Differences-in-Differences & two-way fixed effects

Nils Droste

2021 ClimBEco course

Causal Inference from observational data

Introduction

Diff-in-Diff
- intuition
- potential outcome
- DAGs
- estimation

Fixed effects
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Synopsis: Today, we will be looking into *the* classical research design for inferring causal effects from observational data (i.e. when experiments are unethical or infeasible), and its recent developments

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  - Difference-in-Differences
  - (two-way) fixed-effects regressions

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  - Difference-in-Differences
  - (two-way) fixed-effects regressions
  - staggered treatment

Definition

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Quasi- / natural experiment:

A setting where a subpopulation is treated with an intervention of sorts that occurs due to non-random assignment processes (outside of the researchers influence if its called *natural*).

Recall potential outcome approximation

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We may choose to infer an average treatment effect (ATE) I: i.e. $I = \{A, B...\}$ by comparing the average outcomes of treated individuals a from A with the one of untreated individuals $b \in B$:

$$E\{\Delta Y_i\} \approx E\{Y_a(1)\} - E\{Y_b(0)\} \tag{1}$$

For such a case we can exploit *random chance* within sufficiently large samples to make these groups comparable.

Recall potential outcome approximation

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$$E\{\Delta Y_i\} \approx E\{Y_a(1)\} - E\{Y_b(0)\} \qquad (1)$$

For such a case we can exploit *random chance* within sufficiently large samples to make these groups comparable.

But what if we do not have a random assignment (and there may be a selection-bias and / or substantial differences between groups)?

a famous case

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By comparing a treated with an untreated group over 2+ periods, we can control for (time-constant) differences between groups.

a famous case

By comparing a treated with an untreated group over 2+ periods, we can control for (time-constant) differences between groups.

A classic example is the Card and Krueger (AER, 1994), comparing fast-food worker employment in Pennsylvania (PA) and New Jersey (NJ) before and after a minimum wage raise in NJ in 1992.

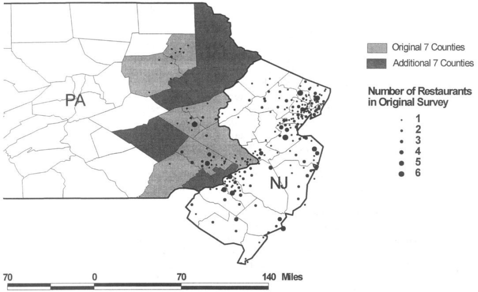

FIGURE 1. AREAS OF NEW JERSEY AND PENNSYLVANIA COVERED BY ORIGINAL SURVEY AND BLS DATA

Image source: Card and Krueger 2000

results

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Here is a (tweaked) version of Card and Krueger 1994, Figure 1.

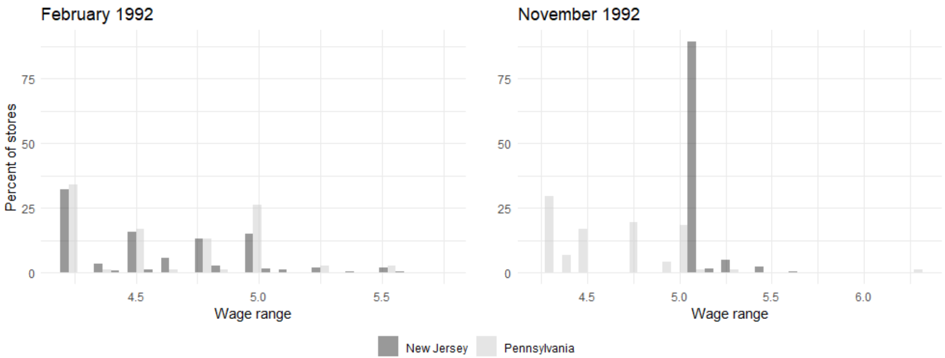

Image source: Card and Krueger 1994

potential outcome notation

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Here, we are interested in the average treatment effect on the treated (ATT)

$$ATT = E[Y_i(1) - Y_i(0)|D = 1] \tag{2}$$

potential outcome notation

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For this to be a consistent estimator, we will need a set of conditions to hold, some of which we can test, others we will need to assume.

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In particular, the parallel-trends assumption:

$$E[Y_{it}(0) - Y_{it-1}(0)|D = 1] = E[Y_{it}(0) - Y_{it-1}(0)|D = 0] \tag{3}$$

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$$E[Y_{it}(0) - Y_{it-1}(0)|D = 1] = E[Y_{it}(0) - Y_{it-1}(0)|D = 0] \tag{3}$$

because then, we can assume

$$ATT = E[Y_t - Y_{t-1}|D = 1] - E[Y_t - Y_{t-1}|D = 0] \tag{4}$$

Directed acyclic graphs

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Difference-in-Differences (DID)

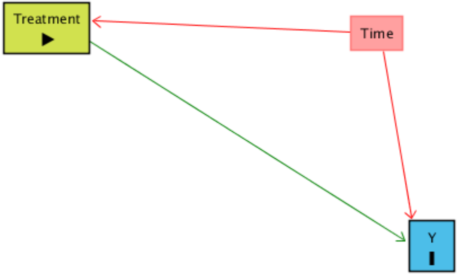

Image source: Huntington-Klein 2018

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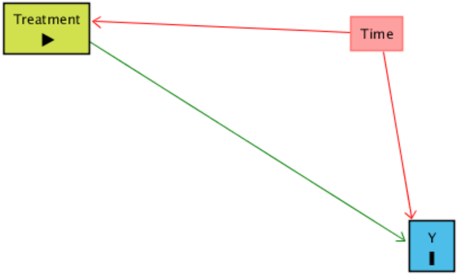

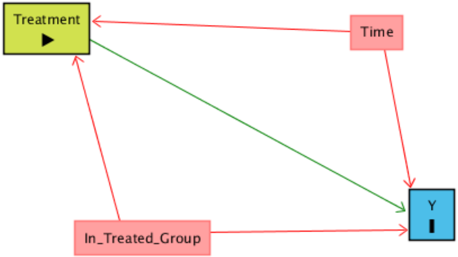

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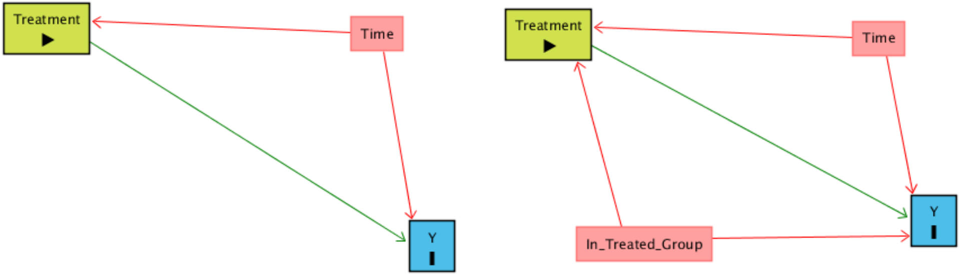

Image source: Huntington-Klein 2018

→ Accounting for differences between groups over time enables not just the estimation of time and group effects but also the differences-in-differences (i.e. the interaction of time and group effects).

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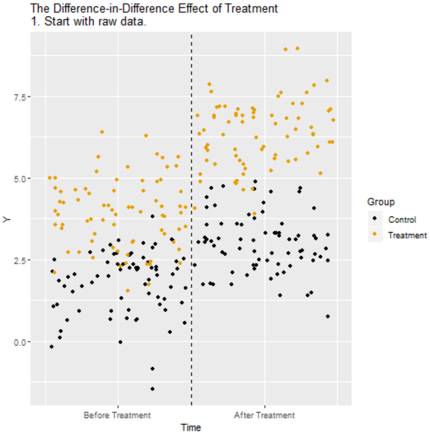


DID Estimator

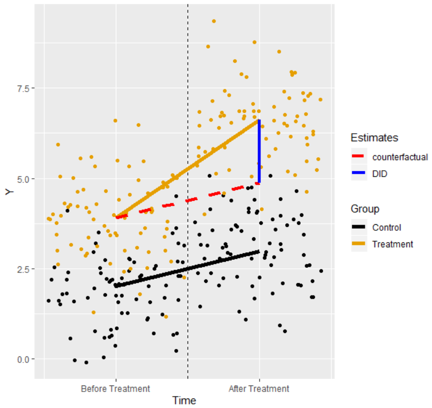
assume n individual units i, and $t = 2$ time periods, we can estimate the effect of a treatment ocurring at $P_{t=1}$, affecting the treated subpopulation $D_i = 1$

$$Y_i = \beta_0 + \beta_1 D_i + \beta_2 P_t + \beta_3 D_i \times P_t + \varepsilon_i \tag{5}$$

with D_i = Treatment,
P_t = Period Dummy.

β_3 gives us an estimate of the diff-in-diff treatment effect.

Estimation



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regression

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To estimate an example ATT, we can use the Card and Krueger (1994) data

```
> did_model <- lm(emptot ~ time + treated + time:treated,
                  data = card_krueger_1994_mod)
> summary(did_model)

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)   23.331       1.072  21.767   <2e-16 ***
time          -2.166       1.516  -1.429   0.1535
treated       -2.892       1.194  -2.423   0.0156 *
time:treated   2.754       1.688   1.631   0.1033
```

Note: heteroskedasticity and autocorrelation robust standard errors should be computed

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A difference-in-differences approach allows us to

- compare a treatment group with an untreated quasi-counterfactual
- even under conditions of a non-random assignment
- assuming that the groups behave comparably enough

Panel Data

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Let us suppose a situation with repeated measurements for multiple individual(s) (units), i.e. cross-sectional time-series, or panel data.

An example panel data structure

individual	**time**	**Y**	**X**	**D**
A	1	0.8	0.3	0
A	2	0.7	0.2	0
A	3	0.5	0.2	1
B	1	1.2	0.4	0
B	2	1.1	0.5	0
B	3	0.9	0.6	1
...	...	...	...	...

Fixed-Effects

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An exemplary study

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ANALYSIS

Environmental pressure group strength and air pollution: An empirical analysis

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Department of Geography and Environment and Center for Environmental Policy and Governance (CEPG), London School of Economics and Political Science, Houghton Street, London WC2A 2AE, UK

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Available online 24 February 2005

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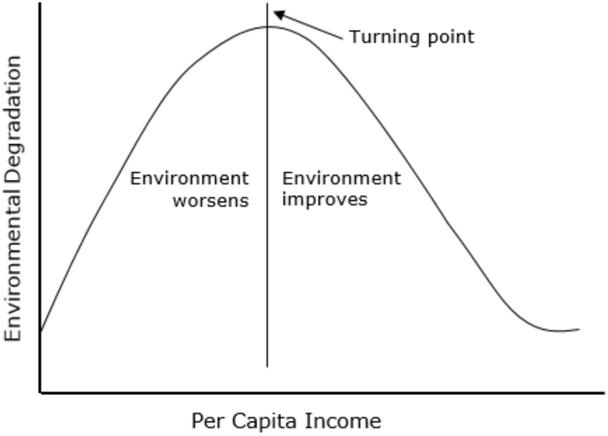
Fixed-Effects

An exemplary study



Theoretical underpinning for Binder and Neumayer 2005: Environmental Kuznets Curve. Image source: Wikipedia

Fixed-Effects

Replicated results from table 1, model 1 Binder and Neumayer 2005

```
Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)   -57.55012   16.60671  -3.465 0.000548 ***
lnengopc       -0.51121    0.11878  -4.304 1.82e-05 ***
lnenergy        1.00887    0.60455   1.669 0.095425 .
lngdp          13.81819    4.17975   3.306 0.000975 ***
lngdpsq        -0.88657    0.27384  -3.238 0.001239 **
polity         -0.05079    0.03023  -1.680 0.093135 .
```

Note: This is not a fixed effects regression but an OLS

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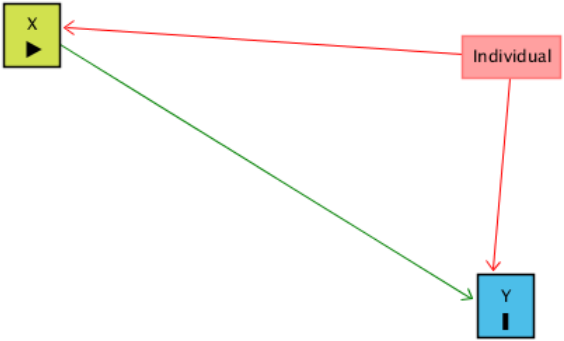
One way fixed-Effects (FE) structure



Accounting for individual fixed effects. Image source: Huntington-Klein 2018

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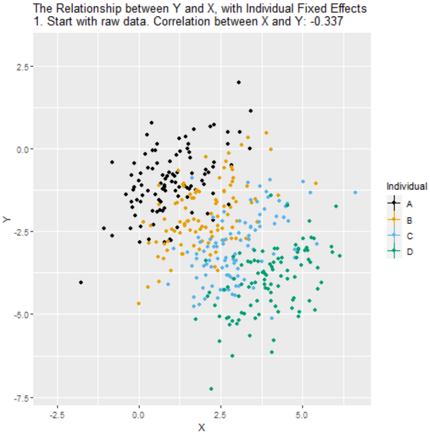

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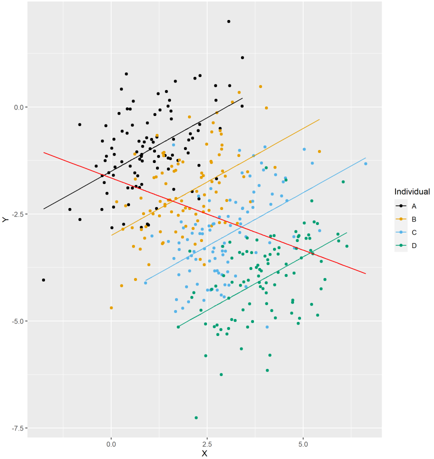

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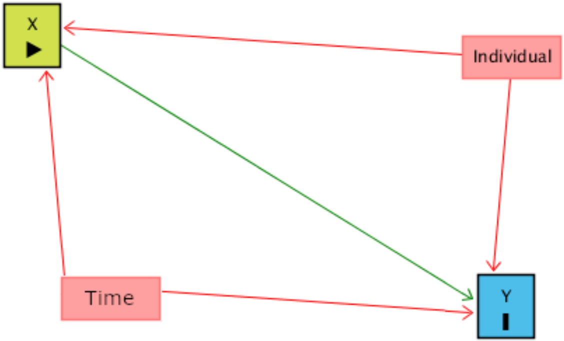
FE Estimator

$$Y_i = \alpha_i + \beta X_{it} + \varepsilon_{it} \quad (6)$$

with α_i = individual, time-invariant effect, and X_i = a variable of interest. The so called *within* transformation accounts for α_i through demeaning such that we can consistently estimate $\partial Y / \partial X$

Fixed-Effects

Two way fixed-effects



Accounting for individual and time (two-way) fixed effects. Image source: Huntington-Klein 2018

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The two-way fixed effects model can be formulated as

$$Y_{it} = \alpha_i + \theta_t + T_{it} + X_{it} + \epsilon_i \tag{7}$$

where α individual and θ time fixed effects,
T a binary treatment indicator ($T = D \times P$),
possibly a controls vector X_i,
and error term ϵ_i, assumed to be normally distributed and centered around 0, indepdendent of everything else.

time-trends

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This allows to take both individual differences and shocks in time into account

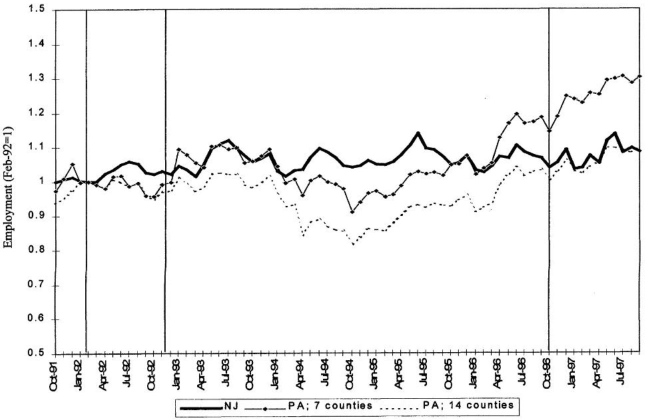

FIGURE 2. EMPLOYMENT IN NEW JERSEY AND PENNSYLVANIA FAST-FOOD RESTAURANTS, OCTOBER 1991 TO SEPTEMBER 1997

Note: Vertical lines indicate dates of original Card-Krueger survey and the October 1996 federal minimum-wage increase.
Source: Authors' calculations based on BLS ES-202 data.

Image source: Card and Krueger 2000

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A two-way fixed effects approach allows us to

- control for time-constant, unobserved heterogeneity between individuals
- control for common time shocks, that affect all individuals
- a multi-period 2WFE approach resembles DiD when
  - treatment is simultaneous
  - effects are homogeneous

Staggered treatment and other current developments

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Over the last 6 or so years, DiD methdology has seen quite some development.

I will briefly introduce

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- staggered treatment / event-time studies

Staggered treatment and other current developments

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- non-parallel trend corrections

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I will briefly introduce

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- non-parallel trend corrections
- heterogeneous treatment corrections

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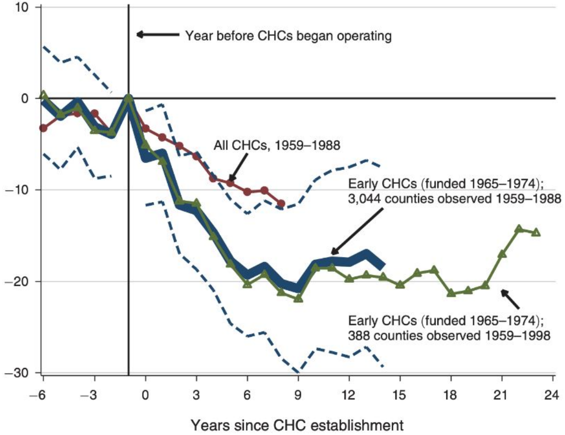
What if treatment happened at different times?



Reduction in mortality by Community Health Centers (CHC). Image source: Bailey and Goodman-Bacon 2015

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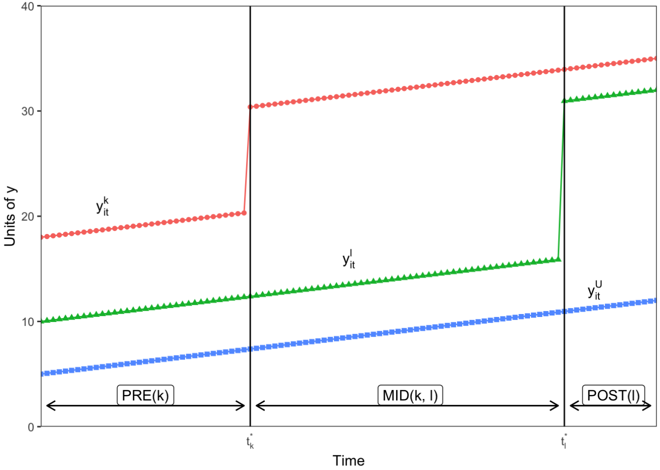
We may run into time series length related weighting problems



DiD with variations in treatment timing. Image source: Goodman-Bacon 2018, as reproduced by A.C. Baker

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Recall,

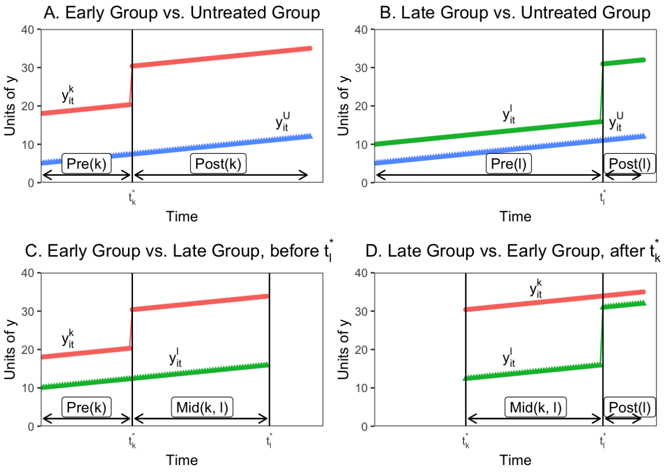
$$ATT = E[Y_t - Y_{t-1}|D = 1] - E[Y_t - Y_{t-1}|D = 0]$$

which is a comparison of mean differences between groups over time. Straightforward for 2 periods.

Now, we have multiple periods.

intuition

Picture a case with multiple periods, three groups, and thus four comparisons



DiD with variations in treatment timing. Image source: Goodman-Bacon 2018, as reproduced by A.C. Baker

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Turns out the 2WFE DiD estimator is a weighted average of all these comparisons

Theorem 1. Difference-in-Differences Decomposition Theorem
Assume that the data contain $k = 1,\ldots,K$ groups of units ordered by the time when they receive a binary treatment, $t_k^* \in (1,T]$. There may be one group, U, that never receives treatment. The OLS estimate, $\widehat{\beta}^{DD}$, in a two-way fixed-effects model (2) is a weighted average of all possible two-by-two DD estimators.

$$\widehat{\beta}^{DD} = \sum_{k\neq U} s_{kU}\,\widehat{\beta}^{2x2}_{kU} + \sum_{k\neq U}\sum_{\ell>k} s_{k\ell}\left[\mu_{k\ell}\,\widehat{\beta}^{2x2,k}_{k\ell} + (1-\mu_{k\ell})\,\widehat{\beta}^{2x2,\ell}_{k\ell}\right] \tag{7}$$

Where the two-by-two DD estimators are:

$$\widehat{\beta}^{2x2}_{kU} \equiv \left(\bar{y}_k^{POST(k)} - \bar{y}_k^{PRE(k)}\right) - \left(\bar{y}_U^{POST(j)} - \bar{y}_U^{PRE(j)}\right)$$

$$\widehat{\beta}^{2x2,k}_{k\ell} \equiv \left(\bar{y}_k^{MID(k,\ell)} - \bar{y}_k^{PRE(k)}\right) - \left(\bar{y}_\ell^{MID(k,\ell)} - \bar{y}_\ell^{PRE(k)}\right)$$

$$\widehat{\beta}^{2x2,\ell}_{k\ell} \equiv \left(\bar{y}_\ell^{POST(\ell)} - \bar{y}_\ell^{MID(k,\ell)}\right) - \left(\bar{y}_k^{POST(\ell)} - \bar{y}_k^{MID(k,\ell)}\right)$$

the weights are:

$$s_{kU} = \frac{n_k n_U \bar{D}_k(1-\bar{D}_k)}{\widehat{var}\,(\tilde{D}_{it})}$$

$$s_{k\ell} = \frac{n_k n_\ell(\bar{D}_k-\bar{D}_\ell)(1-(\bar{D}_k-\bar{D}_\ell))}{\widehat{var}\,(\tilde{D}_{it})}$$

$$\mu_{k\ell} = \frac{1-\bar{D}_k}{1-(\bar{D}_k-\bar{D}_\ell)}$$

and $\sum_{k\neq U} s_{kU} + \sum_{k\neq U}\sum_{\ell>k} s_{k\ell} = 1$.

Proof: See appendix A.

Bacon decomposition theorem. Image source: Goodman-Bacon 2018, see also his tweet-thread

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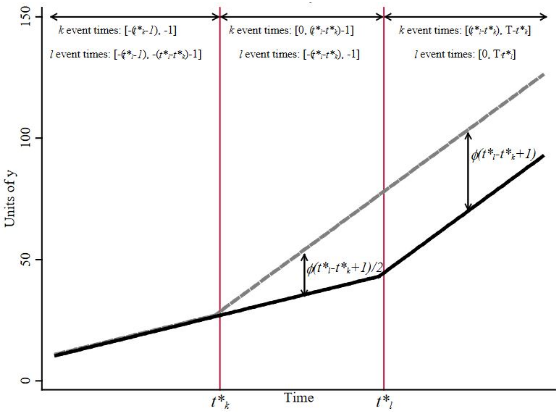
Even worse, a positive but staggered slope change, can even change the sign of the DD estimate



Staggered treatment with linear slope change. Image source: Goodman-Bacon 2018, see also his tweet-thread

Proposed solutions

Several works on the issue:

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Several works on the issue:

- Athey and Imbens 2020
  - under random adoption dates, the DID is unbiased
  - comparing treated with not-yet treated

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  - a time-in-treatment weighted DiD

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Several works on the issue:

- Athey and Imbens 2020
  - under random adoption dates, the DID is unbiased
  - comparing treated with not-yet treated
- Goodman-Bacon 2018
  - a time-in-treatment weighted DiD
- Callaway and Sant'Anna 2020
  - semiparametric, bootstrapped inference with pre-intervention conditioning on co-variates
  - R package did

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Several works on the issue:

- Athey and Imbens 2020
  - under random adoption dates, the DID is unbiased
  - comparing treated with not-yet treated
- Goodman-Bacon 2018
  - a time-in-treatment weighted DiD
- Callaway and Sant'Anna 2020
  - semiparametric, bootstrapped inference with pre-intervention conditioning on co-variates
  - R package did
- Sun and Abraham 2020
  - a time-to-treatment (cohort) weighted approach
  - implemented in fixest R package

Heterogeneous Treatment

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Further works on DiD design / application issues:

- Chaisemartin and D'Haultfœuille 2020
  - allowing for treatment effects "heterogeneous across groups and over time periods"
  - R package DIDmultiplegt
- Imai and Kim 2020
  - identify some proplematic negative weigthing in 2WFE
  - they propose weighting or matching Imai 2020

Non-parallel trends

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However, all these approaches, assume (to some extent) parallel trends

- Roth
  - test for parallel-trends, R package pretends
  - robust inference strategy under non-parralel trends Rambachan and Roth 2020, R package HonestDiD

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Re: DiD and (adjusted) 2WFE estimators

- compare treated individual (units) with a reference group
- who we compare to whom deserves special attention
- constantly being developed further

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