

Lecture 19 EEP118

General Multi Year Panel Data

Assumptions for Fixed Effect (FE) Model

Policy analysis with Panel Data

End chapter 13. Read 14.1

See R code on bcourses and also notebook in datahub for this lecture

Daily Assignment 19 posted as well as solutions

Pset 4 posted see due date in bcourses □ Pset 5 posted soon

Last class, with a panel of 46 cities and two years of data, 82 and 87, we estimated the following model $crimerate_{it} = \alpha_i + \beta_1 unem_{it} + \beta_2 d87 + v_{it}$

β_1 = controlling for all the characteristics of the cities that do not vary over time (α_i fixed effects) and for the general effect of time common to all cities (d87) a one percent point increase in unemployment induces a β_1 increase in crime rate (number crimes per 100 people)

we used Lecture18_CRIME2 .dta

and estimated a model

```
reg6n <- lm(crmrte ~ unem + d87 + offarea + lawexpc + pcinc + factor(city), data = mydata)
summary(reg6n)
```

How did we interpret beta hat for unemployment?

Controlling for all constant characteristics of cities (that do not vary over time) = city fixed effects, and for effect of time (dummy for year 87) that captures changes in 1987 relative to 1982 factors that affect crime rate that are common to all cities, and controlling for officer per area, law expenditures, per capita income, a 1 percentage point increase in unemployment rate induces a significant 2.932 per thousand increase in crime rate

Last lecture we had two years of data

Generalizing to many years is mechanically very easy and will open the door to many new analyses

Illustration of multi-year panel data analysis:

We will measure the impact of Enterprise Zones (EZ) on employment

Data: 22 cities in Indiana, from 1980 to 1988 22 cities and many years of data

Multi-year panel data: Impact of enterprise zones on employment Source: data file EZUNEM (Wooldridge). 22 cities in Indiana, from 1980 to 1988

Six city enterprise zones created in 1984, and 4 more city EZ created in 1985.

```
In [1]: # Load the 'pacman' package
library(pacman)
#packages to use load them now using the pacman "manager"
p_load(dplyr, haven, readr)
#Another great feature of p_load(): if you try to load a package that is not
p_load(ggplot2)

pacman::p_load(lfe, lmtest, haven, sandwich, tidyverse)
# lfe for running fixed effects regression
# lmtest for displaying robust SE in output table
# haven for loading in dta files
# sandwich for producing robust Var-Cov matrix
# tidyverse for manipulating data and producing plots

#change into Lecture 19 directory
#setwd("/Users/sofiavillas-boas/Dropbox/EEP118_Spring2023/Lectures/Lecture19

pacman::p_load(lfe, haven, tidyverse)
```

```
In [2]: #read in a Stata dataset DATA LECTURE 19
mydata <- read_dta("Lecture19_ezunem.dta")
head(mydata)

#when did city 1 get an EZ?
```

A tibble

year	uclms	ez	d81	d82	d83	d84	d85	d86	d87	...
<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	...
1980	166746	0	0	0	0	0	0	0	0	...
1981	83561	0	1	0	0	0	0	0	0	...
1982	158146	0	0	1	0	0	0	0	0	...
1983	83572	0	0	0	1	0	0	0	0	...
1984	45949	1	0	0	0	1	0	0	0	...
1985	48848	1	0	0	0	0	1	0	0	...

City 1 got EZ=1 in 1984 onwards, so in 1984

```
In [3]: # summarize data
summary(mydata)
```

year	uclms	ez	d81
Min. :1980	Min. : 12360	Min. :0.0000	Min. :0.0000
1st Qu.:1982	1st Qu.: 43922	1st Qu.:0.0000	1st Qu.:0.0000
Median :1984	Median : 69170	Median :0.0000	Median :0.0000
Mean :1984	Mean : 95383	Mean :0.2323	Mean :0.1111
3rd Qu.:1986	3rd Qu.:114443	3rd Qu.:0.0000	3rd Qu.:0.0000
Max. :1988	Max. :667208	Max. :1.0000	Max. :1.0000

d82	d83	d84	d85
Min. :0.0000	Min. :0.0000	Min. :0.0000	Min. :0.0000
1st Qu.:0.0000	1st Qu.:0.0000	1st Qu.:0.0000	1st Qu.:0.0000
Median :0.0000	Median :0.0000	Median :0.0000	Median :0.0000
Mean :0.1111	Mean :0.1111	Mean :0.1111	Mean :0.1111
3rd Qu.:0.0000	3rd Qu.:0.0000	3rd Qu.:0.0000	3rd Qu.:0.0000
Max. :1.0000	Max. :1.0000	Max. :1.0000	Max. :1.0000

d86	d87	d88	c1
Min. :0.0000	Min. :0.0000	Min. :0.0000	Min. :0.00000
1st Qu.:0.0000	1st Qu.:0.0000	1st Qu.:0.0000	1st Qu.:0.00000
Median :0.0000	Median :0.0000	Median :0.0000	Median :0.00000
Mean :0.1111	Mean :0.1111	Mean :0.1111	Mean :0.04545
3rd Qu.:0.0000	3rd Qu.:0.0000	3rd Qu.:0.0000	3rd Qu.:0.00000
Max. :1.0000	Max. :1.0000	Max. :1.0000	Max. :1.00000

c2	c3	c4	c5
Min. :0.00000	Min. :0.00000	Min. :0.00000	Min. :0.00000
1st Qu.:0.00000	1st Qu.:0.00000	1st Qu.:0.00000	1st Qu.:0.00000
Median :0.00000	Median :0.00000	Median :0.00000	Median :0.00000
Mean :0.04545	Mean :0.04545	Mean :0.04545	Mean :0.04545
3rd Qu.:0.00000	3rd Qu.:0.00000	3rd Qu.:0.00000	3rd Qu.:0.00000
Max. :1.00000	Max. :1.00000	Max. :1.00000	Max. :1.00000

c6	c7	c8	c9
Min. :0.00000	Min. :0.00000	Min. :0.00000	Min. :0.00000
1st Qu.:0.00000	1st Qu.:0.00000	1st Qu.:0.00000	1st Qu.:0.00000
Median :0.00000	Median :0.00000	Median :0.00000	Median :0.00000
Mean :0.04545	Mean :0.04545	Mean :0.04545	Mean :0.04545
3rd Qu.:0.00000	3rd Qu.:0.00000	3rd Qu.:0.00000	3rd Qu.:0.00000
Max. :1.00000	Max. :1.00000	Max. :1.00000	Max. :1.00000

c10	c11	c12	c13
Min. :0.00000	Min. :0.00000	Min. :0.00000	Min. :0.00000
1st Qu.:0.00000	1st Qu.:0.00000	1st Qu.:0.00000	1st Qu.:0.00000
Median :0.00000	Median :0.00000	Median :0.00000	Median :0.00000
Mean :0.04545	Mean :0.04545	Mean :0.04545	Mean :0.04545
3rd Qu.:0.00000	3rd Qu.:0.00000	3rd Qu.:0.00000	3rd Qu.:0.00000
Max. :1.00000	Max. :1.00000	Max. :1.00000	Max. :1.00000

c14	c15	c16	c17
Min. :0.00000	Min. :0.00000	Min. :0.00000	Min. :0.00000
1st Qu.:0.00000	1st Qu.:0.00000	1st Qu.:0.00000	1st Qu.:0.00000
Median :0.00000	Median :0.00000	Median :0.00000	Median :0.00000
Mean :0.04545	Mean :0.04545	Mean :0.04545	Mean :0.04545
3rd Qu.:0.00000	3rd Qu.:0.00000	3rd Qu.:0.00000	3rd Qu.:0.00000
Max. :1.00000	Max. :1.00000	Max. :1.00000	Max. :1.00000

c18		c19		c20		c21	
Min.	:0.00000	Min.	:0.00000	Min.	:0.00000	Min.	:0.00000
1st Qu.	:0.00000	1st Qu.	:0.00000	1st Qu.	:0.00000	1st Qu.	:0.00000
Median	:0.00000	Median	:0.00000	Median	:0.00000	Median	:0.00000
Mean	:0.04545	Mean	:0.04545	Mean	:0.04545	Mean	:0.04545
3rd Qu.	:0.00000	3rd Qu.	:0.00000	3rd Qu.	:0.00000	3rd Qu.	:0.00000
Max.	:1.00000	Max.	:1.00000	Max.	:1.00000	Max.	:1.00000

c22		luclms		guclms		cez	
Min.	:0.00000	Min.	: 9.422	Min.	:-0.84730	Min.	:0.00000
1st Qu.	:0.00000	1st Qu.	:10.690	1st Qu.	:-0.38671	1st Qu.	:0.00000
Median	:0.00000	Median	:11.144	Median	:-0.21562	Median	:0.00000
Mean	:0.04545	Mean	:11.191	Mean	:-0.15939	Mean	:0.05682
3rd Qu.	:0.00000	3rd Qu.	:11.648	3rd Qu.	: 0.02655	3rd Qu.	:0.00000
Max.	:1.00000	Max.	:13.411	Max.	: 0.79429	Max.	:1.00000
				NA's	:22	NA's	:22

city	
Min.	: 1.0
1st Qu.	: 6.0
Median	:11.5
Mean	:11.5
3rd Qu.	:17.0
Max.	:22.0

We want to estimate the Impact of establishing Enterprise Zones (EZ) on Unemployment

The variable $uclms_{it}$ = Unemployment claims at city i and year t

The variable $EZ_{it}=0$ if no EZ and $=1$ if there is an EZ in city i at time t

$uclms$ is number of unemployment claims file during the year in a city
year 1980 to 1988

$ez = 1$ if have enterprise zone, $=0$ o.w.

$city$ a city identifier from 1 to 22

What is the number of observations? 9 years times 22 cities = 198

What is the unit of observation? -> a city in a year

What percent of observations have $EZ=1$? ---> .2323232

the average of EZ is .2323232

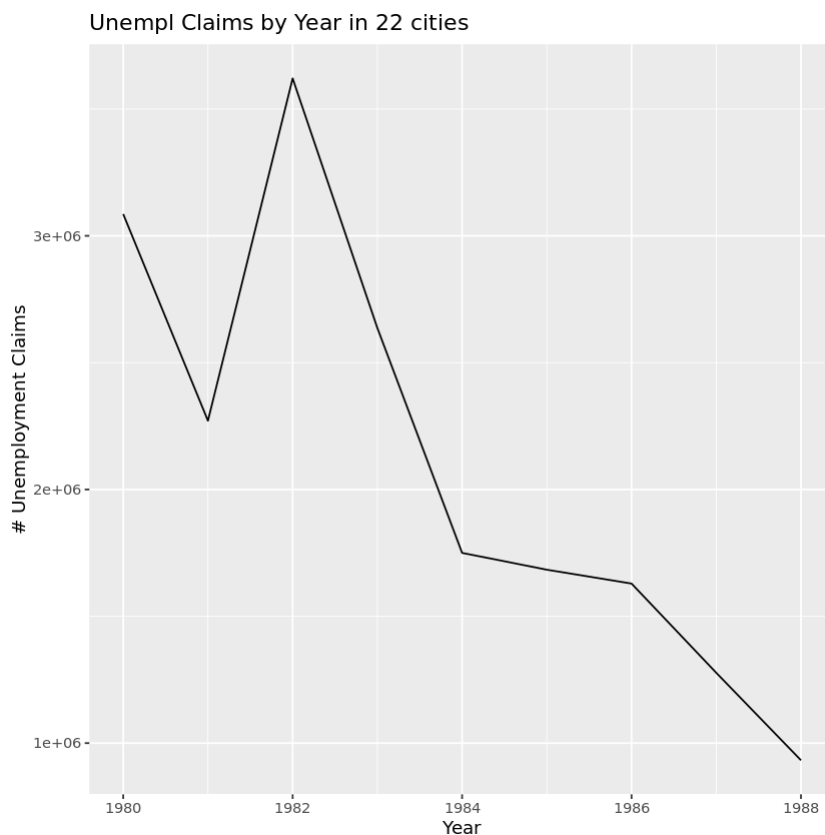
Create a graph to let us look at evolution of Total unemployment over time

```
In [4]: # first generate sum of claims by year
#The command below creates a column in the original data with sum (over all

lec19df <- mydata %>%
  group_by(year) %>%
  mutate(annual_claims = sum(uclms)) %>%
  ungroup
```

make graph of total (sum over all cities) unemployment claims by year

```
In [5]: # plot
ggplot(lec19df, aes(x = year, y = annual_claims)) +
  geom_line() +
  labs(title = "Unempl Claims by Year in 22 cities",
       x = "Year",
       y = "# Unemployment Claims")
```

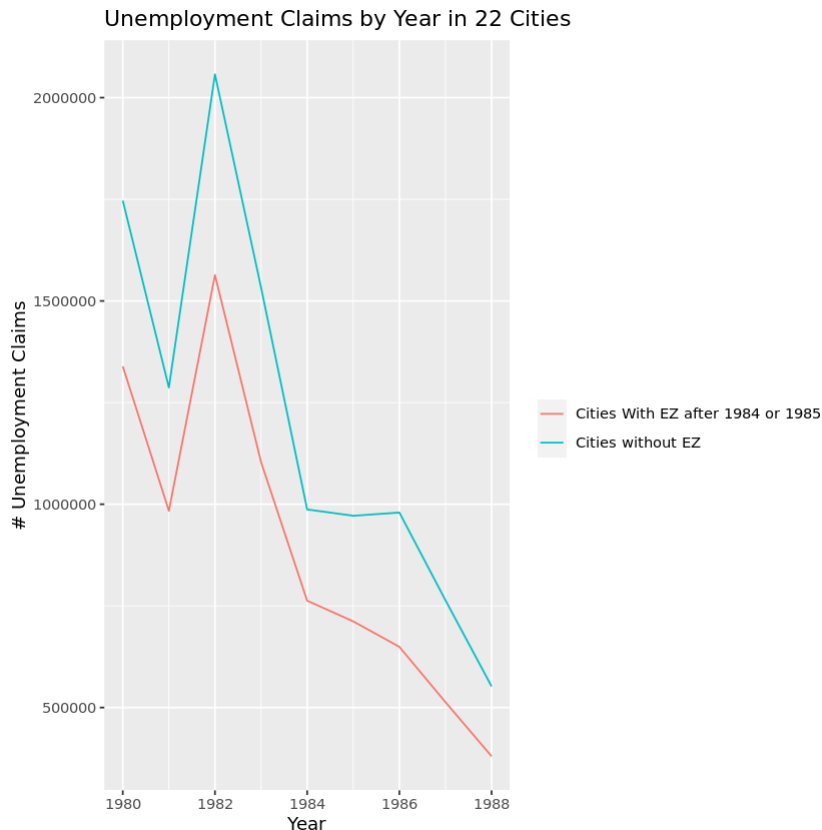


Graph Total unemployment claims (Sum of for EZ cities) and then (Sum for non EZ cities) over time

```
In [6]: # variables for graph for EZ and non EZ cities
lec19df <- mydata %>%
  group_by(city) %>%
  mutate(cityez = ifelse(max(ez)==1, "EZ", "Non-EZ")) %>%
  group_by(year, cityez) %>%
```

```
mutate(annual_claims_ez = sum(uclms)) %>%
ungroup()
```

```
In [7]: # plot for EZ and non EZ cities
ggplot(lec19df, aes(x = year, y = annual_claims_ez, group = cityez, color =
  geom_line() +
  scale_color_discrete(name="",
                        breaks=c("EZ", "Non-EZ"),
                        labels=c("Cities With EZ after 1984 or 1985", "Cities
  labs(title = "Unemployment Claims by Year in 22 Cities",
        x = "Year",
        y = "# Unemployment Claims")
```



What do you see?

1. A drop in 1982
2. B. EZ cities always had and have lower unemployment
3. The difference between red line (cities without EZ) and blue line before 1984 had nothing to do with EZ. Since EZ only happens after 1984 for some cities
4. The switches to EZ are in 1984 and in 1985
5. The path of the blue line cannot be fully attributed to EZ

The empirical question is :

Does the difference in the two lines increase or decrease when cities adopt EZs?

Regression

Lets estimate a regression model to investigate whether EZ caused an impact on unemployment

Lets consider the relationship between unemployment and EZ over time and across the 22 cities in the data using T years (T=9 here)

Model- city j year t

$$\ln(uclms)_{jt} = \beta_1 EZ_{jt} + \{a_j\} + \{dt\} + v_{jt}$$

Unemployment marginal effect: $(\partial \ln(uclms))/(\partial EZ) = \beta_1$ percent change in unemployment claims, controlling for constant factors by city and factors common to all cities by year, with city fixed effects, and also year fixed effects, respectively.

a_j captures all the characteristics of city j that are constant over time and affect unemployment -> that is, it controls for the overall level of unemployment in a city j, a city fixed effect.

dt captures overall time patterns, year by year, that is the factors changing over time, that change year by year that affect unemployment and that are common to all cities, a year fixed effect.

Short writing for one dummy for ALL BUT ONE city: a_2, a_3, \dots, a_{22} .

And one dummy for all but ONE year ($d_{81}, d_{82}, \dots, d_T$) exclude 1980

For city j in 1980 to 1983 no EZ ($EZ=0$ for all j and $t < 1984$)

$$\ln(uclms)_{j80} = \beta_0 + a_j + v_{j80} \text{ in 1980}$$

---> constant β_0 is 1980 (when all other dyears=0)

$$\ln(uclms)_{j81} = a_j + d_{81} + v_{j81} \text{ in 1981}$$

For city j at time t, notation,

$$\ln(uclms)_{jt} = \beta_0 + \beta_1 EZ_{jt} + a_j + dt + v_{jt}$$

```
In [8]: #regression in levels
reg1 <- lm(uclms ~ ez, data = lec19df)
summary(reg1)
```



```
Call:
lm(formula = uclms ~ ez, data = lec19df)
```

```
Residuals:
    Min       1Q   Median       3Q      Max
-94003 -48961 -20850  24958 560845
```

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)   106364      7066   15.052 < 2e-16 ***
ez            -47262     14661   -3.224  0.00148 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 87120 on 196 degrees of freedom
Multiple R-squared:  0.05035,    Adjusted R-squared:  0.04551
F-statistic: 10.39 on 1 and 196 DF,  p-value: 0.001482
```

```
In [9]: #regression in log unemployment
reg0 <- lm(luclms ~ ez, data = lec19df)
summary(reg0)
```

```
Call:
lm(formula = luclms ~ ez, data = lec19df)
```

```
Residuals:
    Min       1Q   Median       3Q      Max
-1.87835 -0.49217 -0.01882  0.48605  2.11029
```

```
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)   11.30057    0.05575  202.685 < 2e-16 ***
ez            -0.47257    0.11567   -4.085 6.41e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 0.6874 on 196 degrees of freedom
Multiple R-squared:  0.07847,    Adjusted R-squared:  0.07377
F-statistic: 16.69 on 1 and 196 DF,  p-value: 6.411e-05
```

We see that EZ from 0 to 1 reduced ln of log unemployment claims by -0.47

Significantly. Or reduced unclms by 47%. Significant at 1% level. p value is p-value: 6.411e-05

Fixed effects regression

And one dummy for all but ONE year (d81, d82, ...dT) exclude 1980

One dummy for ALL BUT ONE city: a2, a3, ...,a22. exclude city1

```
In [10]: #reg with fixed effects and log of unemployment claims as Y variable
reg <- lm(luclms ~ ez + factor(year) + factor(city), data = lec19df)
```

```
summary(reg)
```

Call:

```
lm(formula = luelms ~ ez + factor(year) + factor(city), data = lec19df)
```

Residuals:

Min	1Q	Median	3Q	Max
-0.57618	-0.10837	-0.00977	0.11364	0.49623

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	11.67615	0.08008	145.807	< 2e-16	***
ez	-0.10441	0.05542	-1.884	0.061291	.
factor(year)1981	-0.32163	0.06046	-5.320	3.30e-07	***
factor(year)1982	0.13550	0.06046	2.241	0.026332	*
factor(year)1983	-0.21926	0.06046	-3.627	0.000381	***
factor(year)1984	-0.57915	0.06232	-9.293	< 2e-16	***
factor(year)1985	-0.59179	0.06550	-9.036	3.92e-16	***
factor(year)1986	-0.62126	0.06550	-9.486	< 2e-16	***
factor(year)1987	-0.88895	0.06550	-13.573	< 2e-16	***
factor(year)1988	-1.22763	0.06550	-18.744	< 2e-16	***
factor(city)2	-0.19349	0.09941	-1.946	0.053292	.
factor(city)3	-0.37894	0.09941	-3.812	0.000194	***
factor(city)4	-0.54118	0.09941	-5.444	1.83e-07	***
factor(city)5	0.01103	0.09472	0.116	0.907423	
factor(city)6	0.55458	0.09452	5.867	2.32e-08	***
factor(city)7	0.75006	0.09452	7.935	2.90e-13	***
factor(city)8	-0.05876	0.09472	-0.620	0.535888	
factor(city)9	0.35342	0.09472	3.731	0.000261	***
factor(city)10	1.64501	0.09941	16.548	< 2e-16	***
factor(city)11	-0.13032	0.09941	-1.311	0.191694	
factor(city)12	-0.03498	0.09941	-0.352	0.725377	
factor(city)13	-0.83258	0.09941	-8.375	2.15e-14	***
factor(city)14	-0.87363	0.09472	-9.223	< 2e-16	***
factor(city)15	-0.23542	0.09941	-2.368	0.019020	*
factor(city)16	0.43574	0.09941	4.383	2.06e-05	***
factor(city)17	-0.44523	0.09452	-4.710	5.18e-06	***
factor(city)18	-0.04289	0.09941	-0.431	0.666677	
factor(city)19	0.09341	0.09941	0.940	0.348780	
factor(city)20	-0.35098	0.09452	-3.713	0.000279	***
factor(city)21	0.45779	0.09452	4.843	2.90e-06	***
factor(city)22	0.21864	0.09941	2.199	0.029229	*

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2005 on 167 degrees of freedom

Multiple R-squared: 0.9332, Adjusted R-squared: 0.9212

F-statistic: 77.75 on 30 and 167 DF, p-value: < 2.2e-16

EZ from 0 to 1 reduced log of unemployment claims by -0.10

Significantly. Or reduced unclms by 10%. Significant at 6% level.

what does the intercept estimate mean?

Ln uclms hat for city=1 and 1980

dummy for all but ONE year to take into account annual differences- exclude 1980

One dummy for ALL BUT ONE city exclude city1, to take into account city constant differences

If we want to control for FE but not necessarily have all the estimates printed out as output, an equivalent command is in R:

```
In [11]: #xtreg equivalent using felm
reg2 <- felm(luclms ~ ez | year + city, data = lec19df)
summary(reg2)
```

Call:

```
felm(formula = luclms ~ ez | year + city, data = lec19df)
```

Residuals:

Min	1Q	Median	3Q	Max
-0.57618	-0.10837	-0.00977	0.11364	0.49623

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
ez	-0.10441	0.05542	-1.884	0.0613

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2005 on 167 degrees of freedom

Multiple R-squared(full model): 0.9332 Adjusted R-squared: 0.9212

Multiple R-squared(proj model): 0.02081 Adjusted R-squared: -0.1551

F-statistic(full model):77.75 on 30 and 167 DF, p-value: < 2.2e-16

F-statistic(proj model): 3.55 on 1 and 167 DF, p-value: 0.06129

Make a Table

```
In [13]: #make table
#library(stargazer)
#stargazer(list(reg2), type="text",keep.stat=c("n","rsq"))

#the above work in R Studio
```

Panel Data Estimates of the Effects of Death Penalty Laws, and Executions on Murder Rates 1960-2000

Another data set now:

TODAY, as an example, “Panel Data Estimates of the Effects of Death Penalty Laws on Murder Rates 1960-2000”

Using data from FBI that I collected in March 22, 2017

To try to perform a Replication of Donohue and Wolfers (2006) analysis

```
In [14]: #open data
mydata2 <- read_dta("dataLecture19murder.dta")
head(mydata2)
# summarize data
summary(mydata2)

#with variables to use
#by number of executions

#ex10=1 if ex10>0

#active=legal*ex10

#passive=legal*(ex10==0)
```

year	state	popul	pc_mur	pc_rob	pc_assa	pc_burg	pc_larc	pc_auto	r_in
<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1930	NA	NA	NA	NA	NA	NA	NA	NA	1
1931	NA	NA	NA	NA	NA	NA	NA	NA	1
1932	NA	NA	NA	NA	NA	NA	NA	NA	1
1933	2	NA	NA	NA	NA	NA	NA	NA	1
1934	2	NA	NA	NA	NA	NA	NA	NA	1
1935	2	NA	NA	NA	NA	NA	NA	NA	1

year	state	popul	pc_mur
Min. :1930	Min. : 1	Min. : 96.0	Min. : 0.000
1st Qu.:1948	1st Qu.:13	1st Qu.: 983.5	1st Qu.: 2.900
Median :1967	Median :26	Median : 2657.0	Median : 5.400
Mean :1967	Mean :26	Mean : 3940.5	Mean : 6.958
3rd Qu.:1986	3rd Qu.:39	3rd Qu.: 4757.5	3rd Qu.: 9.400
Max. :2004	Max. :51	Max. :35484.4	Max. :80.600
	NA's :153	NA's :250	NA's :322
pc_rob	pc_assa	pc_burg	pc_larc
Min. : 0.4	Min. : 0.5	Min. : 67.8	Min. : 59.9
1st Qu.: 30.3	1st Qu.: 44.8	1st Qu.: 387.3	1st Qu.: 553.9
Median : 67.5	Median : 119.8	Median : 642.5	Median :1151.2
Mean : 101.9	Mean : 170.3	Mean : 764.5	Mean :1499.7
3rd Qu.: 126.2	3rd Qu.: 246.9	3rd Qu.:1059.9	3rd Qu.:2394.3
Max. :1635.1	Max. :1557.6	Max. :2906.7	Max. :5372.7
NA's :284	NA's :296	NA's :308	NA's :994
pc_auto	r_infd	prisoner	r_execut
Min. : 32.2	Min. : 382.1	Min. : 129	Min. : 0.0000
1st Qu.: 163.6	1st Qu.: 940.3	1st Qu.: 1262	1st Qu.: 0.0000
Median : 251.4	Median :1510.0	Median : 2952	Median : 0.0000
Mean : 311.8	Mean :1688.6	Mean : 7858	Mean : 0.3258
3rd Qu.: 403.5	3rd Qu.:2360.0	3rd Qu.: 7922	3rd Qu.: 0.0742
Max. :1839.9	Max. :5658.7	Max. :164933	Max. :12.4046
NA's :289	NA's :1136	NA's :265	NA's :365
r_death	cri_prop	cri_viol	pc_pris
Min. : 0.000	Min. : 124.2	Min. : 3.21	Min. : 20.32
1st Qu.: 2.031	1st Qu.: 565.5	1st Qu.: 93.80	1st Qu.: 78.34
Median : 3.078	Median : 925.3	Median : 203.80	Median : 112.59
Mean : 3.749	Mean :1078.1	Mean : 281.68	Mean : 161.00
3rd Qu.: 4.870	3rd Qu.:1472.0	3rd Qu.: 388.10	3rd Qu.: 184.22
Max. :32.527	Max. :4342.3	Max. :2865.70	Max. :1785.01
NA's :606	NA's :311	NA's :328	NA's :327
pcpris_1	c_pris_1	region	r_black
Min. : 20.32	Min. :0.0104	Min. :1.000	Min. :0.0000
1st Qu.: 78.34	1st Qu.:0.0740	1st Qu.:2.000	1st Qu.:0.0112
Median : 112.59	Median :0.1185	Median :3.000	Median :0.0506
Mean : 161.00	Mean :0.1357	Mean :2.667	Mean :0.0965
3rd Qu.: 184.22	3rd Qu.:0.1799	3rd Qu.:4.000	3rd Qu.:0.1429
Max. :1785.01	Max. :0.8702	Max. :4.000	Max. :0.7107
NA's :327	NA's :415	NA's :153	NA's :386
r_urban	r_15_24	r_25_44	r_45_64
Min. :0.1433	Min. :0.0177	Min. :0.2042	Min. :0.1223
1st Qu.:0.4942	1st Qu.:0.1510	1st Qu.:0.2589	1st Qu.:0.1812
Median :0.6293	Median :0.1679	Median :0.2812	Median :0.1948
Mean :0.6180	Mean :0.1662	Mean :0.2813	Mean :0.1916
3rd Qu.:0.7464	3rd Qu.:0.1815	3rd Qu.:0.3032	3rd Qu.:0.2053
Max. :1.0000	Max. :0.2340	Max. :0.3898	Max. :0.2374
NA's :357	NA's :896	NA's :386	NA's :896
r_0_14	r_0_24	r_ue	stname
Min. :0.1622	Min. :0.2716	Min. : 0.100	Length:3825
1st Qu.:0.2393	1st Qu.:0.3889	1st Qu.: 1.900	Class :character
Median :0.2725	Median :0.4272	Median : 2.800	Mode :character
Mean :0.2739	Mean :0.4280	Mean : 3.192	
3rd Qu.:0.3063	3rd Qu.:0.4635	3rd Qu.: 4.100	
Max. :0.4454	Max. :0.6441	Max. :13.900	
NA's :896	NA's :386	NA's :1053	

execs	pc_exec	execrate	execrt
Min. : 0.000	Min. : 0.00	Min. : 0.000	Min. :0.0000
1st Qu.: 0.000	1st Qu.: 0.00	1st Qu.: 0.000	1st Qu.:0.0000
Median : 0.000	Median : 0.00	Median : 0.000	Median :0.0000
Mean : 1.151	Mean : 40.09	Mean : 6.047	Mean :0.0605
3rd Qu.: 1.000	3rd Qu.: 22.38	3rd Qu.: 2.954	3rd Qu.:0.0295
Max. :40.000	Max. :1935.48	Max. :359.755	Max. :3.5976
NA's :255	NA's :301	NA's :377	NA's :377
st	klssample	fips	_merge_age
Length:3825	Min. :1	Min. : 1.00	Min. :1.000
Class :character	1st Qu.:1	1st Qu.:16.00	1st Qu.:1.000
Mode :character	Median :1	Median :29.00	Median :1.000
	Mean :1	Mean :28.96	Mean :1.164
	3rd Qu.:1	3rd Qu.:42.00	3rd Qu.:1.000
	Max. :1	Max. :56.00	Max. :3.000
	NA's :1981	NA's :3111	NA's :408
_merge_race	_merge_census2000	_merge_urban	age15to19
Min. :1.000	Min. :1.000	Min. :1.000	Min. :0.0565
1st Qu.:1.000	1st Qu.:1.000	1st Qu.:1.000	1st Qu.:0.0741
Median :1.000	Median :1.000	Median :1.000	Median :0.0841
Mean :1.298	Mean :1.015	Mean :1.029	Mean :0.0836
3rd Qu.:1.000	3rd Qu.:1.000	3rd Qu.:1.000	3rd Qu.:0.0923
Max. :3.000	Max. :2.000	Max. :3.000	Max. :0.1262
NA's :408	NA's :357	NA's :357	NA's :411
age20to24	nonwhite	_merge_DSensus	_merge_CPSunemp
Min. :0.0513	Min. :0.00000	Min. :1.000	Min. :1.00
1st Qu.:0.0701	1st Qu.:0.03620	1st Qu.:1.000	1st Qu.:1.00
Median :0.0783	Median :0.08196	Median :1.000	Median :1.00
Mean :0.0786	Mean :0.13046	Mean :1.204	Mean :1.75
3rd Qu.:0.0863	3rd Qu.:0.17886	3rd Qu.:1.000	3rd Qu.:3.00
Max. :0.1241	Max. :0.75895	Max. :3.000	Max. :3.00
NA's :411	NA's :264	NA's :357	NA's :153
_merge_ManpowerUnemp	ur	_merge_ur	population
Min. :1.000	Min. : 1.800	Min. :1.00	Min. : 226167
1st Qu.:1.000	1st Qu.: 4.300	1st Qu.:3.00	1st Qu.: 1099000
Median :1.000	Median : 5.400	Median :3.00	Median : 3096612
Mean :1.556	Mean : 5.668	Mean :2.75	Mean : 4531744
3rd Qu.:3.000	3rd Qu.: 6.700	3rd Qu.:3.00	3rd Qu.: 5387250
Max. :3.000	Max. :17.400	Max. :3.00	Max. :35484453
NA's :153	NA's :1530	NA's :153	NA's :1581
murderandnonnegligentmanslaughte	violentcrimerate	murderrate	
Min. : 1	Min. : 9.5	Min. : 0.200	
1st Qu.: 46	1st Qu.: 177.2	1st Qu.: 3.300	
Median : 180	Median : 328.1	Median : 5.850	
Mean : 348	Mean : 396.2	Mean : 7.016	
3rd Qu.: 443	3rd Qu.: 539.4	3rd Qu.: 9.300	
Max. :4096	Max. :2921.8	Max. :80.600	
NA's :1581	NA's :1581	NA's :1581	
forcibleraperate	robberyrate	aggravatedassaultrate	propertycrimerate
Min. : 0.80	Min. : 1.9	Min. : 3.6	Min. : 573.1
1st Qu.: 14.60	1st Qu.: 38.8	1st Qu.: 103.0	1st Qu.:2660.5
Median : 25.75	Median : 96.4	Median : 193.7	Median :3834.2
Mean : 27.30	Mean : 131.5	Mean : 230.4	Mean :3791.3
3rd Qu.: 37.40	3rd Qu.: 164.8	3rd Qu.: 317.9	3rd Qu.:4755.5
Max. :102.20	Max. :1635.1	Max. :1557.6	Max. :9512.1
NA's :1581	NA's :1581	NA's :1581	NA's :1581

burglaryrate	larcenythefttrate	motorvehiclethefttrate	_merge_ucr
Min. : 182.6	Min. : 293.3	Min. : 48.3	Min. : 1.000
1st Qu.: 625.1	1st Qu.: 1715.2	1st Qu.: 198.2	1st Qu.: 1.000
Median : 914.6	Median : 2508.9	Median : 328.4	Median : 3.000
Mean : 978.9	Mean : 2440.7	Mean : 371.6	Mean : 2.222
3rd Qu.: 1246.8	3rd Qu.: 3052.0	3rd Qu.: 481.4	3rd Qu.: 3.000
Max. : 2906.7	Max. : 5833.8	Max. : 1839.9	Max. : 3.000
NA's : 1581	NA's : 1581	NA's : 1581	NA's : 153
pop	murders	rpc_inc	_merge_realy
Min. : 226167	Min. : 0.0	Min. : 9.769	Min. : 3
1st Qu.: 1099000	1st Qu.: 38.0	1st Qu.: 62.327	1st Qu.: 3
Median : 3096612	Median : 158.0	Median : 95.563	Median : 3
Mean : 4531744	Mean : 297.5	Mean : 98.216	Mean : 3
3rd Qu.: 5387250	3rd Qu.: 400.0	3rd Qu.: 131.880	3rd Qu.: 3
Max. : 35484452	Max. : 4096.0	Max. : 274.235	Max. : 3
NA's : 1581	NA's : 322	NA's : 187	NA's : 153
statename	_merge_infantmortality	_merge_prisoners	c_pris
Length: 3825	Min. : 1.000	Min. : 1.000	Min. : 0.0105
Class : character	1st Qu.: 1.000	1st Qu.: 1.000	1st Qu.: 0.0727
Mode : character	Median : 1.000	Median : 1.000	Median : 0.1179
	Mean : 1.667	Mean : 1.778	Mean : 0.1351
	3rd Qu.: 3.000	3rd Qu.: 3.000	3rd Qu.: 0.1788
	Max. : 3.000	Max. : 3.000	Max. : 0.8702
	NA's : 153	NA's : 153	NA's : 415
_merge_executions	prisondeaths	_merge_prisondeaths	nfpayrolls
Min. : 1.000	Min. : 0.00	Min. : 1.000	Min. : 34.8
1st Qu.: 3.000	1st Qu.: 5.00	1st Qu.: 1.000	1st Qu.: 368.0
Median : 3.000	Median : 15.00	Median : 1.000	Median : 833.5
Mean : 2.639	Mean : 35.94	Mean : 1.694	Mean : 1537.8
3rd Qu.: 3.000	3rd Qu.: 45.00	3rd Qu.: 3.000	3rd Qu.: 1905.3
Max. : 3.000	Max. : 454.00	Max. : 3.000	Max. : 14601.9
NA's : 153	NA's : 2554	NA's : 153	NA's : 535
lnnfpayrolls	trendpayrollslambda10	empgap	_merge_nfpayrolls
Min. : 3.550	Min. : 3.591	Min. : -0.2028	Min. : 1.000
1st Qu.: 5.908	1st Qu.: 5.914	1st Qu.: -0.0117	1st Qu.: 3.000
Median : 6.726	Median : 6.721	Median : -0.0003	Median : 3.000
Mean : 6.731	Mean : 6.731	Mean : 0.0000	Mean : 2.792
3rd Qu.: 7.552	3rd Qu.: 7.552	3rd Qu.: 0.0118	3rd Qu.: 3.000
Max. : 9.589	Max. : 9.593	Max. : 0.0805	Max. : 3.000
NA's : 535	NA's : 535	NA's : 535	NA's : 153
demp	age1519	age2024	_merge_dsdemographics
Min. : -0.1237	Min. : 0.05651	Min. : 0.05128	Min. : 1.000
1st Qu.: 0.0068	1st Qu.: 0.07447	1st Qu.: 0.07037	1st Qu.: 3.000
Median : 0.0240	Median : 0.08451	Median : 0.07879	Median : 3.000
Mean : 0.0254	Mean : 0.08401	Mean : 0.07903	Mean : 2.853
3rd Qu.: 0.0413	3rd Qu.: 0.09263	3rd Qu.: 0.08675	3rd Qu.: 3.000
Max. : 0.3995	Max. : 0.13111	Max. : 0.12411	Max. : 3.000
NA's : 586	NA's : 264	NA's : 264	
police	_merge_statepolice	ipolice	legal
Min. : 71	Min. : 1.000	Min. : 71	Min. : 0.000
1st Qu.: 474	1st Qu.: 1.000	1st Qu.: 446	1st Qu.: 1.000
Median : 946	Median : 3.000	Median : 884	Median : 1.000
Mean : 1442	Mean : 2.093	Mean : 1378	Mean : 0.755
3rd Qu.: 1723	3rd Qu.: 3.000	3rd Qu.: 1659	3rd Qu.: 1.000
Max. : 10626	Max. : 3.000	Max. : 10626	Max. : 1.000
NA's : 2016		NA's : 1816	

decade	statdec	regyear	stid	sample_ds
Min. :193.0	Min. : 1.0	Min. : 1.0	Min. : 1	Min. :1
1st Qu.:194.0	1st Qu.:102.0	1st Qu.: 95.0	1st Qu.:13	1st Qu.:1
Median :196.0	Median :204.0	Median :164.0	Median :26	Median :1
Mean :196.3	Mean :204.3	Mean :156.5	Mean :26	Mean :1
3rd Qu.:198.0	3rd Qu.:306.0	3rd Qu.:218.0	3rd Qu.:39	3rd Qu.:1
Max. :200.0	Max. :408.0	Max. :288.0	Max. :51	Max. :1
		NA's :153		NA's :1816

sample_kls	decade_ds	ex10	active
Min. :1	Min. :1930	Min. :0.0000	Min. :0.0000
1st Qu.:1	1st Qu.:1940	1st Qu.:0.0000	1st Qu.:0.0000
Median :1	Median :1960	Median :1.0000	Median :1.0000
Mean :1	Mean :1963	Mean :0.5948	Mean :0.5464
3rd Qu.:1	3rd Qu.:1980	3rd Qu.:1.0000	3rd Qu.:1.0000
Max. :1	Max. :2000	Max. :1.0000	Max. :1.0000
NA's :1917			

passive

Min. :0.0000
1st Qu.:0.0000
Median :0.0000
Mean :0.2086
3rd Qu.:0.0000
Max. :1.0000

Run regressions and Make table of results

```
In [15]: # death penalty and murders
REG1<-lm(pc_mur~legal,mydata2)
REG2<-felm(pc_mur~legal| state+year+decade_ds, data=mydata2)
REG3<-felm(pc_mur~legal+rpc_inc+ ur+ ipolice+ nonwhite +age15to19 +age20to24
REG4<-felm(pc_mur~active+ passive| state+year+decade_ds, data=mydata2)
REG5<-felm(pc_mur~active+ passive+rpc_inc+ ur+ ipolice+ nonwhite +age15to19

In [19]: #make table
#stargazer(list(REG1,REG2,REG3, REG4, REG5), type="text",keep.stat=c("n","rs
```


Dependent variable:					
	OLS		pc_mur		
	(1)	(2)	(3)	(4)	(5)
legal	0.903*** (0.249)	-1.945*** (0.258)	-0.100 (0.143)		
rpc_inc			0.018*** (0.005)		0.016*** (0.005)
ur			-0.099*** (0.032)		-0.106*** (0.032)
ipolice			-0.00001 (0.0001)		-0.00000 (0.0001)
nonwhite			9.989*** (1.835)		9.410*** (1.827)
age15to19			62.965*** (13.681)		66.959*** (13.613)
age20to24			41.779*** (8.088)		44.250*** (8.049)
active				-2.186*** (0.289)	-0.527*** (0.165)
passive				-1.815*** (0.268)	0.028 (0.144)
Constant	6.286*** (0.214)				
Observations	3,503	3,503	2,009	3,503	2,009
R2	0.004	0.738	0.866	0.738	0.868

Note:

*p<0.1; **p<0.05; ***p<0.01

Active=1 if legal and there are executions, passive =1 if legal but no executions

What do you conclude?

Placebos

```
In [20]: #placebo on other murders
PREG1<-felm(pc_mur~active+ passive+rpc_inc+ ur+ ipolice+ nonwhite +age15to19
PREG2<-felm(violentcrimerate~active+ passive+rpc_inc+ ur+ ipolice+ nonwhite
PREG3<-felm(pc_rob~active+ passive+rpc_inc+ ur+ ipolice+ nonwhite +age15to19
PREG4<-felm(pc_larc~active+ passive+rpc_inc+ ur+ ipolice+ nonwhite +age15to19
```

```
PREG5<-felm(pc_burg~active+ passive+rpc_inc+ ur+ ipolice+ nonwhite +age15to1
PREG6<-felm(pc_auto~active+ passive+rpc_inc+ ur+ ipolice+ nonwhite +age15to1

#make table
stargazer(list(PREG1,PREG2,PREG3, PREG4, PREG5, PREG6), type="text",keep.sta
```

Dependent variable:					
rg	pc_mur pc_auto	violentcrimerate	pc_rob	pc_larc	pc_bu
(6)	(1)	(2)	(3)	(4)	(5)
active	-0.527***	18.579*	-1.501	205.816***	-17.9
76	47.203***				
	(0.165)	(10.098)	(4.570)	(39.999)	(18.65
8)	(10.940)				
passive	0.028	11.167	-3.272	99.714***	-2.86
0	11.022				
	(0.144)	(8.854)	(4.007)	(34.761)	(16.35
8)	(9.592)				
rpc_inc	0.016***	0.874***	0.703***	6.990***	0.06
3	0.907***				
	(0.005)	(0.313)	(0.142)	(1.474)	(0.57
8)	(0.339)				
ur	-0.106***	2.944	2.306***	71.184***	39.580
***	5.974***				
	(0.032)	(1.952)	(0.883)	(7.905)	(3.60
6)	(2.114)				
ipolice	-0.00000	0.059***	0.029***	-0.008	0.031*
**	0.050***				
	(0.0001)	(0.005)	(0.002)	(0.028)	(0.00
9)	(0.005)				
nonwhite	9.410***	-3.595	-93.149*	4,276.654***	-3,558.6
61***	-133.465				
	(1.827)	(111.964)	(50.674)	(784.116)	(206.8
67)	(121.299)				
age15to19	66.959***	2,460.854***	2,116.539***	9,794.005**	3,940.5
29**	3,422.675***				
	(13.613)	(834.453)	(377.662)	(3,945.919)	(1,541.
748)	(904.023)				
age20to24	44.250***	-1,911.505***	-157.160	-10,137.260***	-552.8
86	3,065.014***				
	(8.049)	(493.377)	(223.295)	(2,339.760)	(911.5
69)	(534.510)				
Observations	2,009	2,009	2,009	1,519	2,00
9	2,009				
R2	0.868	0.882	0.857	0.944	0.87

=====

Note:

*p<0.05; ***p<0.01

*p<0.1; *

Even more convincing, show that active legal death penalty has deterrence on murder but not on other crimes (e.g., auto theft)

Upcoming Lectures

Learn methods to approach a policy impact analysis like the soda tax

<https://news.berkeley.edu/2019/04/02/berkeley-soda-tax-election-changed-drinking-habits-months-before-prices-went-up/?fbclid=IwAR0NeswpSOdW82qoLZas348ZJpxyQLJ5oF3ZBI0j2pyrG3OIk3rvOKK1v5g>

Correlation is not causation , check these crazy spurious correlations:

<http://www.tylervigen.com/spurious-correlations>