MQE: Economic Inference from Data: Module 4: Randomized Control Trials

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6/9/2020

Causal Inference with non-random assignment:

Randomizing treatment is not always possible:

- the program or policy has already happened
- randomization in unfeasible
- randomizing treatment would be unethical (ex: randomizing exposure to pollutants)

Causal Inference with non-random assignment:

With no randomized control trial we have to assume that the treatment was not randomly assigned:

- treatment will depend on observable and/or unobservable characteristics
- their are important differences between our treated and untreated units that we cannot control for
- Leaving these variables out in the error term will cause OVB.

Differences-in-differences is a way of getting around non-random assignment of a treatment.

DID: Example and intuition[1]

2002: Craigslist opens a new section called "erotic services" in San Francisco:

- mostly used by sex workers to advertise and solicit clients.
- Sex workers claimed it made them safer, because they could solicit indoors from their computers and learn more about the men contacting them.
- Activists and law enforcement worried that it was facilitating sex trafficking and increasing violence against women.

Which was it? Was erotic services (ERS) making women safer, or was it placing them in harm's way?

[1] This section is borrowed from scunning.com

SOS Empiricist!

This is an empirical question: What is the effect of ERS on female safety?

- The fundamental problem of causal inference strikes again!
- We can't know what effect it had because we are missing the data for the counterfactual:

$$E[\tau] = E[\underbrace{Y_{SF,2003}(D_{SF,2003} = 1)}_{\text{observed}}] - E[\underbrace{Y_{SF,2003}(D_{SF,2003} = 0)}_{\text{unobserved}}]$$

In 2003 only the first occurs, and the second is a counterfactual. So how do we proceed?

Diff-in-Diff to the rescue:

The standard differences-in-differences strategy (DiD):

- Define the intervention, $D=$ the availability of the Craigslist ERS webpage.
- We want to know the causal effect, τ of D on $Y=$ female murders.

Can we just compare SF murders in, say, 2003 with some other city, like Pittsburgh?

Differencing A:

....City....	...........Outcome.............
San Francisco	$Y_{SF,2003} = \alpha_{SF} + \tau$
Pittsburgh	$Y_{P,2003} = \alpha_P$

- α_{SF} is a San Francisco fixed effect
- α_P is a Pittsburgh fixed effect.

If make a simple comparison between Pittsburgh and SF:

$$\tilde{\tau} = Y_{SF,2003} - Y_{P,2003} = \alpha_{SF} + \tau - \alpha_P.$$

Differencing A:

The simple difference is biased because of the difference in the underlying murder rates between the two cities:

$$\tilde{\tau} - \tau = \alpha_{SF} - \alpha_{P}.$$

Differencing B:

What if we compare SF to itself? Say in 2003 to 2001?

.....City....	..Time..	...........Outcome..............
San Francisco	Before	$Y_{SF,2001} = \alpha_{SF}$
	After	$Y_{SF,2003} = \alpha_{SF} + \lambda_{03} + \tau$

Again, this doesn't lead to an unbiased estimate of τ since:

$$\tilde{\tau} = \alpha_{SF} + \lambda_{03} + \tau - \alpha_{SF} = \lambda_{03} + \tau$$

We eliminated the city fixed effect but not the changes in the murder rate over time which will bias my estimate:

$$\tilde{\tau} - \tau = \lambda_{03}$$

How can I identify and control for these time effects?

Differencing A+B= Diff-in-Diff

Combining the two approaches to eliminate both the city effects and the time effects:

...City...	..Time..	........Outcome........	1st Diff	2nd Diff
SF	Before	$Y_{SF,2001} = \alpha_{SF}$		
	After	$Y_{SF,2003} = \alpha_{SF} + \lambda_{03} + \tau$	$\lambda_{03} + \tau$	
				τ
Pittsburgh	Before	$Y_{P,2001} = \alpha_P$		
	After	$Y_{P,2003} = \alpha_P + \lambda_{03}$	λ_{03}	

The idea

Sometimes treatment and control group outcomes move in parallel in the absence of treatment.

When they do, the divergence of a post-treatment path from the trend established by a comparison group may signal a treatment effect.

The mechanics

Difference-in-differences can be implemented as follows:

1) Compute the difference in the mean outcome variable Y in the post treatment period ($t = 1$) and the before treatment period ($t = 0$) for the control group C:

$$\bar{Y}_{C,1} - \bar{Y}_{C,0} = \Delta \bar{Y}_C$$

$\Rightarrow$ allows us to cancel out the control group fixed effect and identify the time fixed effect since

$$\bar{Y}_{C,1} - \bar{Y}_{C,0} = \alpha_C + \lambda_1 - \alpha_C = \lambda_1 = \Delta \bar{Y}_C$$

The mechanics

2) Compute the difference in the mean outcome variable Y in the post treatment period ($t = 1$) and the before treatment period ($t = 0$) for the treated group T:

$$\bar{Y}_{T,1} - \bar{Y}_{T,0} = \Delta \bar{Y}_T$$

which allows us to cancel out the treated group fixed effect

$$\bar{Y}_{T,1} - \bar{Y}_{T,0} = \alpha_T + \lambda_1 + \tau - \alpha_T = \lambda_1 + \tau = \Delta \bar{Y}_T$$

The mechanics

3) Treatment impact is then measured by the difference-in-differences:

$$(\bar{Y}_{T,1} - \bar{Y}_{T,0}) - (\bar{Y}_{C,1} - \bar{Y}_{C,0}) = (\Delta \bar{Y}_T - \Delta \bar{Y}_C)$$

since by comparing the differences we can cancel out the time fixed effect and isolate the treatment effect of interest:

$$\Delta \bar{Y}_T - \Delta \bar{Y}_C = \lambda_1 + \tau - \lambda_1 = \tau$$

DID Regressions:

This can be done in a regression framework:

$$Y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 GetsTreat_i + \beta_3 Post_t \times GetsTreat_i + u_{it}$$

- $Post_t$ is an indicator for the post treatment period,
- $GetsTreat_i$ is an indicator for observations in the treatment group that eventually gets treated.

DID Regressions:

β_3 is the difference-in-differences estimator:

- estimates the differential impact of being in the post treatment period if you are in the treated group since

$$E[Y_{C,1}] - E[Y_{C,0}] = (\beta_0 + \beta_1) - (\beta_0) = \beta_1$$
$$E[Y_{T,1}] - E[Y_{T,0}] = (\beta_0 + \beta_1 + \beta_2 + \beta_3) - (\beta_0 + \beta_2) = \beta_1 + \beta_3$$

$$(E[Y_{T,1}] - E[Y_{T,0}]) - (E[Y_{C,1}] - E[Y_{C,0}]) = \beta_3$$

A simulation:

Suppose you are a principal of a school:

- ten 4th grade classrooms of 30 students each.
- Starting in 2001 school year, teachers can enroll their class in the scholastic book club
- 4 of your fourth grade teachers opted to enroll.

You are interested in estimating the effect of participation in the book club on 4th grade reading scores.

A simulation:

```r
set.seed(6000)
scores<-as.data.frame(rep(c(1,2,3,4,5,6,7,8,9,10),times=30))
names(scores)<-c("class")
scores <- fastDummies::dummy_cols(scores, select_columns = "class")

scores$error<-rnorm(300, mean=0, sd=10)

#suppose teachers in the better performing classes (classes, 7,8,9,10) select to participate in the book cl
scores$treat<-0
scores$treat[scores$class%in%c(7,8,9,10)]<-1

tau<-10

#the data generating process
scores$read4<-(85+tau*scores$treat
                +(-10)*scores$class_1+(-15)*scores$class_2+(-5)*scores$class_3
               +(-8)*scores$class_4+(-7)*scores$class_5+(-13)*scores$class_6
               +(11)*scores$class_7+(8)*scores$class_8+(10)*scores$class_9
               +(12)*scores$class_10
               +scores$error)

scores$year<-"2001"
scores01<-scores
rm(scores)
```

A simulation:

```
scores<-as.data.frame(rep(c(1,2,3,4,5,6,7,8,9,10),times=30))
names(scores)<-c("class")
scores <- fastDummies::dummy_cols(scores, select_columns = "class")

scores$error<-rnorm(300, mean=0, sd=10)

scores$treat<-0
scores$treat[scores$class%in%c(7,8,9,10)]<-1

#the data generating process
scores$read4<-(78
               +(-10)*scores$class_1+(-15)*scores$class_2+(-5)*scores$class_3
               +(-8)*scores$class_4+(-7)*scores$class_5+(-13)*scores$class_6
               +(11)*scores$class_7+(8)*scores$class_8+(10)*scores$class_9
               +(12)*scores$class_10
               +scores$error)

scores$year<-"2000"
scores00<-scores
rm(scores)

scores<-rbind(scores01, scores00)
```

A simulation:

```r
regnodid<-felm(read4~treat,scores[scores$year=="2001",])

scores$post<-0
scores$post[scores$year=="2001"]<-1
regdid<-felm(read4~post+treat+post*treat,scores)

regdidfe<-felm(read4~post+treat+post*treat|class,scores)
```

```
## Warning in chol.default(mat, pivot = TRUE, tol = tol): the matrix is either
## rank-deficient or indefinite
```

A simulation:

```
stargazer(regnodid, regdid,regdidfe, type="latex", header=FALSE,
          add.lines = list(c("Class FE", "No", "No", "Yes")), omit.stat = c("ser","rsq", "adj.rsq"))
```

Table 4

	Dependent variable:		
	read4		
	(1)	(2)	(3)
post		7.612***	7.612***
		(1.073)	(1.023)
treat	27.482***	18.387***	
	(1.141)	(1.200)	
post:treat		9.095***	9.095***
		(1.697)	(1.617)
Constant	76.775***	69.163***	
	(0.721)	(0.759)	
Class FE	No	No	Yes
Observations	300	600	600
Note:			*p$<$0.1; **p$<$0.05; ***p$<$0.01

Identifying Assumption:

Key assumption:

the difference between before and after in the comparison group is a good counterfactual for the treatment group.

- the trend in outcomes of the comparison group is what we would have observed in the treatment group absent the treatment

Identifying Assumption: Parallel Trends

Absent treatment, the outcome of the treated group would have followed a trend that was parallel to that of the control group

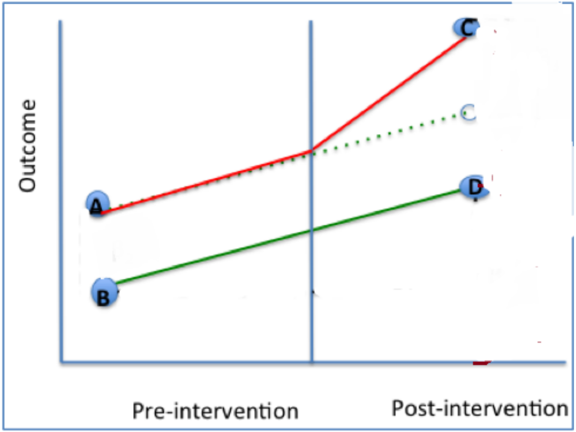


Figure 1: Green: Never Treated, Red: Treated

The Parallel Trends Assumption:

- We are treating the dashed green line as the counterfactual for the treated group
- Any deviation from this counterfactual is attributed to the treatment effect
- This assumption is straightforward but fundamentally **untestable**, because we will never actually observe this counterfactual of what would have happened to the treated group had they not been treated.

DID visually:

$$Y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 GetsTreat_i + \beta_3 Post_t \times GetsTreat_i + u_{it}$$

Which number corresponds to which coefficient? $\Rightarrow$ Top Hat

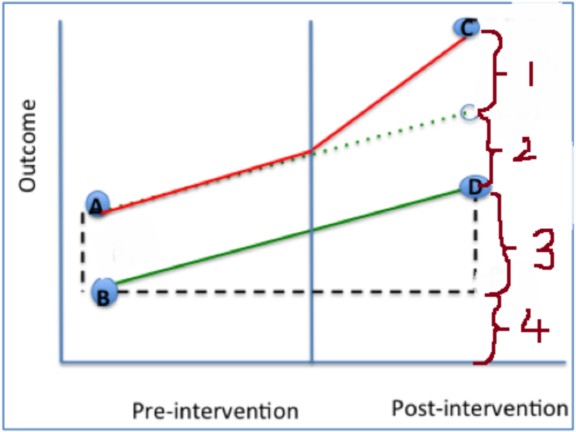


Figure 2: Green: Never Treated, Red: Treated

Identifying Assumption:

$$Y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 GetsTreat_i + \beta_3 Post_t \times GetsTreat_i + u_{it}$$

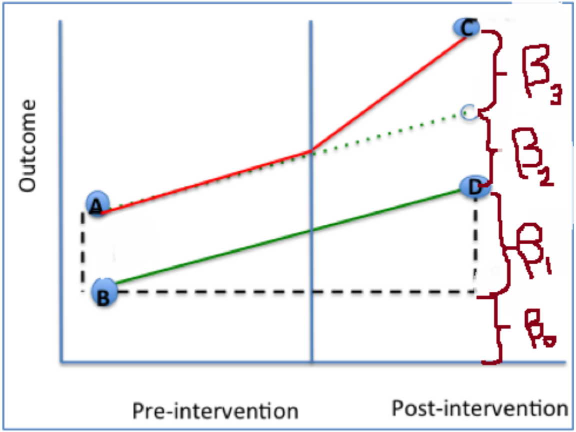


Figure 3: Green: Never Treated, Red: Treated

Problems with the Parallel Trends assumption

The parallel trends assumption is a fairly big assumption in many circumstances:

- policymakers may select treatment and control based on differences in the anticipated effects of treatment, or pre-existing differences in outcomes

In this case, the parallel trends assumption does not hold.

Example: Ashenfelter dips

Individuals who are “Treated” by job training programs are often individuals who just experienced a “dip” in earnings due to a job loss. When they get rehired their earnings increase substantially.

- If I compare their change in earnings to the change experienced by people who did not sign up for job training, I will see a large differential increase in earnings associated with program participation.
- This is due to who selects into training, not the causal effect of training.

Verifying Parallel trends

How can we check to see if the parallel trends assumption is likely to hold?

- Fundamentally untestable assumption
- use deduction to check this assumptions validity.

$\Rightarrow$ if the pre-treatment trends were parallel between the two groups, then wouldn't it stand to reason that the post-treatment trends would have been too?

Note: parallel pre-treatment trends does not ***prove*** that the assumption holds. But it does give some confidence that it does (absent some unobserved group specific time shock).

Verifying Parallel trends

Including leads into the DiD model is an easy way to check the pre-treatment trends. (Lags can also be included to see if treatment effect change over time).

Suppose treatment occurs right after period $t = 0$, estimate

$$Y_{it} = \beta_0 + \beta_2 GetsTreat_i + \sum_{t=-n}^{m} \beta_{3t} Period_t \times GetsTreat_i + \lambda_t + u_{it}.$$

If parallel trends holds:

- $E[\hat{\beta}_{3,t<1}] = 0$ since there is no treatment in these time periods.
- If $\tau \neq 0$, $E[\hat{\beta}_{3,t>0}] \neq 0$.

These results are typically best presented graphically.

Graphing DID estimates

Two main types of graphs

- plots of the mean outcome for both the treatment and control for several periods before and after treatment,
- and/or a graph that plots the $\hat{\beta}_{3t}$ estimates from the specification above.

Simulation: With leads and Lags

```
set.seed(1999)
scoresbase<-as.data.frame(rep(c(1,2,3,4,5,6,7,8,9,10),times=30))
names(scoresbase)<-c("class")
scoresbase <- fastDummies::dummy_cols(scoresbase, select_columns = "class")

#suppose teachers in the better performing classes (classes, 7,8,9,10) select to participate in the book cl
scoresbase$treat<-0
scoresbase$treat[scoresbase$class%in%c(7,8,9,10)]<-1
```

Simulation: With leads and Lags

```r
yr<-c(1995,1996,1997,1998,1999,2000,2001,2002,2003,2004,2005)
tauyr<-c(0,0,0,0,0,0,10,10,10,10,10)
yrfe<-c(72,77,75,79,81,79,83,77,82,84,81)

for(i in 1:11){
  name<-paste("scores", yr[i], sep="_")
  scores<-scoresbase
  scores$error<-rnorm(300, mean=0, sd=10)
  tau<-tauyr[i]
  yearfe<-yrfe[i]
  #the data generating process
  scores$read4<-(yearfe+tau*scores$treat+scores$error
             +(-10)*scores$class_1+(-15)*scores$class_2+(-5)*scores$class_3
             +(-8)*scores$class_4+(-7)*scores$class_5+(-13)*scores$class_6
             +(11)*scores$class_7+(8)*scores$class_8+(10)*scores$class_9
             +(12)*scores$class_10)

  scores$year<-yr[i]
  assign(name, scores)
  rm(scores)
}

allscores<-rbind(scores_1995,scores_1996,scores_1997,scores_1998,scores_1999,
                 scores_2000,scores_2001,scores_2002,scores_2003,scores_2004,scores_2005)
```

Simulation: With leads and Lags

```
allscores$post<-0
allscores$post[allscores$year%in%c(2001,2002,2003,2004,2005)]<-1

allscores <- fastDummies::dummy_cols(allscores, select_columns = "year")

regdidall2<-felm(read4~treat
                 +year_1995*treat+year_1996*treat+year_1997*treat+year_1998*treat
                 +year_1999*treat+year_2001*treat+year_2002*treat+year_2003*treat
                 +year_2004*treat+year_2005*treat,
                 allscores)
```

Simulation: With leads and Lags

```
stargazer( regdidall2, type="latex",no.space=TRUE, header=FALSE, single.row=TRUE, omit.stat = "all")
```

Table 5

	Dependent variable:
	read4
treat	18.774*** (1.207)
year_1995	$-$5.842*** (1.080)
year_1996	$-$2.945*** (1.080)
year_1997	$-$1.696 (1.080)
year_1998	0.027 (1.080)
year_1999	2.636** (1.080)
year_2001	5.125*** (1.080)
year_2002	$-$2.235** (1.080)
year_2003	1.849* (1.080)
year_2004	4.430*** (1.080)
year_2005	2.533** (1.080)
treat:year_1995	0.431 (1.707)
treat:year_1996	1.427 (1.707)
treat:year_1997	$-$2.476 (1.707)
treat:year_1998	0.568 (1.707)
treat:year_1999	$-$0.573 (1.707)
treat:year_2001	10.204*** (1.707)
treat:year_2002	12.290*** (1.707)
treat:year_2003	11.188*** (1.707)
treat:year_2004	11.186*** (1.707)
treat:year_2005	10.217*** (1.707)
Constant	69.542*** (0.764)
Note:	*p$<$0.1; **p$<$0.05; ***p$<$0.01

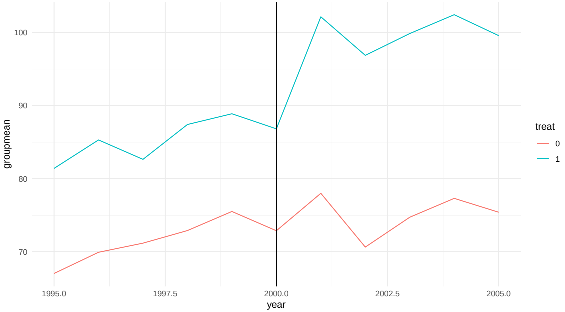
Simulation: With leads and Lags

```
#start with plot of group means

#calculateing the mean score for each year by treatment status
grp_mean<-allscores%>%
    group_by(year,treat)%>%
    dplyr::summarize(groupmean = mean(read4, na.rm=TRUE))
```

```
## `summarise()` regrouping output by 'year' (override with `.groups` argument)
```

```
grp_mean$treat<-as.factor(grp_mean$treat)

#difference in means plot
didmeans<-ggplot(grp_mean, aes(year, groupmean, group=treat, color = treat)) +
    stat_summary(geom = 'line') +
    geom_vline(xintercept = 2000) +
    theme_minimal()
```

Simulation: With leads and Lags



Simulation: With leads and Lags

```r
#plot of differences coefficients

res<-coef(summary(regdidall2))
res<-as.data.frame(res)

res<-res[13:22,]

a<-c(0,0,0,0)

res<-rbind(res,a)

year<-c(1995,1996,1997,1998,1999,2001,2002,2003,2004,2005,2000)
res<-cbind(res,year)
res$ci<-1.96*res$`Std. Error`

names(res)<-c("Estimate","se", "t",  "p", "year", "ci")
# Use 95% confidence interval instead of SEM
didplot2<-ggplot(res, aes(x=year, y=Estimate)) +
    geom_errorbar(aes(ymin=Estimate-ci, ymax=Estimate+ci),width=.1) +
    geom_vline(xintercept = 2000)+
      geom_hline(yintercept = 0)+
     geom_point()
```

Simulation: With leads and Lags