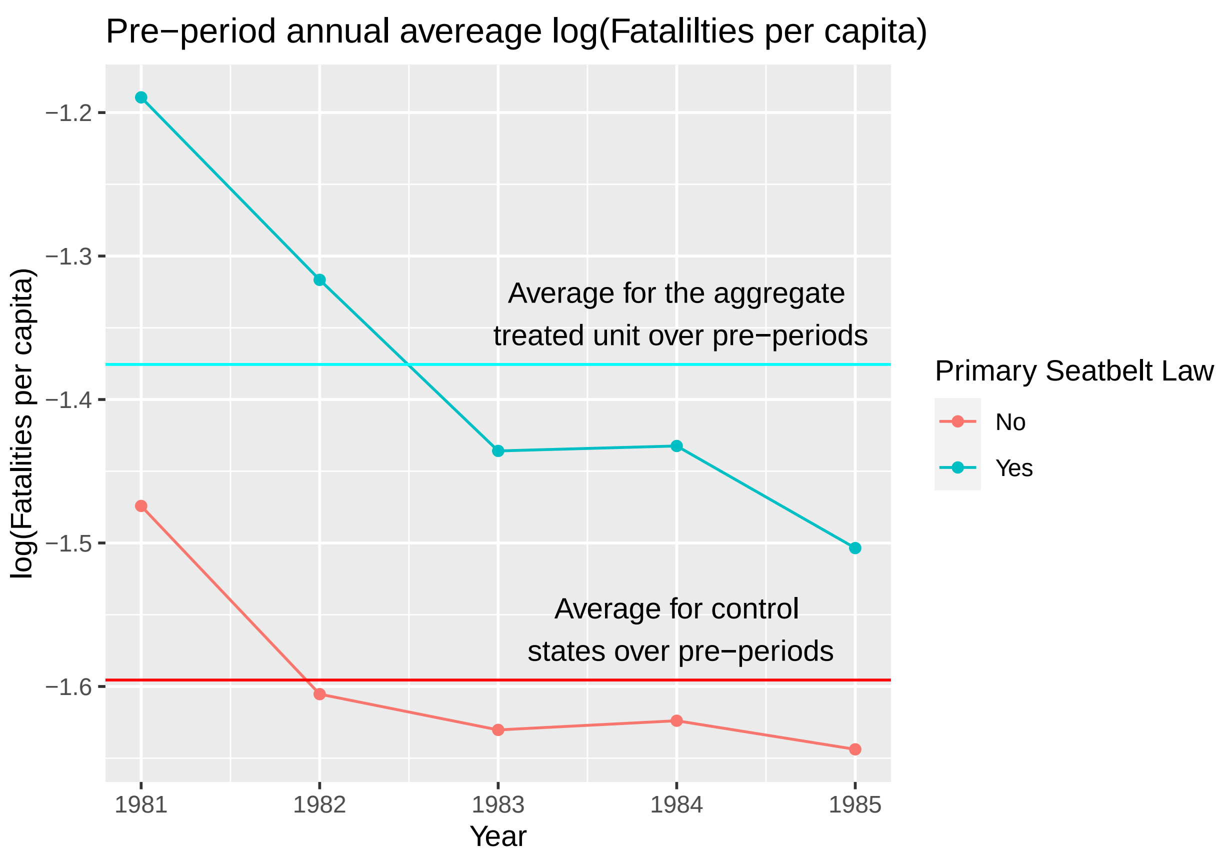
We created an aggregate "treatment" state (state number 99 or "TU") which combines the (population weighted) data from the first 4 states to have a primary seatbelt law (CT, IA, NM, TX). Please use this state as the "treatment" state in the synthetic control analysis.

—— **a.i**

Compare the average pre-period log traffic fatalities per capita of the TU site to that of the average of all the "control" states. Next, graph the pre-period log traffic fatalities by year for the pre-period for both the TU and the average of the control group. Interpret.

Table 5: Average Pre-period log(traffic fatalities per capita)

Aggregate Treatment State	Aggregate Control State
-1.375546	-1.595503



—— **a.ii**

Compare the dependent variable between the TU site and each control state for the year before the treatment. Which control state best matches the TU? Now compare this state's covariates with the TU covariates. Do they appear similar? What might this imply for in terms of using this state as the counterfactual state?

Table 6: Dependent variable in 1985 for treated (99) and control states

State ID	log(fatatilities per captia)	Absolute difference between this state and treated
99	-1.503526	0.0000000
47	-1.512943	0.0094169
44	-1.528011	0.0244846
2	-1.470088	0.0334382
40	-1.454592	0.0489344
14	-1.608368	0.1048414
8	-1.389040	0.1144866
23	-1.363415	0.1401115
11	-1.360526	0.1430004
15	-1.646608	0.1430818
28	-1.668061	0.1645347
22	-1.680986	0.1774596
39	-1.681263	0.1777369
42	-1.690492	0.1869652
24	-1.304958	0.1985685
31	-1.304588	0.1989382
5	-1.714055	0.2105290
19	-1.730826	0.2272997
3	-1.271162	0.2323642
38	-1.244085	0.2594411
43	-1.766389	0.2628626
48	-1.190119	0.3134070
46	-1.853388	0.3498619
33	-1.878806	0.3752799
36	-1.894083	0.3905567
27	-1.900066	0.3965393
21	-1.927277	0.4237503
12	-2.005066	0.5015393
26	-2.017831	0.5143042
17	-2.072787	0.5692603
37	-2.184871	0.6813450

We can see from Table 6 that state # 47 is the control state that is closest to the aggregate treatment state in the dependent variable.

Table 7: Dependent variable in 1985 for treated (99) and control states

	Control State 47	Aggregate Treatment State
state	47.0000	99.0000
college	0.1189	0.2339
beer	1.1100	1.5643
population	1906.8310	12009.3484
unemploy	13.0000	6.9451
totalvmt	12664.0000	104389.7266
precip	3.6542	2.4307
snow32	0.8333	0.1511
rural_speed	55.0000	55.0000
urban_speed	55.0000	55.0000
fat_pc	0.2203	0.2223

From Table 7, we can see that there are identical speed limits between state 47 and the aggregate treatment state. But most of the other covariates are very far apart in the distributions – total vehicle miles traveled is different by an order of magnitude and are in different sides of the distribution; both snow and preciptiation are on different sides of their distributions; the unemployment rates, population levels, and college rates are very far apart as well.

Part (b)

Apply the synthetic control method using the available covariates and pre-treatment outcomes to construct a synthetic control group.

—— b.i

Discuss the synthetic control method including its benefits and potential drawbacks.

—— b.ii

Use the software package provided by Abadie et al to apply the synthetic control method. (You are free to use either Stata, Matlab, or R but answers will be provided in Stata and R only). Please be sure to state precisely what the command is doing and how you determined your preferred specification.

Part (c)

Graphical interpretation and treatment significance.

—— c.i

Generate graphs plotting the gap between the TU and the synthetic control group under both your preferred specification and a few other specifications you tried.

—— c.ii

Compare the graph plotting the gap between the TU and the synthetic control group under your preferred specification with the graphs plotting the gap between each control state and its "placebo" treatment. Do you conclude that the treatment was significant? Why or why not?

—— c.iii

Create a graph of the post-treatment/pre-treatment prediction ratios of the Mean Squared Prediction Errors (MSPE) for the actual and "plecebo" treatment gaps in (ii). [See Abadie et al. for an example]. Do you conclude that the treatment was significant? Why or why not?

Part (d)

How do your synthetic control results compare to your fixed effects results from Question (3) in the last problem set? Interpret any differences.

Appendix A: R Code

```
rm(list=ls())
knitr::opts_chunk$set(echo = F)
# stargazer table type (html, latex, or text)
# Change to latex when outputting to PDF, html when outputting to html
table_type = "latex"

# install.packages("Synth")
# install.packages('kableExtra')
library(tidyverse)
library(haven)
library(stargazer)
library(ggplot2)
library(tinytex)
library(Synth)
library(kableExtra)
# library(plm)
# library(lmtest)
# library(sandwich)
# library(gridExtra)
# library(grid)
# library(gtable)
library(fastDummies)
# library(EnvStats)
# Load data from PS2a with previous log variables
data = read_dta('traffic_safety2.dta') %>%
    mutate(fat_pc = fatalities/population,
           ln_fat_pc = log(fat_pc),
           ln_tvmt_pc = log(totalvmt/population),
           ln_precip = log(precip),
           ln_rspeed = log(rural_speed),
           ln_uspeed = log(urban_speed))

# Create list of event dates for states that passed primary laws in our study
event_dates = data %>%
    group_by(state) %>%
    mutate(event = primary - lag(primary), # event=1 ==> first year primary=1
           event_year = year) %>%
    filter(event == 1) %>%
    select(state, event_year)

# Add year of primary event and event time (t) to dataframe
data = data %>%
    left_join(event_dates, by='state') %>%
    mutate(j = ifelse(is.na(event_year), 99, year - event_year))
    # t = 99 ==> control state (doesn't pass primary during study period)

# Table of max and min event times
# Shouldn't these be our event study thresholds?
df_temp = data %>%
    filter(j < 99) %>%
    group_by(state) %>%
```

```
    summarize(min_j = min(j), max_j = max(j))

max_j_inclusive = min(df_temp$max_j, na.rm = T)
min_j_inclusive = max(df_temp$min_j, na.rm = T)
max_j = max(filter(data, j<99)$j, na.rm = T)
min_j = min(filter(data, j<99)$j, na.rm = T)
data.frame(max_j = max_j, min_j = min_j) %>%
  kbl(caption = "Maximum \\& Minimum Event Time Values",
      col.names = c('Max j', 'Min j'),
      align = 'cc') %>%
  kable_styling(latex_options = "HOLD_position")
df_temp %>%
    arrange(max_j) %>%
    filter(!is.na(max_j), max_j < 99) %>%
    select(max_j) %>%
    ggplot(aes(x=max_j), data=.) +
    geom_histogram() +
    xlab("max event period")
# Function for adding dummies to a dataframe for all uniuqe values between given numbers
create_dummies = function(df, colname, min_value, max_value) {
    # Create dummies for each value of colname between min_value and max_value
    df1 = df
    for (val in min_value:max_value) {
        df1 = mutate(df1, "{colname}_{val}" := ifelse(eval(as.symbol(colname)) == val, 1, 0))
    }
    return(df1)
}

# Create order of dummies for dataframe (then used for regression table)
name_order1 = paste('j', min_j_inclusive:max_j_inclusive, sep='_')
# Create Dummies that make a balanced panel
# (only dummies for event times j that are shared across all states)
df_few_dummies = create_dummies(data,
                              colname = 'j',
                              min_value = min_j_inclusive,
                              max_value = max_j_inclusive) %>%
    relocate(all_of(name_order1)) %>%
    # Change "j_..." to "..._ET" because LaTeX doesn't like j_-3 type variable names
    rename_with(~ paste0(str_replace(., 'j_', ''), '_ET'), contains("j_"))

# Create order of dummies for dataframe (then used for regression table)
name_order2 = paste('j', min_j:max_j, sep='_')
# Create Dummies for all possible event times
# (results in unbalanced panel over event times j)
df_all_dummies = dummy_cols(data, select_columns = 'j') %>%
    select(-j_99) %>%
    filter(state != 99)  %>%
    relocate(all_of(name_order2)) %>%
    rename_with(~ paste0(str_replace(., 'j_', ''), '_ET'), contains("j_"))
reg_1a = df_all_dummies %>%
    mutate(state=factor(state), year=factor(year)) %>%
    select(ln_fat_pc, state, year, contains('_ET')) %>%
    lm(ln_fat_pc ~ ., data = .)
```

```r
reg_1b = df_all_dummies %>%
    mutate(state=factor(state), year=factor(year)) %>%
    select(ln_fat_pc, state, year, contains('_ET'), -`-1_ET`) %>%
    lm(ln_fat_pc ~ ., data = .)

stargazer(reg_1a, reg_1b,
          title = "Event Study Regressions\\label{tab:event-study-dummy-trap}",
          dep.var.caption = "Log(Fatality per Population)",
          dep.var.labels.include = FALSE,
          column.labels = c("Event Study a", "Event Study b"),
          omit = c("state", "year"),
          add.lines=list(c('Chose dummy to omit', 'No', 'Yes')),
          font.size = "footnotesize", column.sep.width = "1pt", no.space = TRUE,
          omit.stat=c("f", "ser"),
          single.row = TRUE,
          digits = 4, type = table_type, header = FALSE)


# Function for adding dummies to a dataframe for all uniuqe values between given numbers
create_dummies_threshold = function(df, colname, min_value, max_value, suffix = NULL) {
    # Create indicator variables for each value of colname between min_value and max_value
    # then create indicator variables for all values of colname below min_value
    # and another for above max_value
    if (is.null(suffix)) {suffix = colname}
    df1 = df
    # add aggregate indicator for all values below min_value
    df1 = mutate(df1, "below_{suffix}" := ifelse(eval(as.symbol(colname)) < min_value, 1, 0))
    # add all indicators in between min and max_value
    for (val in min_value:max_value) {
        df1 = mutate(df1, "{val}_{suffix}" := ifelse(eval(as.symbol(colname)) == val, 1, 0))
    }
    # add aggregate indicator for all values above max_value
    df1 = mutate(df1, "above_{suffix}" := ifelse(eval(as.symbol(colname)) > max_value, 1, 0))
    return(df1)
}


# Create Dummies that make a balanced panel
# (only dummies for event times j that are shared across all states)
df_threshold_dummies = create_dummies_threshold(data,
                                          colname = 'j',
                                          min_value = -5,
                                          max_value = 5,
                                          suffix = 'ET')

reg_1c = df_threshold_dummies %>%
    mutate(state=factor(state), year=factor(year)) %>%
    select(ln_fat_pc, state, year, contains('_ET'), -`-1_ET`) %>%
    lm(ln_fat_pc ~ ., data = .)

stargazer(reg_1c,
          title = "Event Study Regression with Threshold Indicators\\label{tab:event-study-thresholds}"
          dep.var.caption = "Log(Fatality per Population)",
```

```r
          dep.var.labels.include = FALSE,
          column.labels = c("Event Study c"),
          omit = c("state", "year"),
          add.lines=list(c('Chose dummy to omit', 'Yes'), c('Agg. Threshold Indicators', 'Yes')),
          font.size = "footnotesize", column.sep.width = "1pt", no.space = TRUE,
          omit.stat=c("f", "ser"),
          single.row = TRUE,
          notes = c("below\\_ and above\\_ variables are aggregate indicators for",
                    "all event times that are below -5 and above 5, respectively."),
          digits = 4, type = table_type, header = FALSE)

plot_text1 = "(red) Plot of all possible event-time coefficients and 95\\% confidence intervals from Ta

new_varname = function(oldname, min_value, max_value) {
    name = str_replace_all(oldname, "`","")
    name = str_replace(name, "_ET", "")
    name = str_replace(name, "below", paste("<", min_value))
    name = str_replace(name, "above", paste(">", max_value))
    return(name)
}

xvalue = function(oldname, min_value = NULL, max_value = NULL) {
    name = str_replace_all(oldname, "`","")
    name = str_replace(name, "_ET", "")
    if (!is.null(min_value)) {
        name = str_replace(name, "below", as.character(min_value - 1))
        name = str_replace(name, "above", as.character(max_value + 1))
    }
    return(as.numeric(name))
}

regression_dataframe = function(reg, reg_type, min_value = NULL, max_value = NULL, suffix = 'ET') {
    df = data.frame(coef = names(reg$coefficients),
                    value = reg$coefficients,
                    lower = confint(reg)[,1],
                    upper = confint(reg)[,2],
                    reg_type = reg_type) %>%
        filter(grepl(suffix, coef)) %>%
        mutate(x_tick = new_varname(coef, min_value, max_value),
               event_time = xvalue(coef, min_value, max_value)) %>%
        return()
}

df1 = rbind(
    regression_dataframe(reg_1b, "all indicators"),
    regression_dataframe(reg_1c, "max-min indicators", min_value = -5, max_value = 5)
)

df1 %>%
    ggplot(aes(x=event_time, y=value, color = reg_type)) +
    geom_errorbar(aes(ymin=lower, ymax=upper), width=.1) +
    geom_line() +
    geom_point() +
```

```r
    geom_hline(yintercept = 0) +
    labs(color = "Parameters estimated") +
    xlab("Event Time (years since passage of primary seat belt law)") +
    ylab("Coefficient Value") +
    annotate(geom = "segment", x = 3, y = -0.3, xend = 5.7, yend = -0.14,
             arrow = arrow(length = unit(2, "mm"))) +
    annotate(geom = "text", x = 3, y = -0.32,
             label = "(blue) coeffcient on >5 years after passage",
             hjust = "center") +
    annotate(geom = "segment", x = -4.5, y = -0.15, xend = -5.9, yend = 0.018,
             arrow = arrow(length = unit(2, "mm"))) +
    annotate(geom = "text", x = -8, y = -0.17,
             label = "(blue) coeffcient on >5 years before passage",
             hjust = "center")

# Regression with all possible event-time indicators, removing pure control states
reg_1b2 = df_all_dummies %>%
    group_by(state) %>%
    filter(mean(primary) > 0) %>%
    mutate(state=factor(state), year=factor(year)) %>%
    select(ln_fat_pc, state, year, contains('_ET'), -`-1_ET`) %>%
    lm(ln_fat_pc ~ ., data = .)

# Regression with max, min aggregated event-time indicators, removing pure control states
reg_1c2 = df_threshold_dummies %>%
    group_by(state) %>%
    filter(mean(primary) > 0) %>%
    mutate(state=factor(state), year=factor(year)) %>%
    select(ln_fat_pc, state, year, contains('_ET'), -`-1_ET`) %>%
    lm(ln_fat_pc ~ ., data = .)

stargazer(reg_1b, reg_1b2, reg_1c, reg_1c2,
          title = "Event Study Regressions with and without Pure Control States\\label{tab:event-study-r
          dep.var.caption = "Log(Fatality per Population)",
          dep.var.labels.include = FALSE,
          column.labels = c("All indicators",
                            "All indicators",
                            "Min-max indicators",
                            "Min-max indicators"),
          omit = c("state", "year"),
          add.lines=list(c('Agg. Threshold Indicators', 'No', 'No', 'Yes', 'Yes'),
                         c('Include Pure Controls', 'Yes', 'No', 'Yes', 'No')),
          font.size = "footnotesize", column.sep.width = "1pt", no.space = TRUE,
          omit.stat=c("f", "ser"),
          single.row = TRUE,
          digits = 4, type = table_type, header = FALSE)


# Calculate average pre-period log traffic fatalities per capita
preperiod_years = data %>%
    filter(state == 99, primary == 0) %>%
    select(year)
```

```r
data2 = data %>%
    group_by(state) %>%
    mutate(control = ifelse(mean(primary) > 0, 0, 1),
           treated = ifelse(state == 99, 'Yes', 'No')) %>%
    filter(control == 1 | state == 99)

means = data2 %>%
    filter(year %in% preperiod_years$year) %>%
    group_by(control) %>%
    summarize(avg = mean(ln_fat_pc))

means %>%
    select(avg) %>%  # control = 0 on top ==> TU on top
    t() %>%  # control = 0 on left ==> TU on left
    kbl(caption = "Average Pre-period log(traffic fatalities per capita)\\label{tab:avg-fat-TU}",
        col.names = c('Aggregate Treatment State', 'Aggregate Control State'),
        row.names = F,
        align = 'cc') %>%
    kable_styling(latex_options = "HOLD_position")

# Plot log fat per cap for pre-treatment years, for treatment and control
data2 %>%
    filter(year %in% preperiod_years$year) %>%
    group_by(year, treated) %>%
    summarize(year_avg = mean(ln_fat_pc)) %>%
    ggplot(aes(x=year, y=year_avg, color=factor(treated))) +
    geom_line() +
    geom_point() +
    geom_hline(yintercept = filter(means, control==0)$avg, color='cyan') +
    geom_hline(yintercept = filter(means, control==1)$avg, color='red') +
    labs(color = "Primary Seatbelt Law") +
    xlab("Year") +
    ylab("log(Fatalities per capita)") +
    ggtitle("Pre-period annual avereage log(Fatalilties per capita)") +
    annotate(geom = "text", x = 1984, y = -1.56,
             label = "Average for control\n states over pre-periods",
             hjust = "center") +
    annotate(geom = "text", x = 1984, y = -1.34,
             label = "Average for the aggregate\n treated unit over pre-periods",
             hjust = "center")

# Compare log(fat per cap) for last pre-treatment year, for treatment and each control
treat_val = (data2 %>%
    filter(year == tail(preperiod_years$year, n=1),
           state == 99))$ln_fat_pc

data2 %>%
    filter(year == tail(preperiod_years$year, n=1)) %>%
    filter(control == 1 | state == 99) %>%
    mutate(diff = abs(treat_val - ln_fat_pc)) %>%
    arrange(diff) %>%
    select(ln_fat_pc, diff) %>%
    # head() %>%
```

```r
    kbl(caption = paste("Dependent variable in",
                        tail(preperiod_years$year, n=1),
                        "for treated (99) and control states\\label{tab:1985-depvar}"),
        col.names = c('State ID', 'log(fatatilities per captia)',
                      'Absolute difference between this state and treated'),
        row.names = F,
        align = 'cc') %>%
    kable_styling(latex_options = "HOLD_position")
# Compare covariates for last pre-treatment year, for treatment and control 47
library(data.table)
data2 %>%
    filter(year == tail(preperiod_years$year, n=1)) %>%
    filter(state %in% c(47, 99)) %>%
    select(college, beer, population, unemploy, totalvmt, precip,
           snow32, rural_speed, urban_speed, fat_pc) %>%
    round(4) %>%
    t() %>%
    kbl(caption = paste("Dependent variable in",
                        tail(preperiod_years$year, n=1),
                        "for treated (99) and control states\\label{tab:1985-covar}"),
        col.names = c('Control State 47', 'Aggregate Treatment State'),
        align = 'cc') %>%
    kable_styling(latex_options = "HOLD_position")
```