Quasi-experiment and Difference-in-differences

Fall 2023

Evaluating policy impact

Suppose you are interested in measuring the effect of a payment policy (e.g. DRG) on hospital performance:

- **Approach #1: For hospitals implementing DRG, take the difference between their outcomes before and after the change**

Any potential problem with this approach?

Evaluating policy impact (cont.)

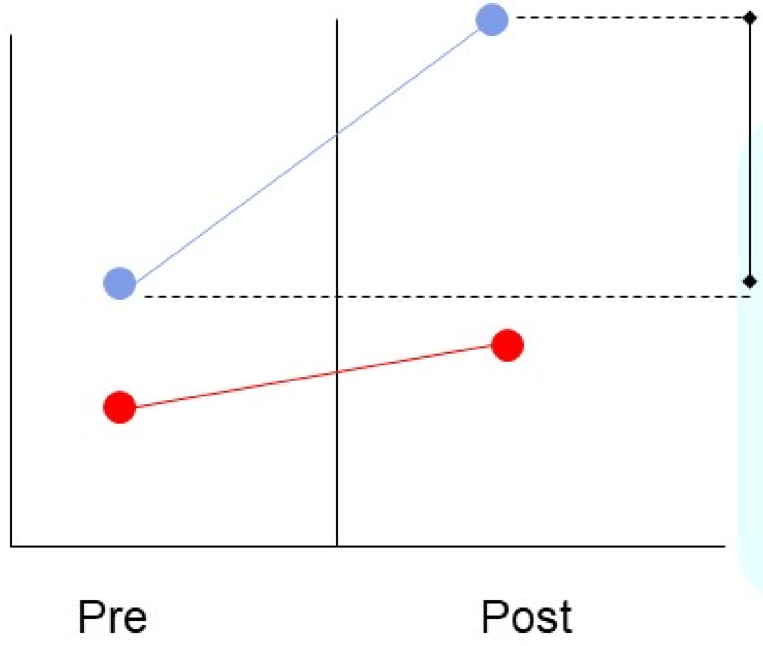
Suppose you are interested in measuring the effect of a payment policy (e.g. DRG) on hospital performance:

- **Approach #2: Compare the outcomes of the hospital implemented DRG with hospitals that have not**

What's the problem now?

Identifying assumption

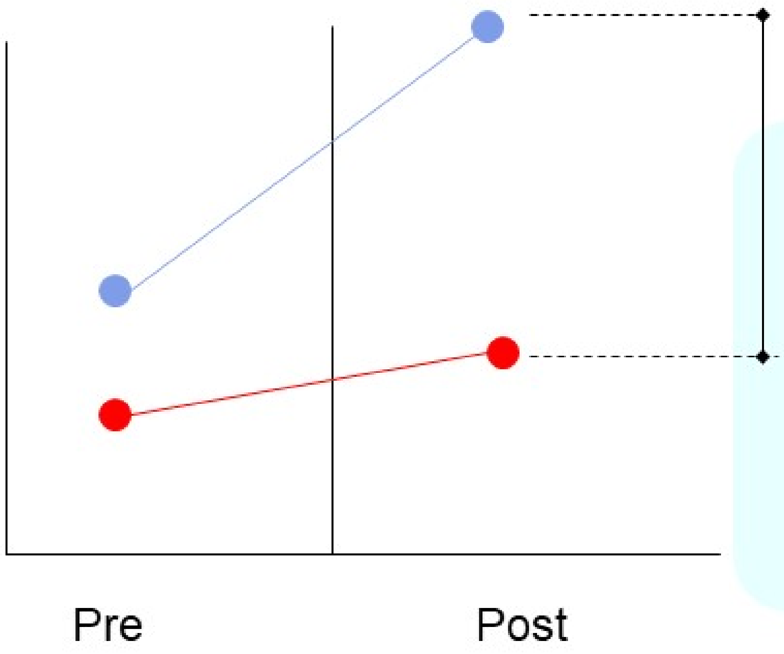
- **Whatever happened to the control group over time = what would have happened to the treatment group in the absence of the program.**



Effect of program using only pre- & post- data from T group (ignoring general time trend).

Identifying assumption

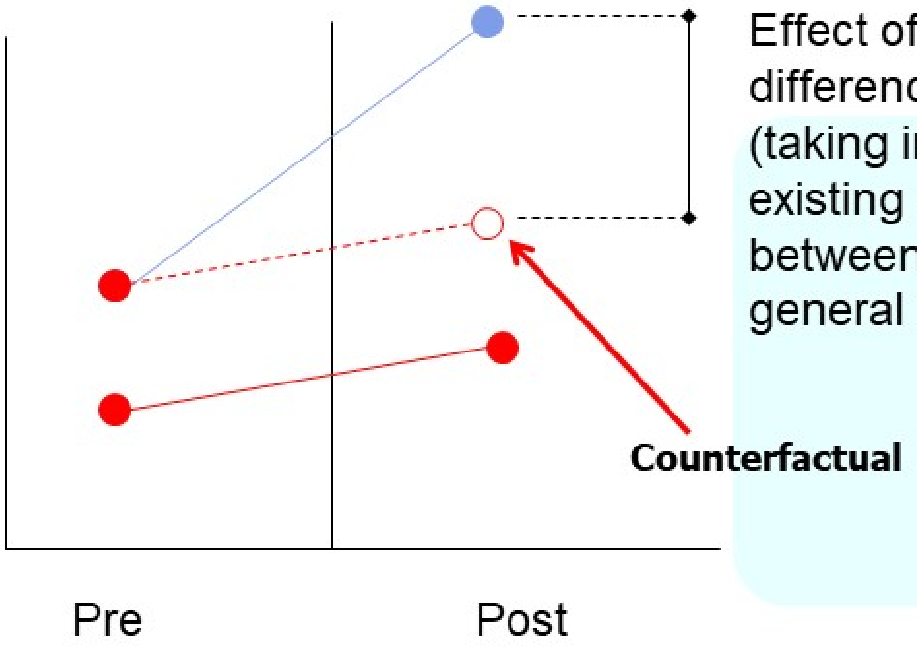
- **Whatever happened to the control group over time = what would have happened to the treatment group in the absence of the program.**



Effect of program using only T & C comparison from post-intervention (ignoring pre-existing differences between T & C groups).

Identifying assumption

- **Whatever happened to the control group over time = what would have happened to the treatment group in the absence of the program.**



Effect of program difference-in-difference (taking into account pre-existing differences between T & C and general time trend).

Recap: Gauss-Markov Theorem

- **1. Linear in the parameters**
- **2. No perfect collinearity**
- **3. Random sample**
- **4. Strick exgoeneity, i,e, Zero-conditional mean:** $E(u \mid X)=E(u)=0$
  - Under 1-4, OLS is unbiased
- **5. Homoskedasticity**
  - Under 1-5, OLS is BLUE
  - Being efficient is the least requirement

However, is unlikely to hold in real practice.

Evaluating policy impact (cont.)

What should we do then?

- **A quasi-experimental design combines both of these approaches by comparing the difference in the change in outcomes before and after the policy change for two groups:**
  - the population affected by the policy change
  - a comparison group of people who are expected to experience *similar secular trends in the outcome*, but who are not themselves affected by the policy change.

- Two or more independently sampled cross sections can be used to evaluate the impact of a certain event or policy change
- Example: The effect of an incinerator construction on house prices

- In 1978, they knew there is going to be a construction, but didn't know where until 1981.
- Assume houses <=3 miles are to be affected (nearinc) → fill back the data retrospectively
- rprice = real selling price

$\underline{rprice = \beta_0 + \beta_1 \, nearinc + u}$

- Regress on year 1981 only:
- What does the constant mean?
- β1 : difference in average selling price of houses that were near the incinerator compared with those that are not near the incinerator (in 1981) .

- **So, the incinerator does affect housing price negatively.**
- **However, is it ALL due to the incinerator?**
  - Changes over the two year? For example, the market moved differently for the two places.
  - Most importantly: The construction does not appear randomly- houses near the incinerator were in the worse location in the first place.
- **To find out: regress for the year 1978 only.**
  - nearinc = -18824.37 → even before the construction, those houses near the incinerator is already at a lower price.

Policy analysis with pooled cross-sections

- **Example: Effect of new garbage incinerator's location on housing prices**
  - Examine the effect of the location of a house on its price before (1978) and after the garbage incinerator was built (1981):

$$\widehat{rprice} = \underset{(3,093.0)}{101,307.5} - \underset{(5,827.71)}{\boxed{30,688.27}}\, nearinc$$

$n = 142, R^2 = .165$

After incinerator was built

$$\widehat{rprice} = \underset{(2,653.79)}{82,517.23} - \underset{(4,744.59)}{\boxed{18,824.37}}\, nearinc$$

$n = 179, R^2 = .082$

Before incinerator was built

Policy analysis with pooled cross-sections (cont.)

- **It would be wrong to conclude from the regression after the incinerator (1981) , the incinerator depresses prices so strongly**
- **-$30688 = effect of incinerator + effect of location (in 1981)**
- **-$18824 = effect of location (because you didn't know there is going to be an incinerator).**
- **Substract and you can cancell out the *effect of incinerator***

- **One has to compare with the situation before the incinerator was built:**

$$\widehat{\delta}_1 = -30,688.27 - (-18,824.37) = -11,863.9$$

Incinerator depresses prices, but their location was one with lower prices anyway

- In the given case, this is equivalent to:

$$\widehat{\delta}_1 = (\overline{rprice}_{1,nr} - \overline{rprice}_{1,fr}) - (\overline{rprice}_{0,nr} - \overline{rprice}_{0,fr})$$

- This is the so called difference-in-differences estimator (DiD): obtained as the difference in two set of differences

```
sum rprice if year==1978 & nearinc==1
```

$63693

```
sum rprice if year==1978 & nearinc==0
```

$82571

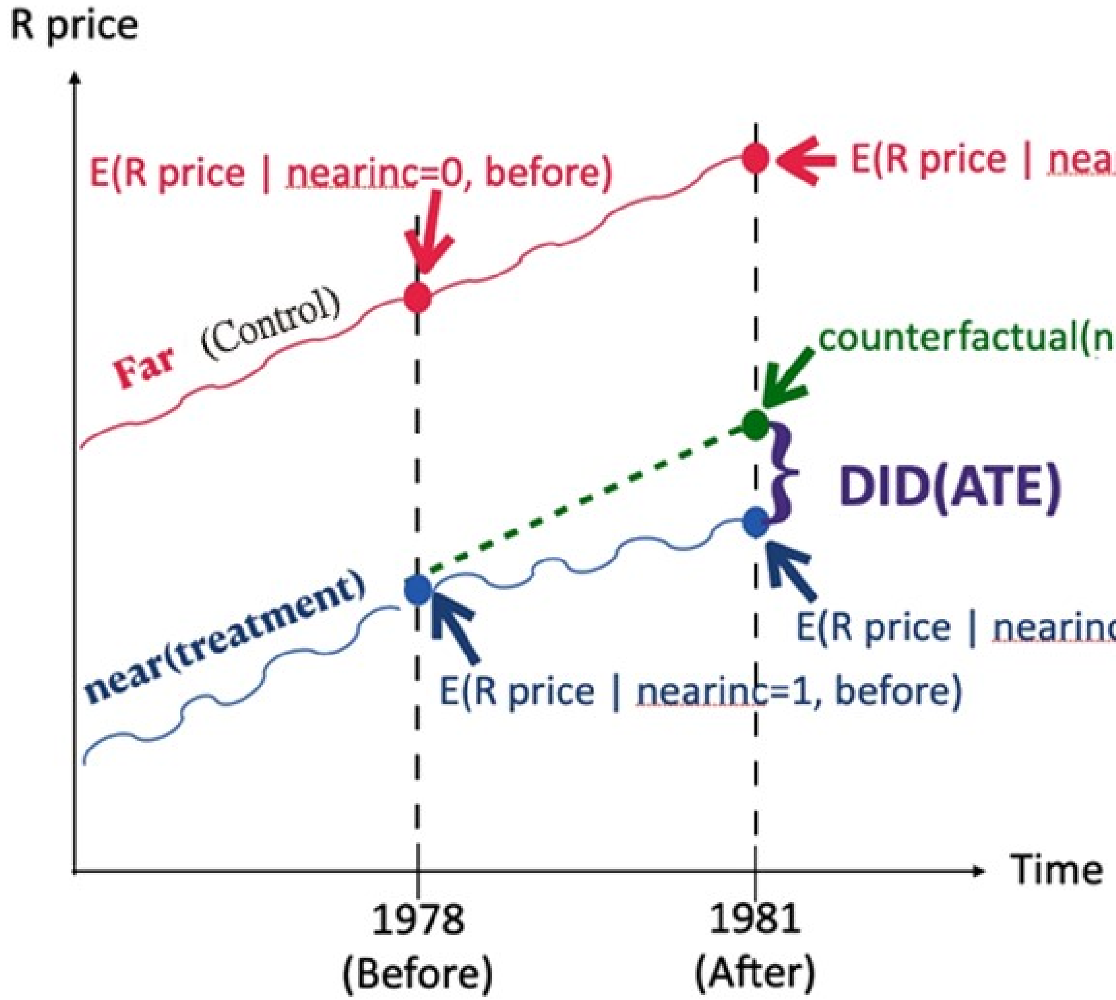
```
sum rprice if year==1981 & nearinc==1
```

$70619

```
sum rprice if year==1981 & nearinc==0
```

$101308

	1978 (Before)	1981 (After)	Difference '81 to '78 (1981-1978)
Near incinerator	$\overline{Price}_{78,near} =$ $\$63\ 692.86$	$\overline{Price}_{81,near} =$ $\$70\ 619.24$	$\triangle Price_{\text{near}} =$ $\overline{Price}_{81,near} - \overline{Price}_{78,near}$ $= \$6\ 926.38$ Note selling price increase (incinerator + time trend)
Far from incinerator	$\overline{Price}_{78,far} =$ $\$82\ 517.23$	$\overline{Price}_{81,far} =$ $\$101\ 307.5$	$\triangle Price_{\text{far}} =$ $\overline{Price}_{81,far} - \overline{Price}_{78,far}$ $= \$18\ 790.27$ Just the time trend effect
Difference Near - Far	$\overline{Price}_{78,near} - \overline{Price}_{78,far}$ $=\$\ -18\ 824.37$ The location effect	$\overline{Price}_{81,near} - \overline{Price}_{81,far}$ $= \$\ -30\ 688.26$ The location + incinerator effect	$\$6\ 926.38 - \$18\ 790.27$ $=\$-30\ 688.26 - (\$-18\ 824.37)$ $= \$\ -11\ 863.89$ - **DID** The incinerator effect


R price
E(R price | nearinc=0, before)
E(R price | nearinc=0, after)
Far (Control)
counterfactual(not observed)
DID(ATE)
near(treatment)
E(R price | nearinc=1, after)
E(R price | nearinc=1, before)
Time
1978
(Before)
1981
(After)

Assumptions of DID (must hold!)

- Assumes if there was no incinerator, those near the incinerator would follow the market trend (and the trend is the same for both types of houses)
- Common trends assumption
- General: "In the absence of treatment, the difference between treatment and control groups is constant over time.
- No formal test!
- Use graphical evidence → Thus if you only have one year pre and post, the evidence is not going to be so strong. Yet, that's what many published study use.

DID in a regression framework

- **Why regression?**
  - Can't tell if there is statically differences
  - Control for other variables

- **Difference-in-differences in a regression**

$$rprice = \beta_0 + \delta_0\, after + \beta_1\, nearinc + \delta_1\, after \cdot nearinc + u$$

Differential effect of being in the location <u>and</u> after the incinerator was built

- β_0: average price of a home not near the incinerator in 1978
- δ_0: changes in ***all*** housing values from 1978 to 1981
- β_1: location effect that is ***not*** due to the presence of the incinerator
- δ_1: decline in housing values due to the incinerator, provided we assume that **houses both near and far from the site dd not appreciate at different rates for other reasons**

nearinc is the "treatment", 1= near, 0 = far
after = dummy variable, 1 = 1981, 0=1978

Same as:
reg rprice nearinc if year==1978

DID in a regression framework (cont.)

- **Implementing DID in a regression has many benefits, e.g.**
  - In this way standard errors for the DID-effect can be obtained
  - Further explanatory variables can be included if houses sold before and after the incinerator was built were systematically different

TABLE 13.2 Effects of Incinerator Location on Housing Prices

Dependent Variable: *rprice*			
Independent Variable	**(1)**	**(2)**	**(3)**
constant	82,517.23 (2,726.91)	89,116.54 (2,406.05)	13,807.67 (11,166.59)
y81	18,790.29 (4,050.07)	21,321.04 (3,443.63)	13,928.48 (2,798.75)
nearinc	−18,824.37 (4,875.32)	9,397.94 (4,812.22)	3,780.34 (4,453.42)
y81·nearinc	−11,863.90 (7,456.65)	−21,920.27 (6,359.75)	−14,177.93 (4,987.27)
Other controls	No	*age*, age^2	Full Set
Observations	321	321	321
R-squared	.174	.414	.660

Full controls further include distance to the interstate in feet (intst), land area in feet (land), house area in feet (area), number of rooms (rooms) and number of baths (baths)

Natural experiment

- **DID is tremendously useful when data arise from natural experiment (or quasi-experiment)– experiment occurs when some *exogenous event* *(e.g. government policy, natural disaster, etc.)***
- **DID mimics true experiment but needs to control for systematic differences between the Treatment and Control**
- $y = \beta_0 + \delta_0 Post + \beta_1 Tx + \delta_1 Post * Tx + other\ factors$

Average treatment effect

TABLE 13.3 Illustration of the Difference-in-Differences Estimator

Baseline average	Before	After	After – Before
Control	β_0	$\beta_0 + \delta_0$	δ_0
Treatment	$\beta_0 + \beta_1$	$\beta_0 + \delta_0 + \beta_1 + \delta_1$	$\delta_0 + \delta_1$
Treatment − Control	β_1	$\beta_1 + \delta_1$	δ_1

Market trend

Location

incinerator

DID assumption

- **The baseline of the treatment group equals the baseline of the control group (layman terms: people in the treatment group would do as *bad* as the control group if they were not treated) and the treatment effect on the treated group equals the treatment effect on the control group (layman terms: people in the control group would do as *good* as the treatment group if they were treated).**
- **These are very strong assumptions which are commonly violated in observational studies and therefore the *ATT* (average treatment effect on the treated) and the *ATE* are not expected to be equal.**
- **But in DID, we assume the two groups are the same, so ATE= ATT.**

Conclusion of the incinerator example

- **The effect of the incinerator construction on the real 1978 USD average selling prices of houses near the incinerator is a decline by $14443, holding other variables fixed.**

Recap: data requirement

- **Two groups (treatment and control)**
- **Both groups have pre- and post- treatment data**
  - Can be panel data or pooled cross-sectional

DID in action

Received: 25 October 2017 | Revised: 2 April 2019 | Accepted: 5 April 2019

DOI: 10.1002/hec.3888

RESEARCH ARTICLE

WILEY Health Economics

Did UberX reduce ambulance volume?

Leon Moskatel[1] | David Slusky[2]

[1] Department of Medicine, Scripps Mercy Hospital, San Diego, California

[2] Department of Economics, University of Kansas, Lawrence, Kansas

Correspondence
David Slusky, Department of Economics, University of Kansas, Lawrence, Kansas.
Email: david.slusky@ku.edu

Funding information
University of Kansas

Abstract

Ambulances are a vital part of emergency medical services. However, they come in single, high intervention form, which is at times unnecessary, resulting in excessive costs for patients and insurers. In this paper, we ask whether UberX's entry into a city caused substitution away from traditional ambulances for low-risk patients, reducing overall volume. Using a city-panel over-time and leverage that UberX enter markets sporadically over multiple years, we find that UberX entry reduced the per capita ambulance volume by at least 6.7%. Our result is robust to numerous specifications.

KEYWORDS

ambulances, emergencies, Uber

- In the US, ambulances are good, but very expensive.
- Is Uber an alternative for "not so urgent" cases?
- Uber entered different places at different time, thus DID makes sense.

- UberX entry reduced the per capita ambulance volume by at least 6.7%

- Other fun facts (based on rigorous studies):
- Uber has positive externality (reduced drinking and driving)
- Uber did bot increase drinking for people who don't drink in the first place but does increase consumption for people who drink at all (risk compensation).
- Uber increased binge drinking for young people
- but Uber did not have effect on unintended pregnancy.
- Uber raised employment in bars.

Example: Card & Krueger (1994) on minimal wage

- Card and Krueger (1994) analyzes the effect of a minimum wage increase in New Jersey (NJ) using DID methodology
- In Feb 1992, NJ increase the state minimum wage from $4.25 to $5.05. Pennsylvania's minimum wage stayed at $4.25

- They surveyed ~400 fast food stores both in NJ and in PA, both before and after the minimum wage increase in NJ

DID table

Variable	Stores by state: PA (i)	NJ (ii)	Difference, NJ − PA (iii)
1. FTE employment before, all available observations	23.33 (1.35)	20.44 (0.51)	−2.89 (1.44)
2. FTE employment after, all available observations	21.17 (0.94)	21.03 (0.52)	−0.14 (1.07)
3. Change in mean FTE employment	−2.16 (1.25)	0.59 (0.54)	$\boxed{2.76\ (1.36)}$

- **Surprisingly, employment *rose* in NJ relative to PA after the minimum wage change**

FTE=Full-time equivalent

DID by regression

- **In the Card & Krueger case, the regression model would be:**

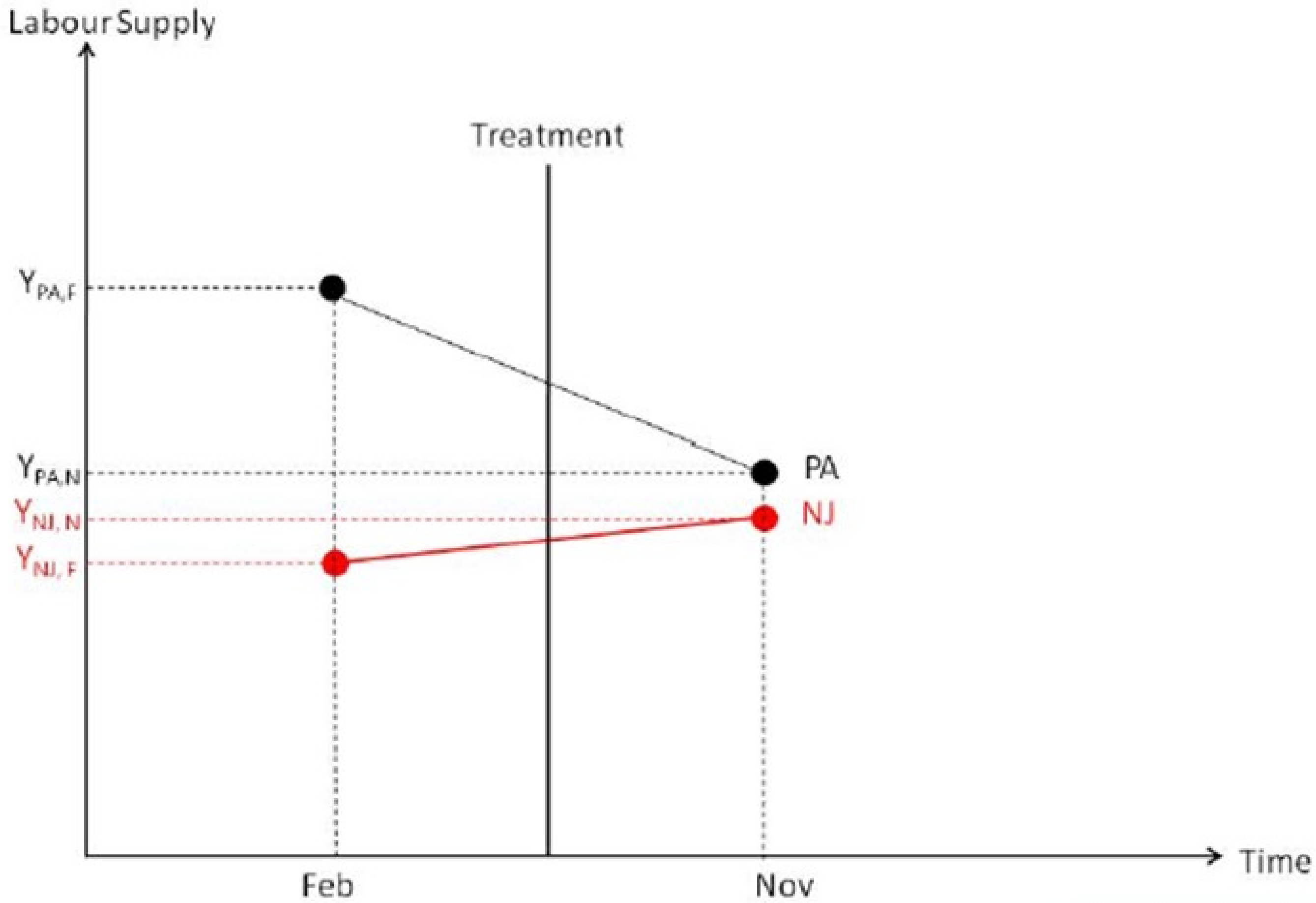
$$Y_{ist} = \alpha + \gamma NJ_s + \lambda d_t + \delta(NJ_s * d_t) + \varepsilon_{ist}$$

  - NJ is a dummy =1 if the observation is from NJ
  - d is a dummy =1 if the observation is after the policy (=November)

- **Employment level takes the following values**
  - PA Pre: α
  - PA Post : $\alpha + \lambda$
  - NJ Pre: $\alpha + \gamma$
  - NJ Post: $\alpha + \gamma + \lambda + \delta$

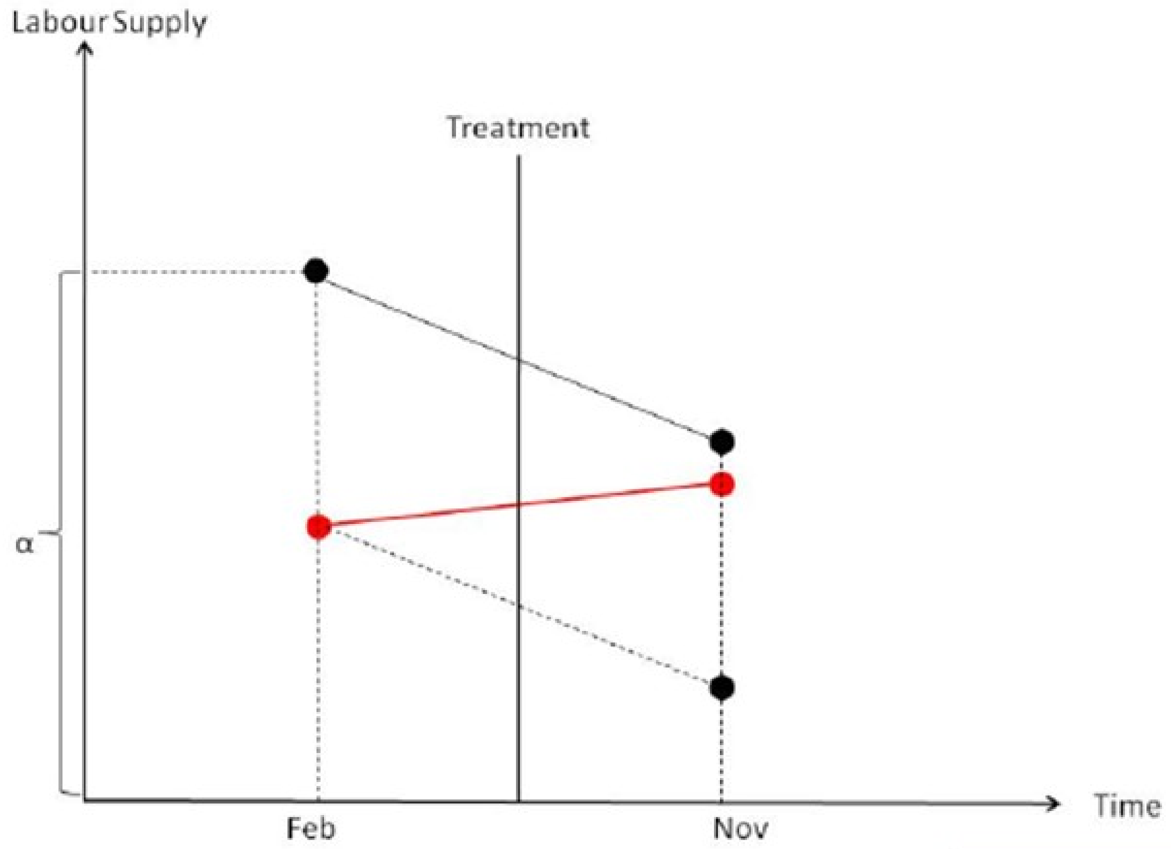
- **DID estimate:** δ (NJ Post- NJ Pre)- (PA Post- PA Pre)

Graphic illustration



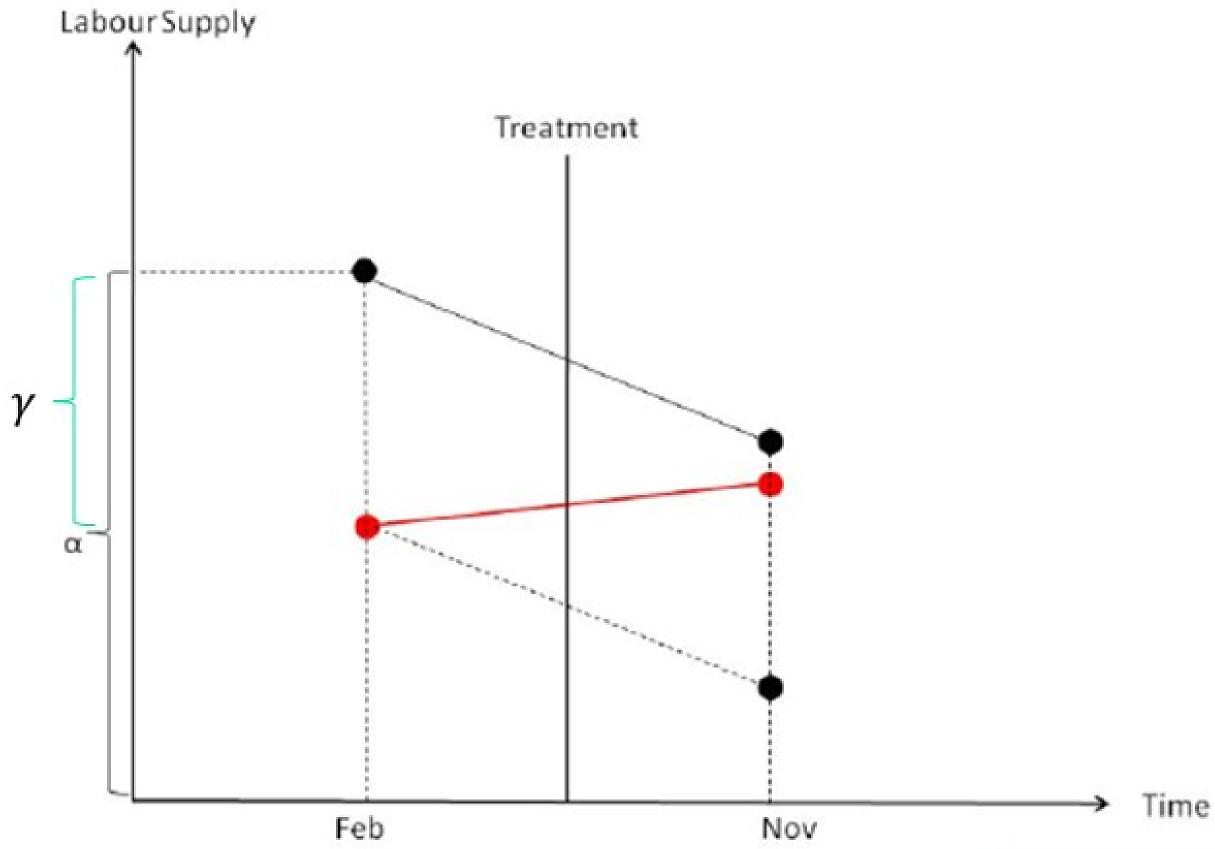
Graphic illustration (cont.)

$$Y_{ist} = \alpha + \gamma NJ_s + \lambda d_t + \delta(NJ_s * d_t) + \varepsilon_{ist}$$



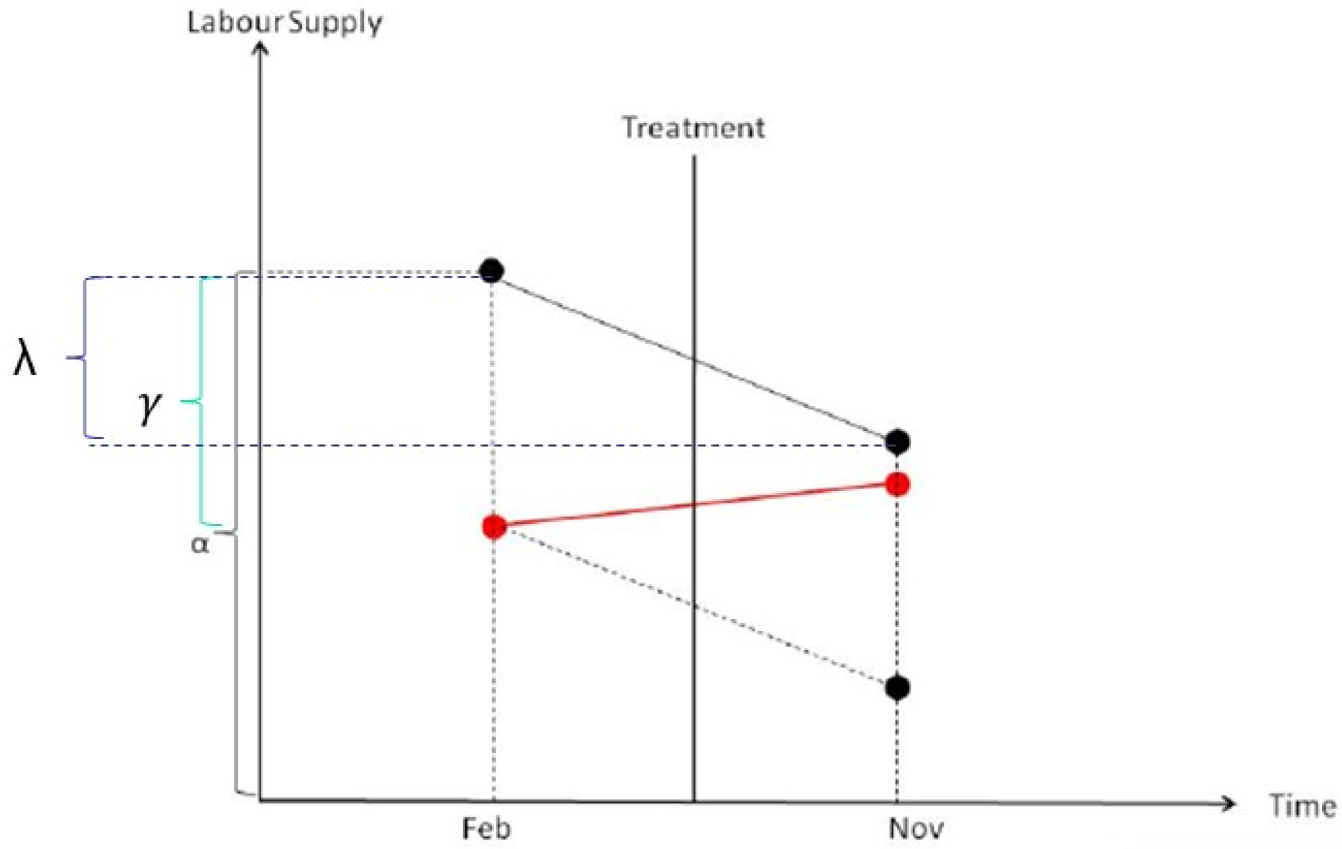
Graphic illustration (cont.)

$$Y_{ist} = \alpha + \gamma NJ_s + \lambda d_t + \delta(NJ_s * d_t) + \varepsilon_{ist}$$



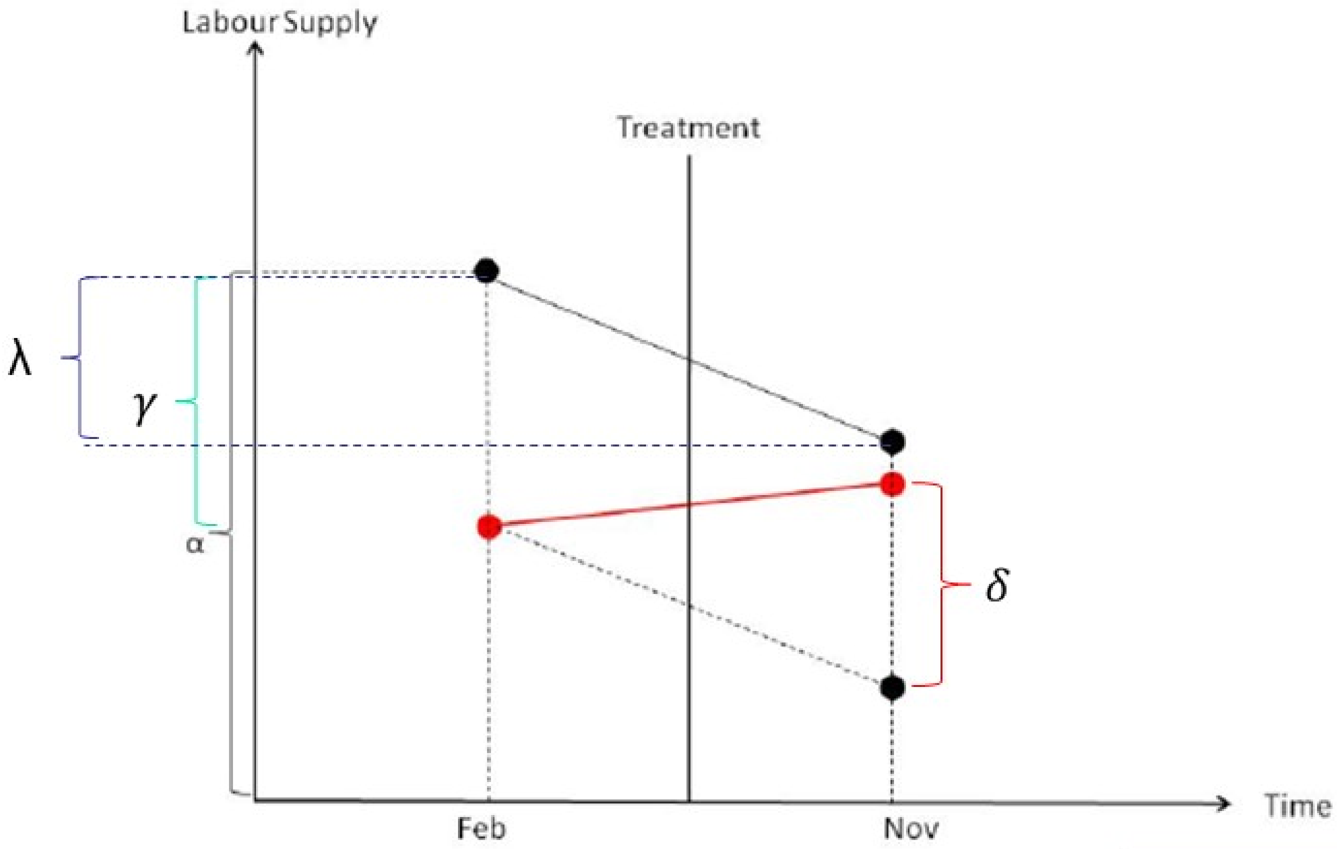
Graphic illustration (cont.)

$$Y_{ist} = \alpha + \gamma NJ_s + \lambda d_t + \delta(NJ_s * d_t) + \varepsilon_{ist}$$



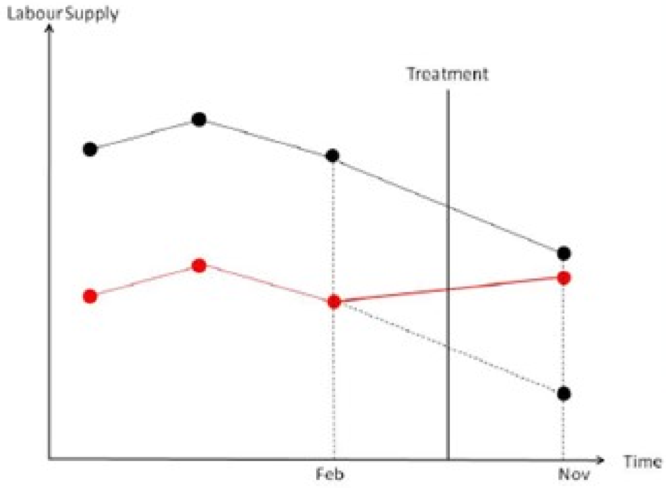
Graphic illustration (cont.)

$$Y_{ist} = \alpha + \gamma NJ_s + \lambda d_t + \delta(NJ_s * d_t) + \varepsilon_{ist}$$



Key identifying assumptions

- **The key assumption: outcome in treatment and control group would follow the *same time trend* in the absence of the treatment, a.k.a. common trends**
- **They do NOT have to have the same average outcome**
- **Common trend assumption is difficult to verify but one often uses pre-treatment data to show common trends**



Robustness checks

- If possible, use data on **multiple pre-program periods** to show that **difference between treated & control is stable**
- If possible, use data on **multiple post-program periods** to show that unusual difference between treated & control occurs only concurrent with program
- Alternatively, use data on **multiple indicators** to show that response to program is **only manifest for those we expect it to be.**

Nonlinear models and DID

- **Be careful with the interpretation!**
- **Recall:**

Linear Models

Coefficient on the interaction term gives the magnitude and sign of interaction effect

Use *t*-test for statistical significance

Easy to compute marginal effects (for continuous variables) or incremental effects (for dummy variables)

E.g $y=\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_1 X_2 + u$

β_{12} is the change in the effect of x_1 on y as x_2 varies.

→ Using t-test, if β_{12} is significant, then you can conclude "there is significant interaction effect"

Interaction effect $= \frac{\delta^2 E[y|x_1,x_2]}{\delta x_1 x_2} = \beta_{12}$ ← This is the cross-derivative

From previous class…

General Formula

- ***Interaction effect*** is double difference or double derivative $(v = x\beta)$

$$\begin{aligned}\frac{\partial^2 F(\cdot)}{\partial x_1 \partial x_2} &= \frac{\partial\left[(\beta_1 + \beta_{12}x_2)\, f(\cdot)\right]}{\partial x_2} \\ &= \beta_{12} f(\cdot) + (\beta_1 + \beta_{12}x_2)(\beta_2 + \beta_{12}x_1)\, f'(\cdot)\end{aligned}$$

The function $f(\cdot) = F'(\cdot)$ and $f'(\cdot) = F''(\cdot)$.

It is obvious the interaction effect is not equal to β_{12}

From previous class…

Conclusions

Interaction effects are more complicated in nonlinear models than in OLS

Only looking at coefficient on the interaction term is wrong:

Wrong magnitude

Wrong sign

Wrong statistical significance (i.e. p-value)

Some possible topics

- Impact of vaping restrictions in public places on smoking and vaping in the United States
- Recreational cannabis legalization and alcohol purchasing
- Analysis of Youth Smoking and a Ban on Sales of Flavored Tobacco Products in San Francisco, California
- Pediatric screening urinalysis: a difference-in-differences analysis of how a 2007 change in guidelines impacted use
- Effect of becoming disabled on income structure
- Effect of getting cancer on diabetes adherence