Fixed effects and DiD

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Fixed Effects

Basic idea

When observations are nested in clusters

- several measurements on the same individuals over time (longitudinal data)
- family members (e.g. siblings, cousins or twins)
- people living in the same neighborhood

And outcome and exposure of interest varies within clusters,

We can estimate effect of exposure by within cluster comparisons

Longitudinal data: individuals serves as their own controls

Family data: sibling control

Why is this useful?

Example: Is there an effect of maternal smoking during pregnancy on the cognitive ability of her offspring?

- Without clustering, we would have to compare children of mothers that smoked with children of mothers that didn’t.

Problem: a lot of confounders here.

Smokers and non-smokers differs in many ways (that also can affect the outcome)

- socio-economic status (education, work, income, living conditions etc.)
- life style (diet, exercise, risk taking, etc.)
- genetics

Hard to adjust for all of them!

Why is this useful?

- If we instead compare siblings where the mother smoked in one pregnancy but not in the other, we adjust for all confounders, *including unobservable ones*, that are stable between pregnancies.
- That might include

  - shared genes: siblings have the same mother (obviously) and father (often)

  - upbringing

  - diet and living conditions probably relatively stable

  - socioeconomic status

  - parents education

Maternal smoking and cognitive ability of offspring - continued

FE quite popular in registry studies (look to Sweden?)

Ralf Kuja-Halkola, Brian M. D'Onofrio, Henrik Larsson & Paul Lichtenstein: *Maternal Smoking During Pregnancy and Adverse Outcomes in Offspring: Genetic and Environmental Sources of Covariance*, Behav Genet (2014) 44:456–467

- Data from Swedish birth-, school-, crime-, conscription- and patient-registries

Here we only consider results for cognitive ability (at conscription)

- Standard regression estimates (comparing children of different mothers) suggests that maternal smoking is associated with a 0.57 points lower score (on a 0-9 ability scale) adjusted for available confounders.
- The FE estimate (between siblings) shows zero effect of smoking. (They also compare half-siblings, and full- and half-cousins)

Conclusion: “(…) SDP seemed to have no direct effect on cognitive and externalizing outcomes when siblings discordant for smoking during pregnancy were compared. These results imply familial confounding for all of the long-term associations.”

Fixed Effects can't fix everything

- While stable confounders are adjusted for, we still have to consider confounders that vary between pregnancies (some are easy to account for, like mother's age or year of birth)
- For binary exposures, like smoking (yes/no), we only compare siblings of mothers that changed smoking status between pregnancies.
  - loss of power (registries are large, but rare outcomes problematic)
  - selected group (might not apply to mothers with stable smoking behavior)
  - mothers that change smoking status, might also change other life-style behaviors (time varying confounding that is hard to adjust for)
- Some of the variables adjusted for might actually not be confounders, but mediators (which we don't always want to adjust for)

Why the name fixed effects?

- Technically within cluster effects can be estimated by introducing a constant term for each mother in a regression. That is, we get as many constant terms as there are mothers. These terms are called fixed effects.

- For binary outcomes, this corresponds to conditional logistic regression
- For time to event outcomes, it is stratified Cox regression

Readings

- Schempf AH, Kaufman JS, *Accounting for context in studies of health inequalities: a review and comparison of analytic approaches*, Ann Epidemiol. 2012 Oct;22(10):683-90.
- Gunasekara FI, Ken Richardson K, Kristie Carter K, Blakely T, *Fixed effects analysis of repeated measures data*, Int J Epidemiol. 2014 Feb;43(1):264-9

With a critical touch (from Sweden):

- Frisell T, Öberg S, Kuja-Halkola R, Sjölander A, *Sibling Comparison Designs: Bias From Non-Shared Confounders and Measurement Error,* Epidemiology. 2012 Sep;23(5):713-20.
- Sjölander A, Zetterqvist J, *Confounders, Mediators, or Colliders: What Types of Shared Covariates Does a Sibling Comparison Design Control For?*, Epidemiology. 2017 Jul;28(4):540-547

Differences-in-differences
DiD

- Method for estimating group effects of interventions or policy changes that do not affect everybody at the same time or in the same way.
- Special case of fixed effects models on aggregated (in stead of individual) data

We want to evaluate the effect of introducing a new policy on some health outcome

The goal is to estimate treatment effect = $E(Y^1 – Y^0)$

Two obvious strategies:

1. Compare the outcome after the new policy is in place with the outcome for a group that is not affected by the policy
   - Problem: the two groups might differ in many ways unrelated to the policy
2. Compare the outcome after the policy is effective with the outcome before policy change in the group that is affected by the new policy
   - Problem: the outcome might have changed over time for reasons unrelated to the policy change

DiD

- DiD: combine the two strategies and solve both problems

- The first difference: Before-after comparison (comparing the groups with themselves) eliminates confounders that are stable over time
- The second difference: difference in before-after differences in the two groups (hence the name DiD) eliminates the time effect

Example: smoking ban and birth outcomes

- In 2004 smoking ban in bars and restaurants was introduced in Norway
- Did this new regulation have an effect on birth outcomes (very low bw) for women who works in bars and restaurants?
- Comparison group were women that works in stores
- Kind of reversed form first slide: smoking was already banned in stores

- First strategy: compare prevalence of vlbw for women that worked in bars and women that worked in stores before smoking ban

workplace	Prevalence of vlbw
bar	Y = B
store	Y = S + TE

Comparing groups we get an estimate of difference between bar workers (without smoking ban) and store workers (with smoking ban) = B - S - TE

This estimate is biased unless the difference in lbwt between bar workers and store workers is only due to smoking. (Ignorability)
Probably not (they might differ in other ways)

- Second strategy: compare prevalence of vlbw for women that worked in bars before and after smoking ban

workplace	Time	Prevalence of vlbw
bar	before	Y = B
	after	Y = B + T + TE

Comparing before and after smoking ban we get an estimate of difference = T + TE

This estimate is biased unless difference in prevalence of lbwt is only due to smoking regulation. (Ignorability) Maybe not, prevalence might change over time for other reasons, especially if we consider a long time span.

DiD: combining strategies

- Before-after difference is T + TE for bar workers and T for store workers
- Difference in differences (bar vs store) is T + TE – T = TE

  which is what we are looking for!
- By differencing twice we have eliminated both the fixed effects, B and S, and the time effect, T.
- Magic? It is not that easy. DiD rests on a few key assumptions

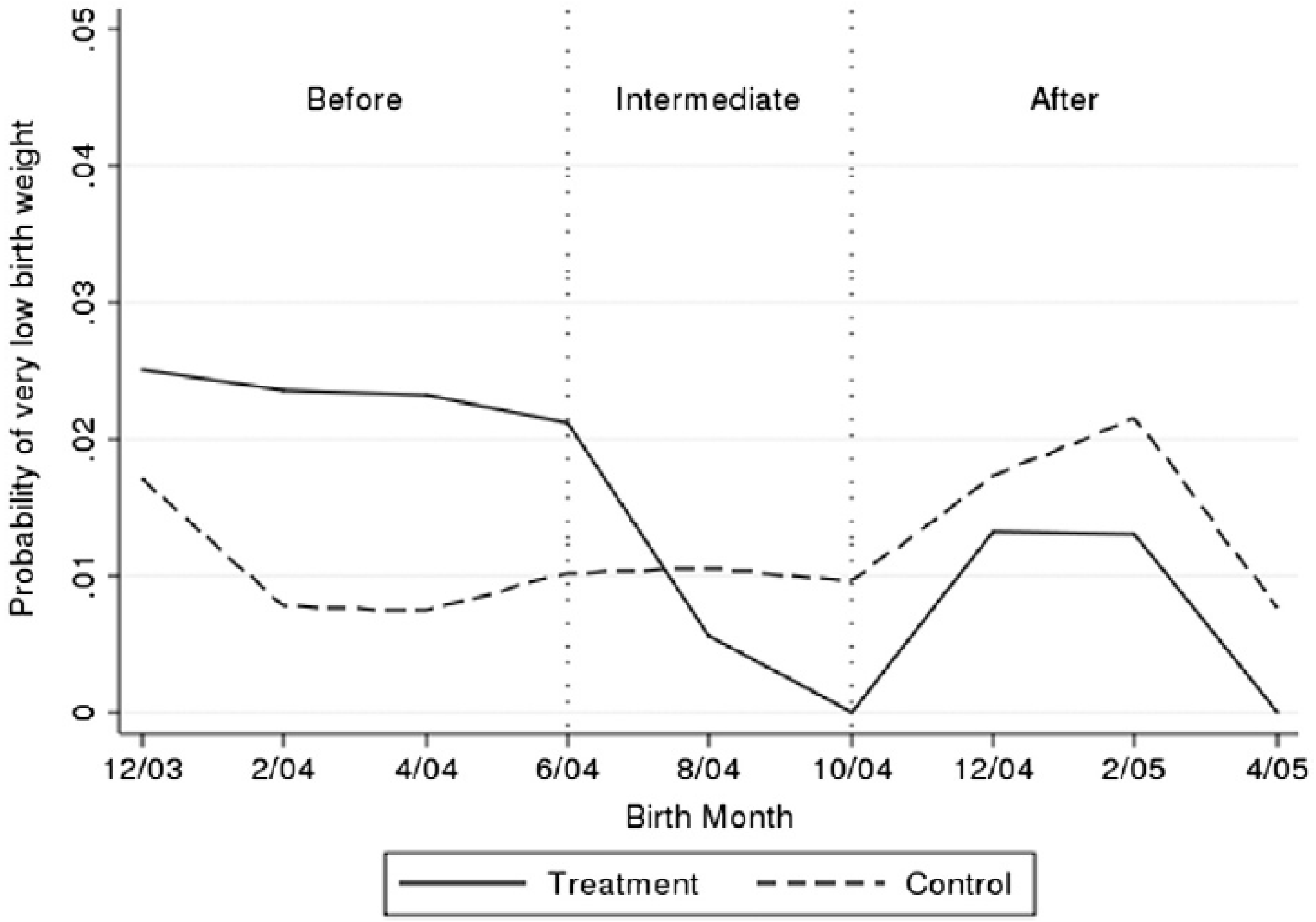
DiD assumptions

- No time-varying workplace specific unobservable confounders. There is nothing unobservable among bar workers that changes over time and also has an effect on birth outcomes.
- The time trend in birth outcomes, T, is the same for bar workers as for store workers without intervention. The parallel trend assumption.

  - Counterfactual: cannot observe what would have happened. Untestable.

  - But, if we have data on longer periods, we can at least check if the trends seemed parallel before the intervention (as they did in the paper).

Parallell trends?



Reference

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Smoking bans, maternal smoking and birth outcomes ☆

Prashant Bharadwaj [a], Julian V. Johnsen [b,*], Katrine V. Løken [b]

[a] Department of Economics, UC San Diego, United States
[b] Department of Economics, University of Bergen, Norway