Impact Evaluation

AECN 396/896-002

Impact (Program) Evaluation

Definition

Impact (program) evaluation is a field of econometrics that focuses on estimating the impact of a program or event.

Examples

- Groundwater use limit in Nebraska ⇒ water use
- Technology adoption (soil moisture sensor) \Rightarrow water use
- Crop insurance ⇒ input use
- Job training program ⇒ productivty
- Food Stamp \Rightarrow health, education, etc

Key challenge

Most of the programs you are interested in are not randomized.



Selection Bias (endogeneity problem arising from self-selection into the program)

Gold Standard

- The best (if feasible) way to tackle the problem of selection bias in impact evaluation is randomized experiment, where who gets treated or not is determined randomly (you design a program or experiment and randomize treatment-control assignment)
- This ensures that the treatment status (dummy variable indicating treated or not) is not correlated with the error term

Example

 $y \text{ (income)} = \beta_0 + \beta_1 program \text{ (financial aid)} + u$

, where E[u|program]=0 (the program is not correlated with the error term). OLS is just fine.

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Example

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, where E[u|program]=0 (the program is not correlated with the error term). OLS is just fine.

Problem

Many of the programs are simply not possible to randomize because of financial and/or ethical reasons.



We need to use data from an event that happened outside our control.

Natural (Quasi) Experiment

Definition

An event or policy change (often a change in government policy) that happens outside of the control of investigators, which changes the environment in which agents (individuals, families, firms, or cities) operate.

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Challenges

The program is most likely correlated with the error term.

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Challenges

The program is most likely correlated with the error term.

Lecture Objectives

- Discuss different ways of estimating the impact of a program
- Understand the strength and weakness of these methods

Example program

Incinerator Construction

- rumored about the incinerator being built in North Andover, Massachusetts, began in 1978
- construction started in 1981

Data collected

Housing prices in 1978 and 1981, and other variables (we observations before and after the incinerator construction)

Various Approaches

- Approach 1: cross-sectional comparison of houses that are close to (treated) and far away from (control) to the incinerator after the incinerator was built (data in 1981)
- Approach 2: comparison of the houses that are close to the incinerator before (control) and after (treated) the incinerator was built (data in 1978 and 1981)
- Approach 3: comparison of differences (close by v.s. far away) in differences (before-after) of house prices (this method will become clearer later)

Approach 1

Run regression on the following model using the 1981 data (cross-sectional data)

$$rpice = \gamma_0 + \gamma_1 nearinc + u$$

- rprice: house price in real terms (inflation-corrected)
- *nearinc*: 1 if the house is near the incinerator, and 0 otherwise
- γ_1 : the difference between the mean house price of houses nearby the incinerator and the rest (not nearby) in 1981

Question

Is nearinc endogenous?

	Model 1
(Intercept)	101.308
	(3.093)
nearinc	-30.688
	(5.828)
Num.Obs.	142
R2	0.165
Std.Errors	IID
+ p < 0.1, p < 0.05, p < 0.01 , p < 0.001	

Question Is this reliable?

Take a look at 1978

Run regression on the following model using the 1978 data (cross-sectional data)

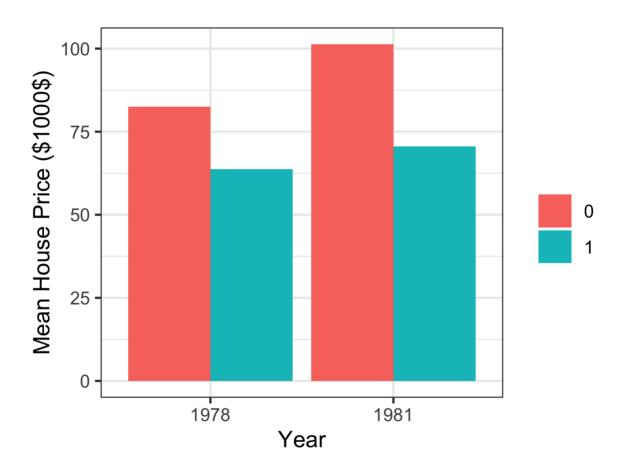
$$rpice = \gamma_0 + \gamma_1 nearinc + u$$

 γ_1 represents the difference between the mean house price of houses nearby the incinerator and the rest (not nearby) before the incinerator was built.

	Model 1
(Intercept)	82.517
	(2.654)
nearinc	-18.824
	(4.745)
Num.Obs.	179
R2	0.082
Std.Errors	IID
+ p < 0.1, <i>p</i> < 0.05, p < 0.01 , p < 0.001	

Critical

Houses nearby the incinerator were already lower than those houses that are not nearby...



treated	before	after
nearinc = 0	γ_0	γ_0+lpha_0+0
nearinc = 1	γ_1	$\gamma_1 + lpha_1 + eta$

- ullet γ_j is the average house price of those that are nearinc=j in 1978 (before)
- α_j is any macro shocks other than the incinerator event that happened between the before and after period to the houses that are nearinc=j
- ullet eta is the true causal impact of the incinerator placement

treated	before	after
nearinc = 0	γ_0	$\gamma_0 + lpha_0 + 0$
nearinc = 1	γ_1	$\gamma_1 + lpha_1 + eta$

- ullet γ_j is the average house price of those that are nearinc=j in 1978 (before)
- α_j is any macro shocks other than the incinerator event that happened between the before and after period to the houses that are nearinc = j
- ullet eta is the true causal impact of the incinerator placement

So, what did we estimate with Approach 1?

treated	before	after
nearinc = 0	γ_0	γ_0+lpha_0+0
nearinc = 1	γ_1	$\gamma_1 + \alpha_1 + \beta$

- ullet γ_j is the average house price of those that are nearinc=j in 1978 (before)
- α_j is any macro shocks other than the incinerator event that happened between the before and after period to the houses that are nearinc = j
- β is the true causal impact of the incinerator placement

So, what did we estimate with Approach 1?

$$egin{aligned} E[rprice|nearinc=1, year=1981] - E[rprice|nearinc=0, year=1981] \ &= (\gamma_1+lpha_1+eta) - (\gamma_0+lpha_0+0) \ &= (\gamma_1-\gamma_0) + (lpha_1-lpha_0) + eta \end{aligned}$$

treated	before	after
nearinc = 0	γ_0	$\gamma_0+\alpha_0+0$
nearinc = 1	γ_1	$\gamma_1 + lpha_1 + eta$

- γ_i is the average house price of those that are nearinc = j in 1978 (before)
- α_j is any macro shocks other than the incinerator event that happened between the before and after period to the houses that are nearinc=j
- β is the true causal impact of the incinerator placement

So, what did we estimate with Approach 1?

$$E[rprice|nearinc=1, year=1981] - E[rprice|nearinc=0, year=1981]$$

$$= (\gamma_1 + \alpha_1 + \beta) - (\gamma_0 + \alpha_0 + 0)$$

$$= (\gamma_1 - \gamma_0) + (\alpha_1 - \alpha_0) + \beta$$

- $\gamma_1-\gamma_0$: pre-existing differences in house price before the incinerator was built
- $\alpha_1 \alpha_0$: differences in the trends in housing price between the two groups

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- $\alpha_1 \alpha_0$: differences in the trends in housing price between the two groups

So, when Approach 1 gives us unbiased estimation of the impact of the incinerator?

- ullet $\gamma_1=\gamma_0$: the average house price between the two groups are the same before the incinerator was built
- $\alpha_1 \alpha_0$: the two groups experienced the same house price trend from 1978 to 1981

Approach 2

Compare of the houses that are close to the incinerator before (control) and after (treated) the incinerator was built (data in 1978 and 1981)

Data

Restrict the data to the houses that are near the incinerator

Model

$$rpice = \beta_0 + \beta_1 y 81 + u$$

- *rprice*: house price in real terms (inflation-corrected)
- y81: 1 if the house is near the incinerator, and 0 otherwise
- β_1 : the difference in the mean house price of houses nearby the incinerator before and after the incinerator was built

	Model 1
(Intercept)	63.693
	(5.296)
y81	6.926
	(8.205)
Num.Obs.	96
R2	0.008
Std.Errors	IID
+ p < 0.1, p < 0.05, p < 0.01, * p < 0.001	

The incinerator increased the average house price (not statistically significant).

treated	before	after
nearinc = 0	γ_0	γ_0+lpha_0+0
nearinc = 1	γ_1	$\gamma_1 + lpha_1 + eta$

- ullet γ_j is the average house price of those that are nearinc=j in 1978 (before)
- α_j is any macro shocks other than the incinerator event that happened between the before and after period to the houses that are nearinc=j
- ullet eta is the true causal impact of the incinerator placement

So, what did we estimate with Approach 2?

treated	before	after
nearinc = 0	γ_0	$\gamma_0+\alpha_0+0$
nearinc = 1	γ_1	$\gamma_1 + lpha_1 + eta$

- γ_{j} is the average house price of those that are nearinc=j in 1978 (before)
- α_j is any macro shocks other than the incinerator event that happened between the before and after period to the houses that are nearinc = j
- β is the true causal impact of the incinerator placement

So, what did we estimate with Approach 2?

$$E[rprice|nearinc=1, year=1981] - E[rprice|nearinc=1, year=1978] \ = (\gamma_1 + lpha_1 + eta) - \gamma_1$$

$$= \alpha_1 + \beta$$

 $egin{aligned} E[rprice|nearinc=1, year=1981] - E[rprice|nearinc=1, year=1978] \ &= (\gamma_1 + lpha_1 + eta) - \gamma_1 \ &= lpha_1 + eta \end{aligned}$

$$egin{aligned} E[rprice|nearinc=1, year=1981] - E[rprice|nearinc=1, year=1978] \ &= (\gamma_1 + lpha_1 + eta) - \gamma_1 \ &= lpha_1 + eta \end{aligned}$$

So, when Approach 2 gives us unbiased estimation of the impact of the incinerator?

 $egin{aligned} E[rprice|nearinc=1, year=1981] - E[rprice|nearinc=1, year=1978] \ &= (\gamma_1 + lpha_1 + eta) - \gamma_1 \ &= lpha_1 + eta \end{aligned}$

Question

So, when Approach 2 gives us unbiased estimation of the impact of the incinerator?

Answer

 $lpha_1=0$: no trend in house price for the houses near the incinerator

Nothing else significant other than the incinerator happened between 1978 and 1981.

Approach 3

Compare of differences (close by v.s. far away) in differences (before-after) of house prices (this method will become clearer later)

- Find the difference in the price of the houses close to the incinerator before and after the incinerator was built
- Find the difference in house price (close to the incinerator) before and after the incinerator was built
- Find the difference in the differences

Note

This method is called DID estimation method (Difference-in- differences).

Data

All the observations

Model

 $rpice = eta_0 + eta_1 y 81 + eta_2 nearinc + eta_3 nearinc imes y 81 + u$

• β_3 : the difference in differences

Data

All the observations

Model

 $rpice = eta_0 + eta_1 y 81 + eta_2 nearinc + eta_3 nearinc imes y 81 + u$

• β_3 : the difference in differences

Let's confirm eta_3 indeed represents the difference in the differences.

 $rpice = eta_0 + eta_1 y 81 + eta_2 nearinc + eta_3 nearinc imes y 81 + u$

$$rpice = \beta_0 + \beta_1 y 81 + \beta_2 nearinc + \beta_3 nearinc \times y 81 + u$$

Expected house price

- $E[rprice|year = 1981, nearinc = 0] = \beta_0 + \beta_1$
- $E[rprice|year=1981,nearinc=1]=eta_0+eta_1+eta_2+eta_3$
- $E[rprice|year = 1978, nearinc = 0] = \beta_0$
- $E[rprice|year = 1978, nearinc = 1] = \beta_0 + \beta_2$

$$rpice = eta_0 + eta_1 y 81 + eta_2 nearinc + eta_3 nearinc imes y 81 + u$$

Expected house price

- $E[rprice|year = 1981, nearinc = 0] = \beta_0 + \beta_1$
- $E[rprice|year = 1981, nearinc = 1] = \beta_0 + \beta_1 + \beta_2 + \beta_3$
- $E[rprice|year = 1978, nearinc = 0] = \beta_0$
- $E[rprice|year = 1978, nearinc = 1] = \beta_0 + \beta_2$

Differences

$$E[rprice|year=1981,nearinc=1]-E[rprice|year=1978,nearinc=1]$$

$$= (\beta_0 + \beta_1 + \beta_2 + \beta_3) - (\beta_0 + \beta_2) = \beta_1 + \beta_3$$

$$E[rprice|year=1981,nearinc=0]-E[rprice|year=1978,nearinc=0]$$

$$= (\beta_0 + \beta_1) - \beta_0 = \beta_1$$

$$rpice = eta_0 + eta_1 y 81 + eta_2 nearinc + eta_3 nearinc imes y 81 + u$$

Expected house price

- $E[rprice|year = 1981, nearinc = 0] = \beta_0 + \beta_1$
- $E[rprice|year = 1981, nearinc = 1] = \beta_0 + \beta_1 + \beta_2 + \beta_3$
- $E[rprice|year = 1978, nearinc = 0] = \beta_0$
- $E[rprice|year = 1978, nearinc = 1] = \beta_0 + \beta_2$

Differences

$$E[rprice|year=1981, nearinc=1] - E[rprice|year=1978, nearinc=1]$$

$$= (\beta_0 + \beta_1 + \beta_2 + \beta_3) - (\beta_0 + \beta_2) = \beta_1 + \beta_3$$

$$E[rprice|year=1981, nearinc=0] - E[rprice|year=1978, nearinc=0]$$

$$= (\beta_0 + \beta_1) - \beta_0 = \beta_1$$

Difference in the differences

$$(\beta_1+\beta_3)-\beta_1=\beta_3$$

	Model 1
(Intercept)	82.517
	(2.727)
nearinc	-18.824
	(4.875)
y81	18.790
	(4.050)
nearinc × y81	-11.864
	(7.457)
Num.Obs.	321
R2	0.174
Std.Errors	IID
+ p < 0.1, p < 0.05, p < 0.01, * p < 0.001	

The incinerator decreased the average house price (not statistically significant).

treated	before	after
nearinc = 0	γ_0	γ_0+lpha_0+0
nearinc = 1	γ_1	$\gamma_1 + lpha_1 + eta$

Question

So, what did we estimate with Approach 3?

treated	before	after
nearinc = 0	γ_0	$\gamma_0 + lpha_0 + 0$
nearinc = 1	γ_1	$\gamma_1 + lpha_1 + eta$

Question

So, what did we estimate with Approach 3?

Answer

$$egin{aligned} E[rprice|nearinc=1, year=1981] - E[rprice|nearinc=1, year=1978] \ &= (\gamma_1 + lpha_1 + eta) - \gamma_1 = lpha_1 + eta \ &= E[rprice|nearinc=0, year=1981] - E[rprice|nearinc=0, year=1978] \end{aligned}$$

$$= (\gamma_0 + \alpha_0) - \gamma_0 = \alpha_0$$

treated	before	after
nearinc = 0	γ_0	$\gamma_0 + lpha_0 + 0$
nearinc = 1	γ_1	$\gamma_1 + lpha_1 + eta$

Question

So, what did we estimate with Approach 3?

Answer

$$E[rprice|nearinc=1, year=1981] - E[rprice|nearinc=1, year=1978]$$

$$= (\gamma_1 + \alpha_1 + \beta) - \gamma_1 = \alpha_1 + \beta$$

$$E[rprice|nearinc=0, year=1981] - E[rprice|nearinc=0, year=1978]$$

$$= (\gamma_0 + \alpha_0) - \gamma_0 = \alpha_0$$

$$\mathsf{Differences} = \alpha_1 - \alpha_0 + \beta$$

Difference

 $\mathsf{Difference} = \alpha_1 - \alpha_0 + \beta$

Question

So, when Approach 3 gives us unbiased estimation of the impact of the incinerator?

Difference

 $\mathsf{Difference} = \alpha_1 - \alpha_0 + \beta$

Question

So, when Approach 3 gives us unbiased estimation of the impact of the incinerator?

Answer

- $\alpha_1=\alpha_0$: the two groups experienced the same trend in house price from 1978 to 1981
- Unlike Approach 1, the pre-existing difference between the two group is not a problem as it is canceled out

Key condition (common/parallel trend assumption)

 $lpha_1=lpha_0$: the two groups experienced the same trend in house price from 1978 to 1981

Common/parallel trend assumption in general

If no treatment had occurred, the difference between the treated group and the untreated group would have stayed the same in the post-treatment period as it was in the pre-treatment period.

Important

This condition/assumption is NOT testable because you never observe what would the treament group be like if it were not for the treatment (we will discuss this further)

Approach 1: $(\gamma_1-\gamma_0)+(lpha_1-lpha_0)+eta$

Approach 2: $lpha_1+eta$

Approach 3: $lpha_1 - lpha_0 + eta$

Approach 1: $(\gamma_1-\gamma_0)+(lpha_1-lpha_0)+eta$

Approach 2: $lpha_1+eta$

Approach 3: $lpha_1 - lpha_0 + eta$

Approach 1: $(\gamma_1-\gamma_0)+(lpha_1-lpha_0)+eta$

Approach 2: $lpha_1+eta$

Approach 3: $lpha_1 - lpha_0 + eta$

Important

• None of these approaches are perfect.

Approach 1: $(\gamma_1-\gamma_0)+(lpha_1-lpha_0)+eta$

Approach 2: $\alpha_1 + \beta$

Approach 3: $lpha_1 - lpha_0 + eta$

- None of these approaches are perfect.
- It is hard to sell Approaches 1 and 2

Approach 1: $(\gamma_1 - \gamma_0) + (lpha_1 - lpha_0) + eta$

Approach 2: $lpha_1+eta$

Approach 3: $lpha_1 - lpha_0 + eta$

- None of these approaches are perfect.
- It is hard to sell Approaches 1 and 2
- Approach 3 (DID) is preferred over Approaches 1 and 2

Approach 1: $(\gamma_1 - \gamma_0) + (\alpha_1 - \alpha_0) + eta$

Approach 2: $\alpha_1 + \beta$

Approach 3: $lpha_1 - lpha_0 + eta$

- None of these approaches are perfect.
- It is hard to sell Approaches 1 and 2
- Approach 3 (DID) is preferred over Approaches 1 and 2
- But, Approach 3 is not certainly perfect and could definitely have a larger bias than Approaches 1 and 2

e.g.,
$$lpha_1=5$$
 and $lpha_0=-5$

DID: Another Example

Cholera

- Back in mid 1800s', Cholera was believed to spread via air
- John Snow believe it was actually through fecally-contaminated water

Setting

- London's water needs were served by a number of competing companies, who got their water intake from different parts of the Thames river.
- Water taken in from the parts of the Thames that were downstream of London contained everything that Londoners dumped in the river, including plenty of fecal matter from people infected with cholera.

Natural Experiment

• Between those two periods of 1849 and 1854, a policy was enacted: the Lambeth Company was required by an Act of Parliament to move their water intake upstream of London.

Treatment

• Switch of where water is taken (downstream to upstream)

Before and After

- "before" (1849): Lambeth took water downstream
- "after" (1854): Lambeth took water upstream

Control and Treatment Groups

- Control group: those who were not served by Lambeth
- Treatment group: those who were served by Lambeth

Data

Supplier	1849	1854
Non-Lambeth only	134.9	130.1
Lambeth + Others	146.6	84.9

DID estimate

Estimate treatment effect is:

DID using R

Well-levle groundwater use data in Kansas

```
(
  lema_data <- readRDS("LEMA_data.rds")
)</pre>
```

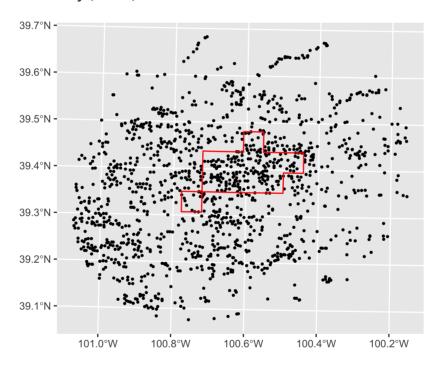
```
site year
                        af used in LEMA
                                                               awc bulkdensity
##
                                            pr
                                                     et0
                                      1 401.9 1047.3311 0.1859333
                                                                      1.359156
##
       1:
            160 1991 195.328540
           160 1992 62.390479
##
       2:
                                      1 463.9 904.0815 0.1859333
                                                                      1.359156
           160 1993
                      40.214699
                                      1 615.6 842.7572 0.1859333
                                                                      1.359156
       4:
            160 1994 155,113840
                                      1 405.5 1028.4635 0.1859333
                                                                      1.359156
       5:
            160 1995 103.093132
                                      1 488.5 890.5116 0.1859333
                                                                      1.359156
  34121: 82261 2019
                       5.277566
                                      0 598.4 961.0884 0.2078054
                                                                      1.383747
  34122: 82288 2018
                       0.007672
                                      0 425.7 1069.7815 0.1823573
                                                                      1.269078
  34123: 82538 2017 195.000000
                                      0 563.2 1027.4662 0.2063358
                                                                      1.287400
## 34124: 82538 2018 158,000000
                                      0 554.7 1092.2203 0.2063358
                                                                      1,287400
## 34125: 82538 2019 136.000000
                                      0 544.8 1011.2639 0.2063358
                                                                      1.287400
```

Main variables

- site: well
- af_used: groundwater used (dependent variable)
- in_LEMA: whether located inside the LEMA region or not
- year: year

Control and Treatment Units

- (to be) treated: wells inside the red boundary (LEMA)
- control: wells outside the red boundary (LEMA)



Before and After

Effective 2013, wells located inside the LEMA can pump groundwater up to a certian amount

• before: ~ 2012

• after: 2013 ~

Data transformation:

before or after

```
lema_data <- mutate(lema_data, before_after = ifelse(year >= 2013, 1, 0))
filter(lema_data, site == 160, year > 2000)
```

```
af used in LEMA
                                                           awc bulkdensity before after
##
       site year
                                                 et0
    1:
       160 2001 145,25044
                                  1 446.5 1015.4708 0.1859333
                                                                   1.359156
    2:
        160 2002 209,93951
                                  1 197.7 1183.5617 0.1859333
                                                                   1.359156
    3:
        160 2003 195.41140
                                  1 312.2 1043.3746 0.1859333
                                                                   1.359156
    4:
        160 2004
                 17.03601
                                  1 414.5 1021.2781 0.1859333
                                                                   1.359156
    5:
        160 2005 166,66206
                                  1 434.0 1072.1092 0.1859333
                                                                   1.359156
    6:
        160 2006 201.07350
                                  1 319.4 1101.8365 0.1859333
                                                                   1.359156
    7:
        160 2007 169.46396
                                  1 365.8
                                           999.9798 0.1859333
                                                                   1.359156
##
    8:
        160 2008 117.59547
                                  1 430.4 1017.9937 0.1859333
                                                                   1.359156
    9:
        160 2009
                  85.44304
                                           913.9900 0.1859333
                                                                   1.359156
                                  1 390.0 1116.1719 0.1859333
                                                                  1.359156
  10:
        160 2010 174.59790
  11:
        160 2011 138,41817
                                  1 426.5 1231.1252 0.1859333
                                                                   1.359156
  12:
        160 2012 208.88136
                                  1 245.3 1376.4707 0.1859333
                                                                   1.359156
## 13:
        160 2013 144.59185
                                  1 325.8 1156.5505 0.1859333
                                                                   1.359156
  14:
        160 2014
                  87.94449
                                  1 428.5 1074.7903 0.1859333
                                                                   1.359156
                                                                  1.359156
## 15:
        160 2015
                  90.21000
                                  1 458.1 1045.0393 0.1859333
                                                                                        1
## 16:
        160 2016 102.01000
                                  1 532.2 1028.5500 0.1859333
                                                                   1.359156
## 17:
        160 2017
                  30.75000
                                  1 577.0 1021.9370 0.1859333
                                                                   1.359156
## 18:
        160 2019
                  65.07085
                                  1 663.4 989.8929 0.1859333
                                                                   1.359156
```

(to be) treated or not

Whether wells are (to be) treated or not is already there in this dataset, represented by in_LEMA

DID estimating equation (in general)

$$y_{i,t} = \alpha_0 + \beta_1 before_after_t + \beta_2 treated_or_not_i + \beta_3 before_after_t \times treated_or_not_i + X_{i,t}\gamma + v_{i,t}$$

The variable of interest is β_3 , which measures the impact of the treatment.

R code

```
did_res <- feols(
  af_used ~ before_after + in_LEMA + I(before_after * in_LEMA) + pr + et0,
  cluster = ~site,
  data = lema_data
)</pre>
```

	Model 1
(Intercept)	185.829
	(7.153)
before_after	-9.035
	(1.034)
in_LEMA	30.002
	(3.225)
I(before_after in_LEMA)	-34.762*
	(2.097)
pr	-0.188*
	(0.005)
et0	0.014
	(0.005)
Num.Obs.	34125
R2	0.108
Std.Errors	by: site
+ n < 0.1 n < 0.05 n < 0.01 n < 0.001	

⁺ p < 0.1, *p* < 0.05, **p < 0.01**, p < 0.001

Note: individual fixed effects

DID does not require panel data. Two periods of cross-setional data are sufficient. But, if you have panel data, you can certainly include individual fixed effects, which would certainly help to control for time-invariant characteristics (both observed and unobserved)

```
did res ife <- feols(</pre>
  af used ~ before after + in LEMA + I(before after * in LEMA) + pr + et0 | site,
  cluster = ~site,
  data = lema_data
```

Notice that in_LEMA was dropped due to perfect collinearity (this is not a problem). in_LEMA is effectively controlled for by including individual fixed effects.

	Model 1
before_after	-8.748
	(0.838)
I(before_after in_LEMA)	-36.551*
	(1.961)
pr	-0.185
	(0.004)
et0	0.019
	(0.004)
Num.Obs.	34125
R2	0.667
Std.Errors	by: site
+ p < 0.1, <i>p</i> < 0.05, p < 0.01 , p < 0.001	

Note: year fixed effects

If you have multiple years of observations in the before and after periods, you can (and should) include year fixed effects.

```
did_res_yfe <- feols(
  af_used ~ before_after + in_LEMA + I(before_after * in_LEMA) + pr + et0 | site + year,
  cluster = ~site,
  data = lema_data
)</pre>
```

Notice that before_after was dropped due to perfect collinearity (this is not a problem). before_after is effectively controlled for by including year fixed effects. Indeed, year fixed effects provide a tighter controls on annual macro shocks.

	Model 1
I(before_after in_LEMA)	-37.150**
	(1.962)
pr	-0.115
	(800.0)
et0	0.053+
	(0.031)
Num.Obs.	34125
R2	0.711
Std.Errors	by: site
0 1 0 0 5 0 0 1 0 001	

⁺ p < 0.1, p < 0.05, p < 0.01, * p < 0.001

How to argue your DID is good

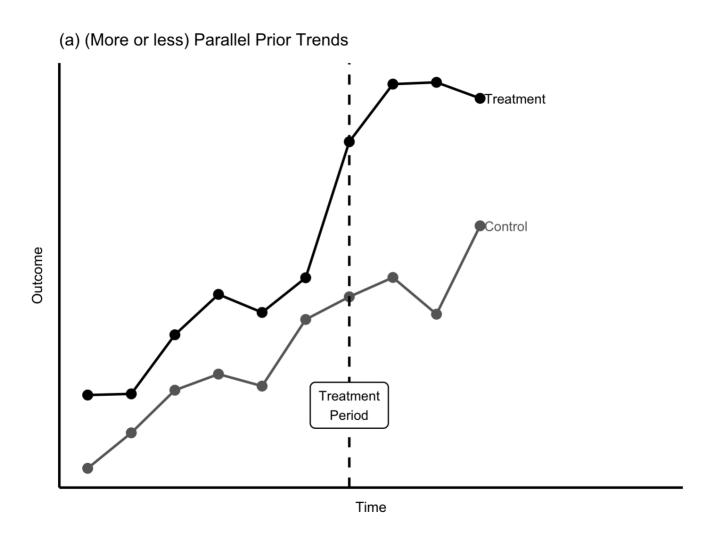
Important

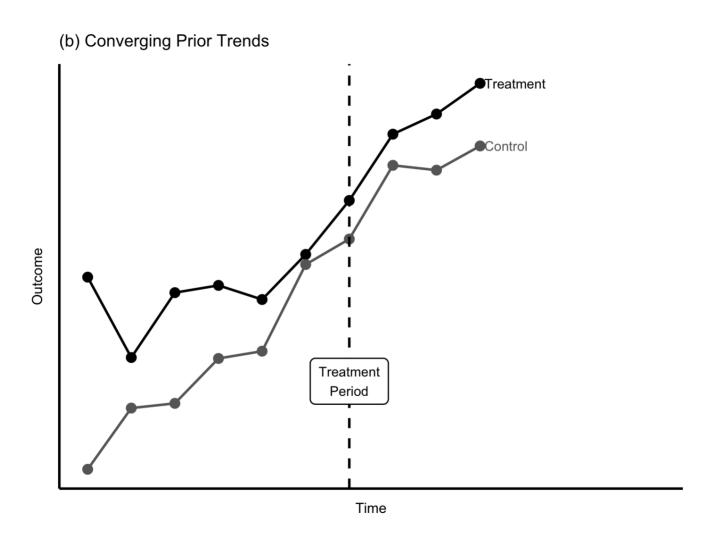
Selecting the right control group is important in DID. If the following conditions are satisfied, it is more plausible that the control and treatment groups would have had the same macro shock $(\alpha_1 = \alpha_0)$ if it were not for the treatment.

- There were no events that could significantly affect the dependent variable of the control group between the "before" and "after" period
- The two groups are generally similar so other factors do not drive the differences between them
- They had similar trajectories of the dependent variable prior to the treatment (possible if you have more than one years of data prior to the treatment)
 - o this does NOT guarantee that the their trends after the treatment are similar

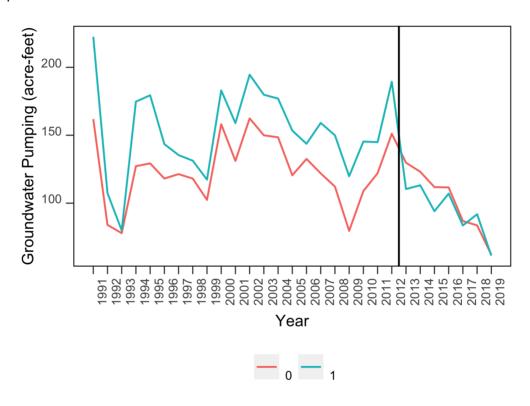
To do

- Show the trajectory of the dependent variable
- Run placebo tests





So, how about our example?



Not too bad. We might want to consider starting from 1993.

Placebo tests

- Look at only the pre-treatment periods
- Pretend that a treatment happend sometime in the middle of the pre-treatment period to the actual treatment group
- Estimate the impact of the fake treatment
- Check if the estimated impact is stastitically insignificantly different from 0
- If statistically significant, that would mean there is likley to be something wrong with the parallel trende assumption

Fake treament for the wells inside LEMA in 2000.

```
pre_lema_data <-
   filter(lema_data, year <= 2012 & year >= 1993) %>%
   #* pretend that a treatment happend in 2000
   mutate(after_2000 = ifelse(year >= 2000, 1, 0))

did_res_placebo <-
   feols(
        af_used ~ I(after_2000 * in_LEMA) + pr + et0 | site + year,
        cluster = ~site,
        data = pre_lema_data
    )</pre>
```

	-
	Model 1
I(after_2000 in_LEMA)	1.988
	(2.589)
pr	-0.214**
	(0.017)
et0	-0.005
	(0.046)
Num.Obs.	23509
R2	0.728
Std.Errors	by: site
0.1 0.05 0.01 0.001	

⁺ p < 0.1, *p* < 0.05, **p < 0.01**, p < 0.001

Fake treament for the wells inside LEMA in 1995.

```
pre_lema_data <-
   filter(lema_data, year <= 2012 & year >= 1993) %>%
   #* pretend that a treatment happend in 1995
   mutate(after_1995 = ifelse(year >= 1995, 1, 0))

did_res_placebo <-
   feols(
        af_used ~ I(after_1995 * in_LEMA) + pr + et0 | site + year,
        cluster = ~site,
        data = pre_lema_data
    )</pre>
```

	Model 1
I(after_1995 in_LEMA)	-2.353
	(2.911)
pr	-0.214**
	(0.017)
et0	0.007
	(0.047)
Num.Obs.	23509
R2	0.728
Std.Errors	by: site
. n . 0.1 n . 0.05 n . 0.01	

+ p < 0.1, p < 0.05, **p < 0.01**, p < 0.001

You can try more years as the starting year of a fake treatment and see what happens.

Note

Statistically insignificant estimated impacts of fake treatments bolster your claim about parallel trend assumption. But, it still does NOT guarantee the assumption is valid. Remember, the assumption is not testable.

What if your data spans from 1991 to 2000 with a treatment occuring at 1993?

```
pre lema data <-
 filter(lema data, year <= 2000) %>%
 #* pretend that a treatment happend in 1993
 mutate(after 1993 = ifelse(year >= 1993, 1, 0))
did_res_placebo <-
 feols(
   af_used ~ I(after_1993 * in_LEMA) + pr + et0 | site + year,
   cluster = ~site,
   data = pre_lema_data
```

	Model 1
I(after_1993 in_LEMA)	-16.386**
	(3.900)
pr	-0.121
	(0.026)
et0	0.114+
	(0.065)
Num.Obs.	11320
R2	0.715
Std.Errors	by: site
+n<0.1 n<0.05 n<0.01 *n<0.001	

+ p < 0.1, p < 0.05, p < 0.01, * p < 0.001

- So, this tells you that if it was a real treatment of which you want to understand the impact, then you would have suffered significant bias.
- This clearly indicates that DID is by no means perfect and indeed can be very dangerous