

Applied Microeconometrics I

Lecture 8: Differences-in-differences

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Lecture Slides

- With every research question it is not possible to run a **randomized controlled trial**.
- We may also try to learn about the impact of a treatment using an empirical strategy **based on observables**:
 - We can compare individuals exposed to the treatment with other individuals that look alike in terms of observables.
 - Unfortunately, this evidence may be subject to selection biases and often it is difficult to interpret.
- Maybe we can look for an **instrumental variable**, but good instruments are difficult to find...
- What else can we do?

Example: the impact of death penalty

- Let us consider the case of a dychotomic treatment
- For instance, we can consider the following question:
 - Does death penalty reduce the homicide rate?
- We will follow the review of the literature by **Donohue and Wolfers 2005** to analyze how different scholars have approached this question.

Example: the impact of death penalty

Before-and-after approach

- Some authors have analyzed how the homicide rate evolves before and after the abolition (or the introduction) of death penalty.
- For instance **Dezhbakhsh and Shepherd (2004)** use data from US states which have either introduced or abolished the death penalty between 1960 and 2000. They show that:
 - when the death penalty is abolished, the homicide rate tends to increase
 - when the death penalty is reinstated, the homicide rate tends to decrease

Table 1: Estimating How Changes in Death Penalty Laws Effect Murder: Selected Before and After Comparisons: 1960-2000

Dependent Variable: % Change in State Murder Rates Around Regime Changes

	Death Penalty Abolition			Death Penalty Reinstatement		
	1-Year Window (1)	2-Year Window (2)	3-Year Window (3)	1-Year Window (4)	2-Year Window (5)	3-Year Window (6)
Panel B: Our Replication: Changes Around Death Penalty Shifts (Treatment)						
Mean Change	10.1%*** (2.9)	16.0%*** (2.3)	21.5%*** (2.6)	-6.3%* (3.4)	-7.0%** (2.9)	-3.8% (2.9)
Median Change	8.5%	13.8%	18.5%	-9.3%	-8.5%	-7.4%
Number of States Where Homicide Increased	35/46	39/46	41/46	12/41	15/39	14/39

- As Donohue and Wolfers (2005) point out, there are two possible interpretations for this empirical evidence:
 - Causal effect: the introduction (abolition) of death penalty decreases (increases) homicides rate
 - Spurious correlation: there some confounding effects

Differences-in-differences

- How can we control for confounding effects?
- Differences-in-differences strategy: We can try to look for a control group which is similarly affected by these confounding effects.
- For instance, we can also examine the evolution of homicide rates during the same period in states that did not experience any policy change.
- Donohue and Wolfers 2005 show that this group exhibits very similar trends (Table 1, panel C).

Table 1: Estimating How Changes in Death Penalty Laws Effect Murder: Selected Before and After Comparisons: 1960-2000

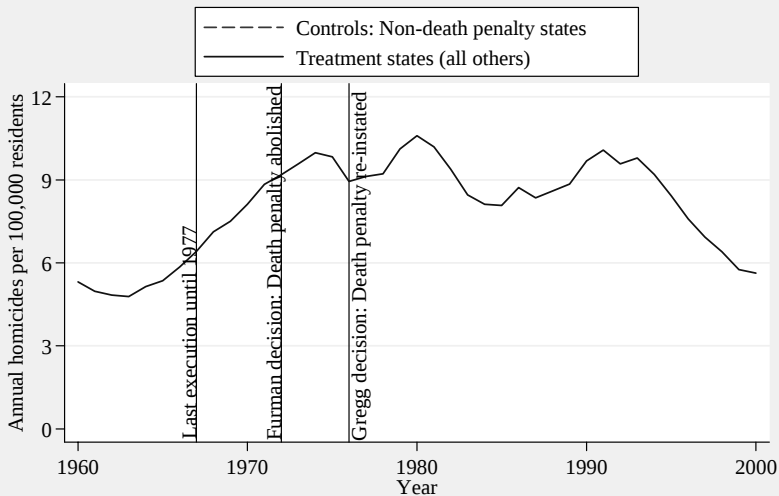
Dependent Variable: % Change in State Murder Rates Around Regime Changes						
	Death Penalty Abolition			Death Penalty Reinstatement		
	1-Year Window (1)	2-Year Window (2)	3-Year Window (3)	1-Year Window (4)	2-Year Window (5)	3-Year Window (6)
Panel B: Our Replication: Changes Around Death Penalty Shifts (Treatment)						
Mean Change	10.1% ^{***} (2.9)	16.0% ^{***} (2.3)	21.5% ^{***} (2.6)	-6.3% [*] (3.4)	-7.0% ^{**} (2.9)	-3.8% (2.9)
Median Change	8.5%	13.8%	18.5%	-9.3%	-8.5%	-7.4%
Number of States Where Homicide Increased	35/46	39/46	41/46	12/41	15/39	14/39
Panel C: Our Innovation: Changes in Comparison States (Control)						
Mean Change	8.7% ^{***} (0.5)	16.0% ^{***} (0.8)	20.6% ^{***} (1.1)	-7.5% ^{***} (1.5)	-6.6% ^{***} (1.5)	-3.7% ^{***} (1.3)
Median Change	8.5%	16.1%	20.9%	-11.5%	-9.8%	-5.2%
Number of States Where Homicide Increased	44/46	44/46	44/46	7/41	8/39	8/39

- If we compare the two groups, states that introduced/abolished death penalty (Panel B) vs. states that did not make any changes (Panel C), there are no significant differences (panel D).

Table 1: Estimating How Changes in Death Penalty Laws Effect Murder: Selected Before and After Comparisons: 1960-2000

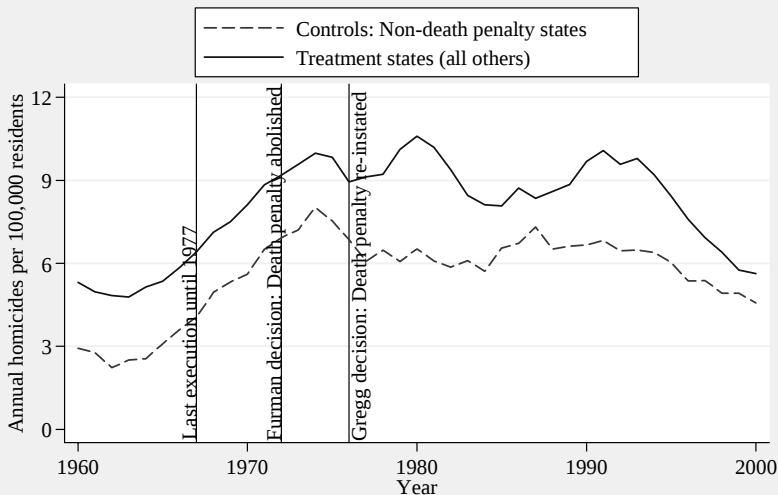
Dependent Variable: % Change in State Murder Rates Around Regime Changes						
	Death Penalty Abolition			Death Penalty Reinstatement		
	1-Year Window	2-Year Window	3-Year Window	1-Year Window	2-Year Window	3-Year Window
	(1)	(2)	(3)	(4)	(5)	(6)
Panel D: Difference-in-Difference Estimates (Treatment-Control)						
Mean Change	1.4% (2.9)	-0.1% (2.4)	0.9% (2.8)	1.2% (3.7)	-0.5% (3.2)	-0.1% (3.2)
Median Change	<0.001% (2.7)	-2.3% (2.5)	-2.4% (3.6)	2.2% (3.5)	1.3% (4.5)	-2.2% (2.0)

- We can also focus on the death penalty moratorium between 1972 and 1978.
- First, let us see how the number of homicides varies in states that have death penalty when:
 - death penalty was abolished
 - death penalty was reinstated



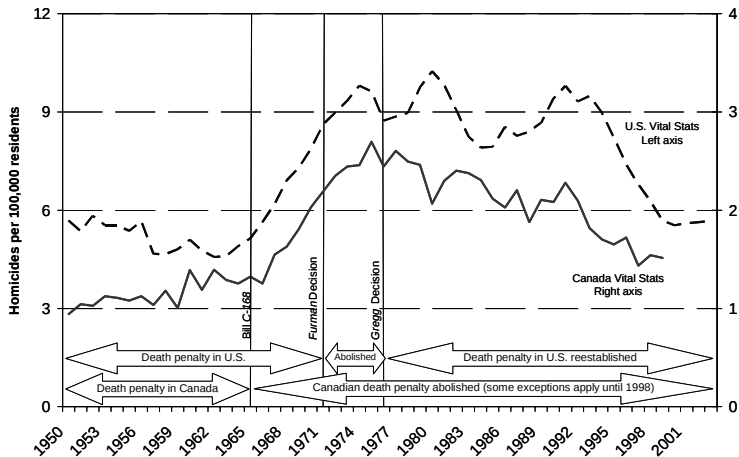
Non-death penalty states are those without a death penalty throughout 1960-2000: AK HI ME MI MN WI

Let us compare it to states that did not have death penalty



Non-death penalty states are those without a death penalty throughout 1960-2000: AK HI ME MI MN WI

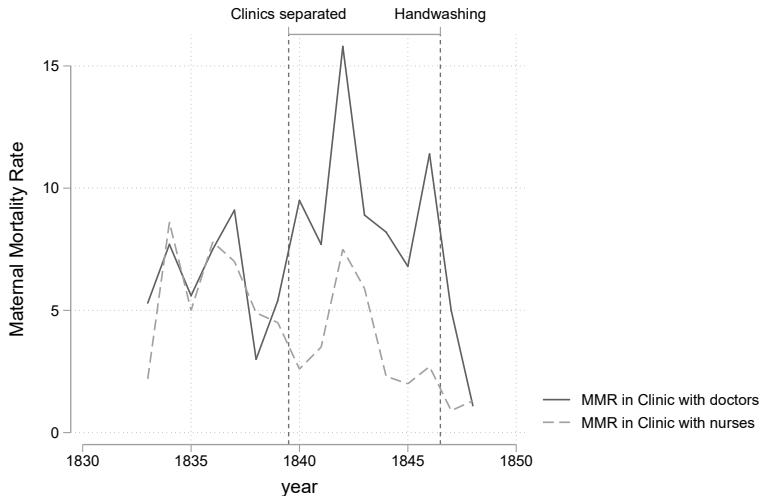
Or if we compare the evolution of homicide rates in the US and Canada



Example: Discovery of the importance of handwashing

- In 1840s the observers of Vienna's maternity hospital noted that death rates from postpartum infections were higher in one wing than the other
 - Wing 1 was attended by doctors and trainee doctors
 - Wing 2 was attended by midwives and trainee midwives
- Doctor Ignaz Semmelweis note that the difference emerged in 1841 when the hospital moved to an "anatomical" training program involving cadavers
 - Only doctors received training with cadavers, not midwives
 - Hypothesis: Transference of "cadaveric particles" explains the difference in death rates
 - Intervention by Semmelweis: Handwashing with chlorine
- Policy implemented in May of 1847

Maternal mortality rates in Vienna's maternity hospital 1833-1848



Differences-in-differences (dif-in-dif)

- The above examples captures the main intuition behind the **differences-in-differences** analysis.
- We use the evolution of the outcome variable in the control group to construct a counterfactual of what would have happened in the treatment group in the absence of the treatment.
- The fundamental identifying assumption is that, in the absence of the treatment, both groups would follow **parallel trends**
- Note that this empirical strategy allows for the existence of time-invariant differences between the two groups, but it assumes that there are no time-variant relevant differences.

Differences-in-differences (dif-in-dif)

- With only two states (A and B) and two periods (t and $t + 1$) dif-in-dif strategy can be illustrated in a very simple way
- Suppose that:
 - **At period 1:** Both states have the death penalty
 - **At period 2:** State A abolishes death penalty while state B keeps it
- Now assume that homicide rate $Y_{i,t}$ in state $i = A, B$ at period $t = 1, 2$ is determined by:

$$Y_{i,t} = \alpha_i + \lambda_t + \rho D_{i,t} + \epsilon_{i,t}$$

where $D_{i,t} = 1$ if death penalty is abolished and zero otherwise and $E(\epsilon_{i,t}) = 0$

- Our goal is to find out the causal effect of the abolishing the death penalty ρ

	A	B	Difference
Period 1	$\alpha_A + \lambda_1$	$\alpha_B + \lambda_1$	$\alpha_A - \alpha_B$
Period 2	$\alpha_A + \lambda_2 + \rho$	$\alpha_B + \lambda_2$	$\alpha_A - \alpha_B + \rho$
Difference	$(\lambda_2 - \lambda_1) + \rho$	$(\lambda_2 - \lambda_1)$	ρ

Differences-in-differences (dif-in-dif)

- This setting allows for several comparisons in which there is variation in the use of death penalty
- Suppose we compared states A and B in period $t = 2$?
(cross-state comparison)
- Suppose we compared state A between periods $t = 1$ and $t = 2$?
(before-after comparison)
- Suppose we compared changes in states A and B between periods $t = 1$ and $t = 2$? (differences-in-differences)
- Which of these comparisons gives us ρ ?

Main threats to validity of dif-in-dif estimates

- ❶ If the groups are different in levels, maybe they evolve differently?
- ❷ Why did the treatment group adopt the policy, and not the control group?
- ❸ Policies are usually implemented in bundles → the outcome variable may be affected by these other policies
- ❹ The treatment should not affect the control group
- ❺ The composition of the treatment and control groups should not change as a result of treatment

- ① The two groups evolved similarly in the past (although note that this is neither a sufficient nor a necessary condition for the validity of the empirical strategy!)
- ② The timing of the adoption of the policy was as good as random
- ③ No other policies were adopted at the same time
- ④ Verify that there is no reason to believe that the control group might be affected

Suppose cadaverous particles adhering to hands caused the same disease among maternity patients that cadaverous particles adhering to the knife caused in Kolletschka. Then if those particles are destroyed chemically, so that in examinations patients are touched by fingers but not by cadaverous particles, the disease must be reduced. Semmelweis, I. quoted in Kadar (2019)