# Identification: Difference-in-Difference estimator

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at Regional Summer School for Young Economists

June 19, 2017

# Today's Class

- Non-experimental Methods: Difference-in-differences
  - Understanding how it works
  - How to test the assumptions
  - Some problems and pitfalls

# Experiments are good, but what if we don’t have an experiment?

- Would like to find a group that is exactly like the treatment group but didn’t get the treatment

- Hard to do because
  - Lots of unobservables
  - Data is limited
  - Selection into treatment

# Water pump on Broadwick street, Soho, London

# Background Information

- Water supplied to households by competing private companies
- Sometimes different companies supplied households in same street
- In south London two main companies:
  - Lambeth Company (water supply from Thames Ditton, 22 miles upstream)
  - Southwark and Vauxhall Company (water supply from Thames)

# In 1853/54 cholera outbreak

- Death Rates per 10000 people by water company
  - Lambeth 10
  - Southwark and Vauxhall 150
- Might be water but perhaps other factors
- Snow compared death rates in 1849 epidemic
  - Lambeth 150
  - Southwark and Vauxhall 125
- In 1852 Lambeth Company had changed supply from Hungerford Bridge

# The effect of clean water on cholera death rates

| | 1849 | 1853/54 | Difference |
|---|---|---|---|
| Lambeth | 150 | 10 | -140 |
| Vauxhall and Southwark | 125 | 150 | 25 |
| Difference | -25 | 140 | -165 |

Counterfactual 2: 'Control' group time difference. Assume this would have been true for 'treatment' group

Counterfactual 1: Pre-Experiment difference between treatment and control—assume this difference is *fixed* over time

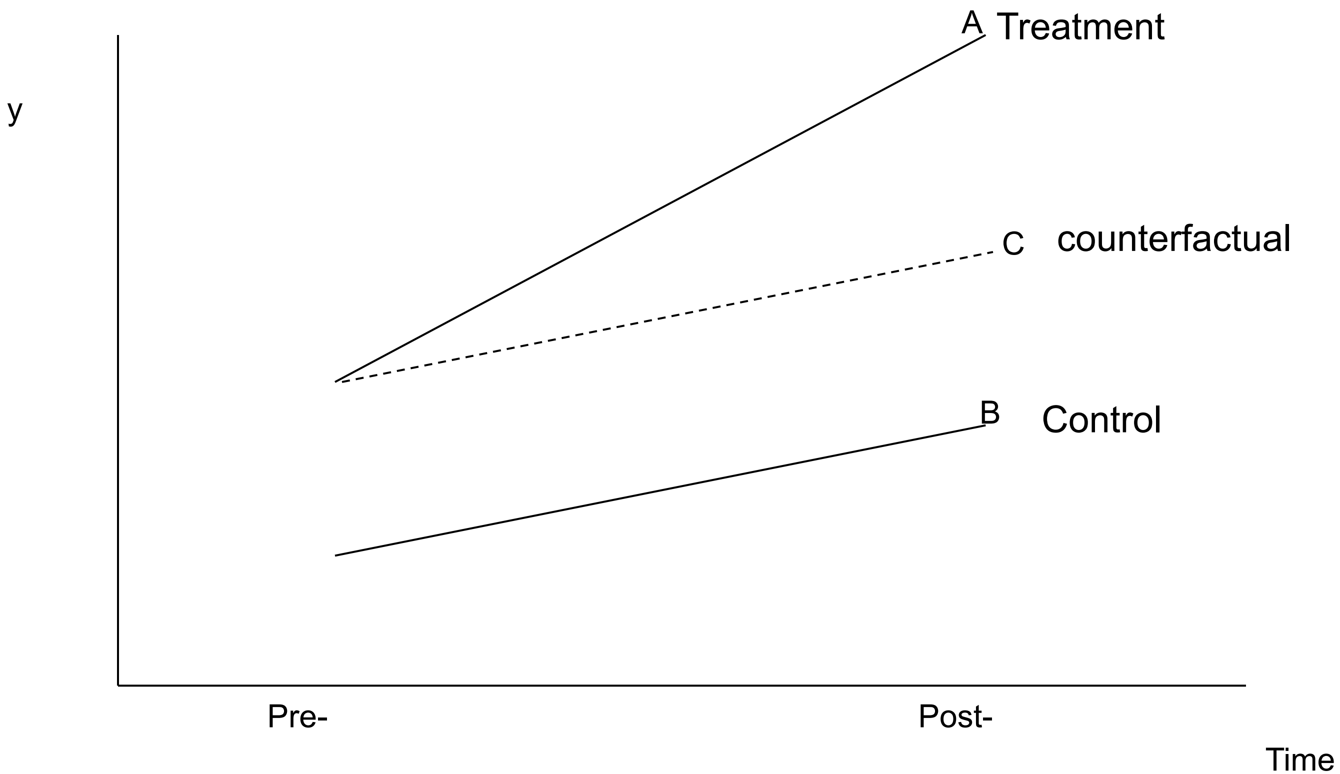
# This is basic idea of Differences-in-Differences

- Have already seen idea of using differences to estimate causal effects
  - Treatment/control groups in experimental data
- We need a counterfactual because we don't observe the outcome of the treatment group when they weren't treated (i.e. ($Y_0$ | $T=1$))
- Often would like to find 'treatment' and 'control' group who can be assumed to be similar in every way except receipt of treatment

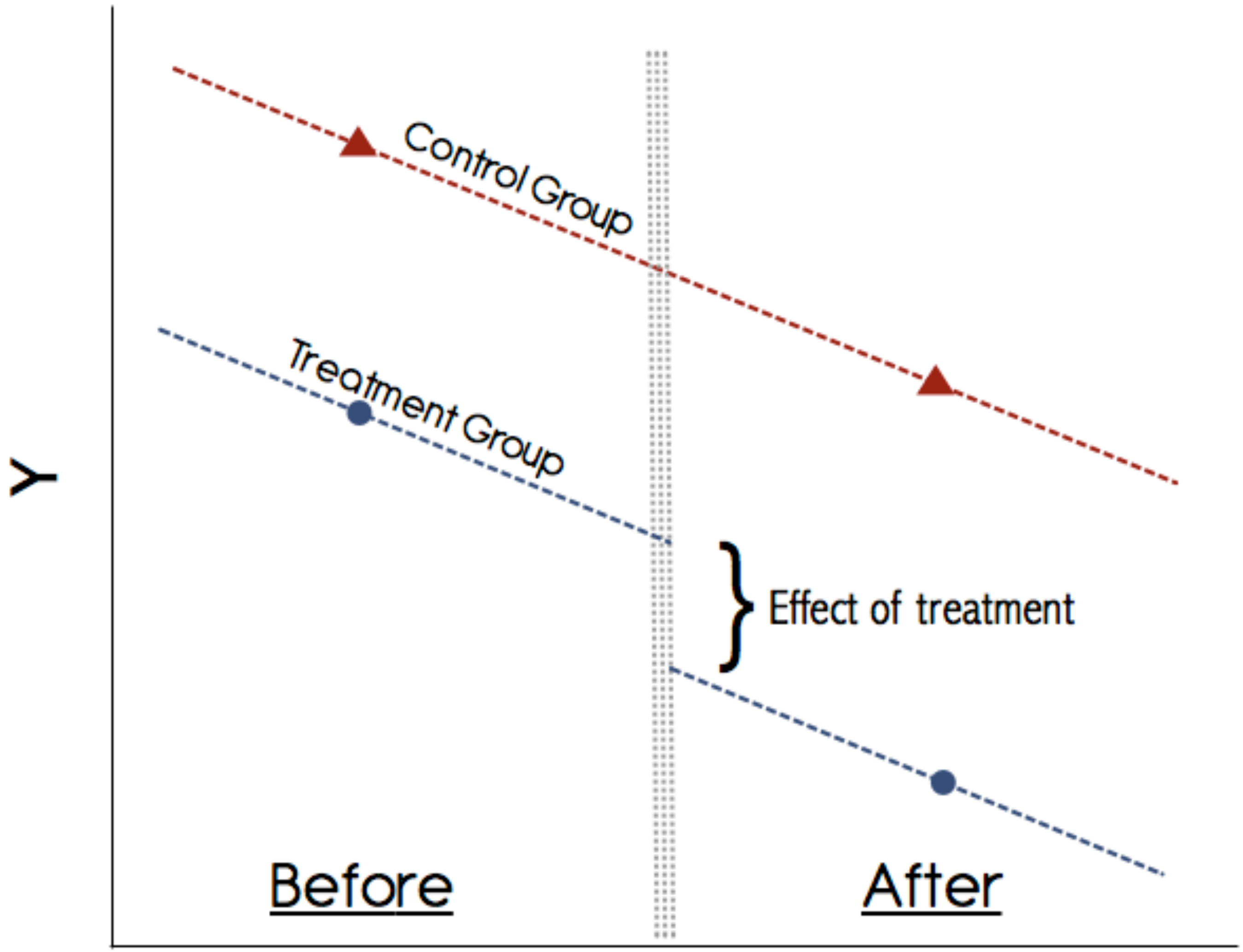
# A Weaker Assumption is..

- Assume that, in absence of treatment, difference between ‘treatment’ and ‘control’ group is constant over time
- With this assumption can use observations on treatment and control group pre- and post-treatment to estimate causal effect
- Idea
  - Difference pre-treatment is ‘normal’ difference
  - Difference pre-treatment is ‘normal’ difference + causal effect
  - Difference-in-difference is causal effect

# A Graphical Representation




A – B = Standard differences estimator
C – B = Counterfactual ‘normal’ difference
A – C = Difference-in-Difference Estimate


Control Group
Treatment Group
Effect of treatment
Y
Before
After

# Assumption of the D-in-D estimate

- D-in-D estimate assumes trends in outcome variables the same for treatment and control groups
  - Fixed difference over time
  - This is not testable because we never observe the counterfactual
- Is this reasonable?
  - With two periods can’t do anything
  - With more periods can see if control and treatment groups ‘trend together’

# Recap: Assumptions for Diff-in-Diff

- Additive structure of effects.
  - We are imposing a linear model where the group or time specific effects only enter additively.
- No spillover effects
  - The treatment group received the treatment and the control group did not
- Parallel time trends:
  - there are fixed differences over time.
  - If there are differences that vary over time then our second difference will still include a time effect.

# Issue 1: Other Regressors

- Can put in other regressors just as usual
  - think about way in which they enter the estimating equation
  - E.g. if level of W affects level of y then should include $\Delta W$ in differences version
- Conditional comparisons might be useful if you think some groups may be more comparable or have different trends than others

# Issue 2: Differential Trends in Treatment and Control Groups

- Key assumption underlying validity of D-in-D estimate is that differences between treatment and control group would have remained constant in absence of treatment
  - Can never test this
  - With only two periods can get no idea of plausibility
  - But can with more than two periods

# Differences-in-Differences: Summary

- A very useful and widespread approach

- Validity does depend on assumption that trends would have been the same in absence of treatment

- Often need more than 2 periods to test:
  - Pre-treatment trends for treatment and control to see if “fixed differences” assumption is plausible or not
  - See if there’s an Ashenfelter Dip