

# Causal Inference (6.S059/15.CO8/17.CO8)

Recitation, Week 11.

**Topic: Difference-in-Differences and Regression  
Discontinuity**

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1/ DID

# Notation for Time Series Data

- Units:  $i \in \{1 \dots N\}$
- Time periods (pre/post):  $t \in \{0, 1\}$
- Treatment *group* indicator:  $D_i \in \{0, 1\}$
- Treatment indicator (whether unit  $i$  has been treated at time  $t$ ):  
 $Z_{it} \in \{0, 1\}^*$

Expected potential outcome for unit  $i$  in period  $t$  is expressed in the form:

$$\mathbb{E}[Y_{it}(z) | D_i = d]$$

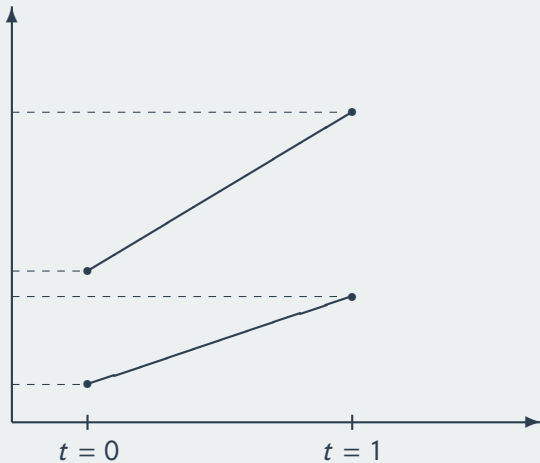
\*Note that  $Z_{it} = D_i$  in the post period

# Notations

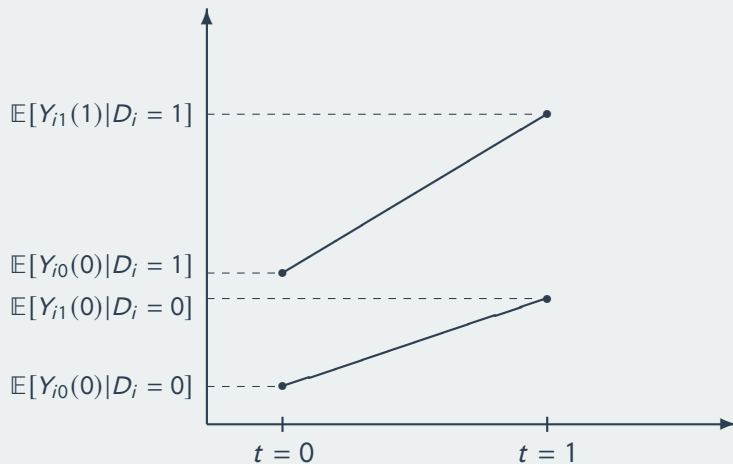
Define the following:

- $\mathbb{E}[Y_{i0}(0)|D_i = 1]$  : Expected potential outcome for units in the *treatment* group, in the period *before* treatment occurs
- $\mathbb{E}[Y_{i1}(1)|D_i = 1]$  : Expected potential outcome for units in the *treatment* group, in the period *after* treatment occurs
- $\mathbb{E}[Y_{i1}(0)|D_i = 0]$  : Expected potential outcome for units in the *control* group, in the period *after* treatment occurs
- $Y_{it}(1) - Y_{it}(0)$  : The causal effect of the treatment for unit  $i$  at time  $t$
- The ATT in the post-treatment period:  $\mathbb{E}[Y_{i1}(1) - Y_{i1}(0)|D_i = 1]$

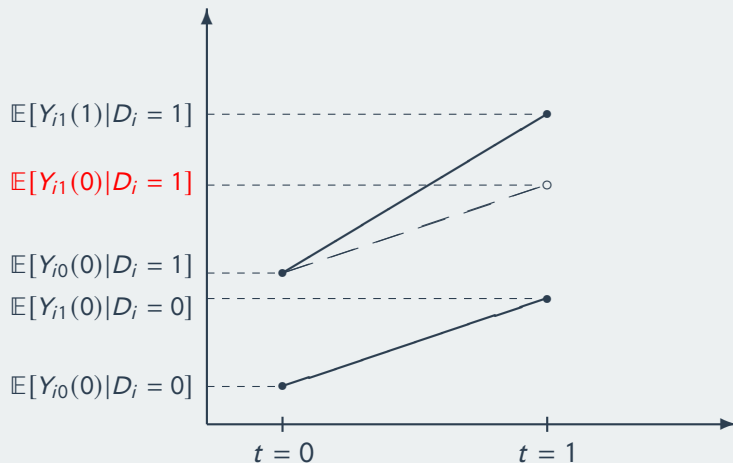
# Graphical Version



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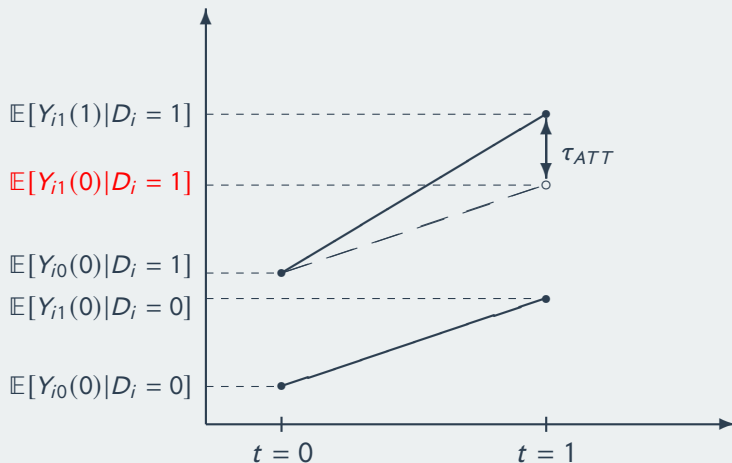


# Graphical Version

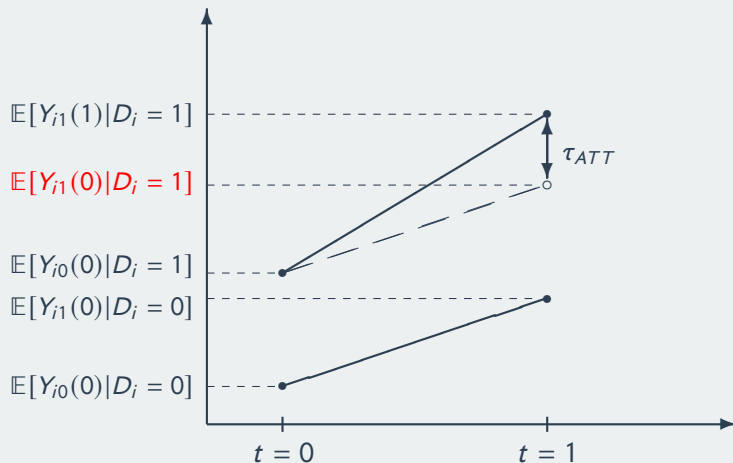




# Graphical Version

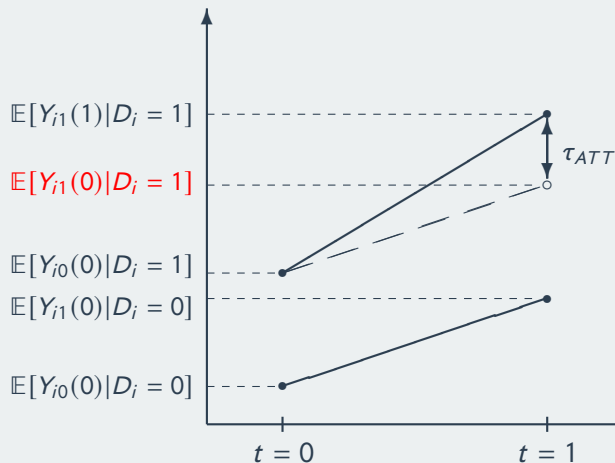


# Graphical Version



What assumption do we need to identify the ATT?

# Graphical Version



What assumption do we need to identify the ATT? **Parallel trends assumption.**

$$\mathbb{E}[Y_{i1}(0)|D_i = 1] - \mathbb{E}[Y_{i0}(0)|D_i = 1] = \mathbb{E}[Y_{i1}(0)|D_i = 0] - \mathbb{E}[Y_{i0}(0)|D_i = 0]$$

# Identification Assumptions

## Identification with Difference-in-Differences

Under the **parallel trends** assumption:

$$\mathbb{E}[Y_{i1}(0) - Y_{i0}(0) | D_i = 1] = \mathbb{E}[Y_{i1}(0) - Y_{i0}(0) | D_i = 0]$$

The ATT can be nonparametrically identified as:

$$\begin{aligned} \tau_{ATT} = & \left\{ \mathbb{E}[Y_{i1} | D_i = 1] - \mathbb{E}[Y_{i1} | D_i = 0] \right\} \\ & - \left\{ \mathbb{E}[Y_{i0} | D_i = 1] - \mathbb{E}[Y_{i0} | D_i = 0] \right\} \end{aligned}$$

# An Example

JAMA 2018: “The April 20 Cannabis Celebration and Fatal Traffic Crashes in the United States”

Methods:

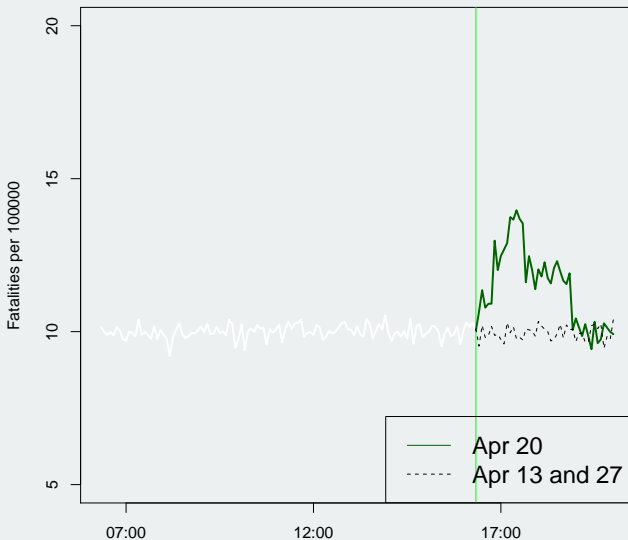
- Compare the # of fatal crashes between 4:20 PM and 11:59 PM on April 20 to the number of fatal traffic crashes during the same time intervals on control days 1 week earlier and 1 week later (i.e. April 13 and April 27).

Results:

- Found a 12% increase in the relative risk of a fatal traffic crash after 4:20 PM on April 20 compared with identical time intervals on control days.

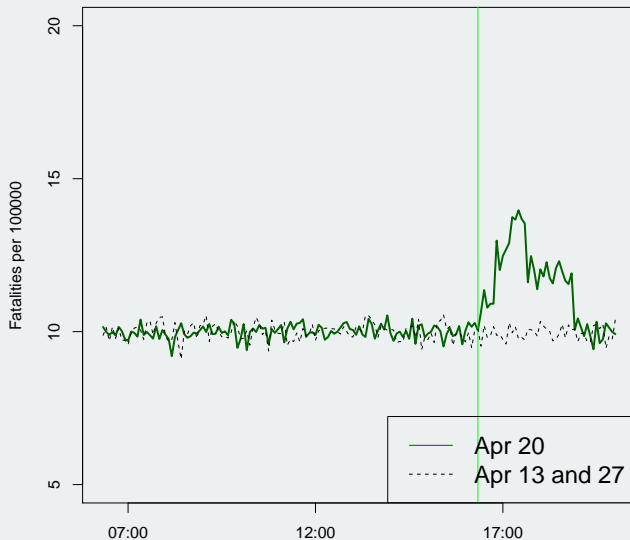
# Cannabis Celebration and Fatal Traffic Crashes

April 20 and Fatal Traffic Crashes



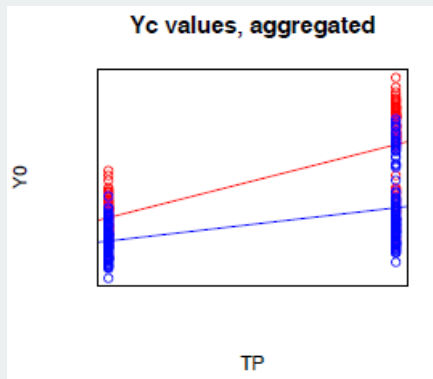
# Cannabis Celebration and Fatal Traffic Crashes

April 20 and Fatal Traffic Crashes



# Conditional DID

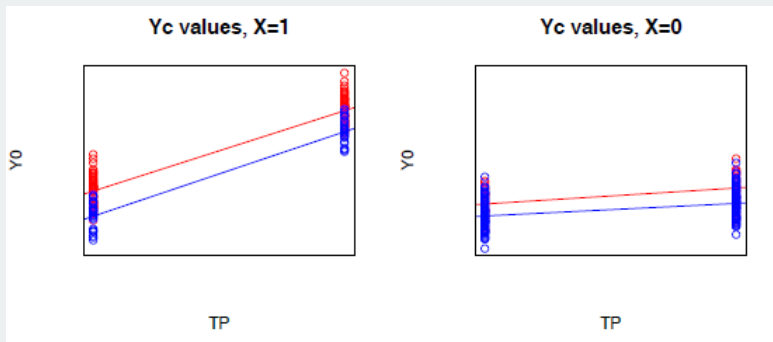
Parallel trends assumption is violated





# Conditional DID

Parallel trends assumption is conditionally satisfied



# Estimation of Conditional DID

Estimation under the Parallel trends assumption

$$Y_i = \mu + \gamma D_i + \delta T_i + \tau D_i T_i$$

where  $\mu$ ,  $\gamma$ ,  $\delta$  and  $\tau$  are OLS regression estimates

Estimation under the Conditional DiD assumption

$$Y_i = \mu + \gamma D_i + \delta T_i + \tau D_i T_i + \tau X_i T_i$$

where  $x$  is a **time-invariant pre-treatment confounder** for unit  $i$ .

# Estimation of Conditional DID

Estimation under the Parallel trends assumption

$$Y_{it}(z) = \alpha_i + \gamma t + \tau z + \varepsilon_{it}$$

where  $\alpha_i$  is a time-invariant unobserved effect for unit  $i$  that may be correlated with treatment.

Estimation under the Conditional DiD assumption

$$Y_{it}(z) = \alpha_i + \gamma t + \lambda t \cdot x + \tau z + \varepsilon_{it}$$

where  $x$  is a time-invariant pre-treatment confounder for unit  $i$ .

## **2/** Regression Discontinuity

# RD Assumptions

What assumption do we need for a RD?

$\mathbb{E} [Y_i(d)|X_i = x]$  is continuous in  $x$  around  $X_i = c$  (for  $d = 0, 1$ )

In words? The expected values of potential outcomes are continuous in  $x$ , i.e., they do not jump at cut-point (threshold)  $c$ .

What is the causal estimand of a RD?

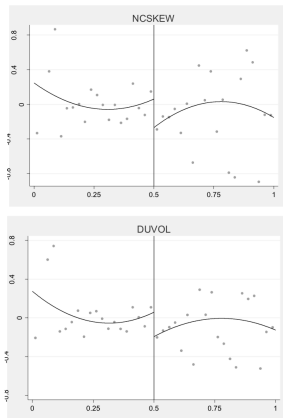
$$\tau_{RD} = \mathbb{E} [Y_i(1) - Y_i(0)|X_i = c]$$

In words? Local ATE at the threshold.

# Choices

- Bandwidth: how far away from the cutoff are your included observations (can outsource this to an algorithm).
- Model for the potential outcomes.
- In both cases we are making a bias-variance trade-off.

# Choices: Be Careful!



Notes. This figure presents regression discontinuity plots using a fitted quadratic polynomial estimate with 95% confidence intervals. The x axis is the percentage of votes favoring unionization and the dots depict the average crash risk variables in each of 20 equally spaced bins (with a 5.0% bin width). Union election results are from the NLRB over 1980-2015. Crash risk variables (*NCSKEW* and *DUVOL*) are calculated from CRSP over 1981-2016.

## CURVE-FITTING METHODS AND THE MESSAGES THEY SEND

