Causal inference week 7: Panel diff-in-diff

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Introduction

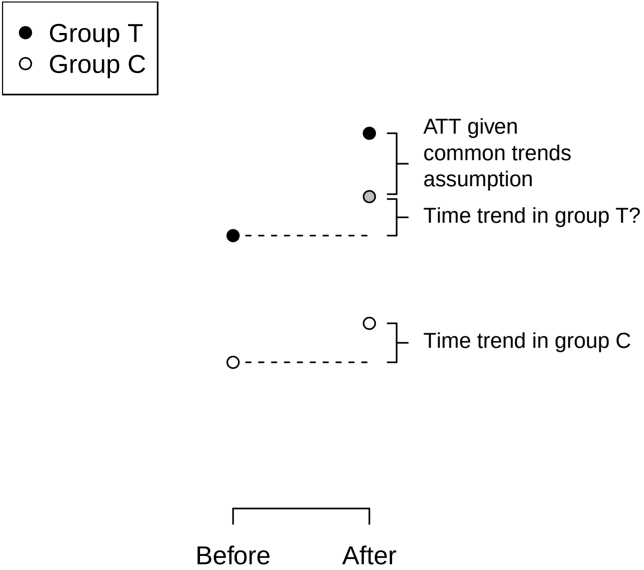
Overview

Strategies for estimating effects of treatments so far:

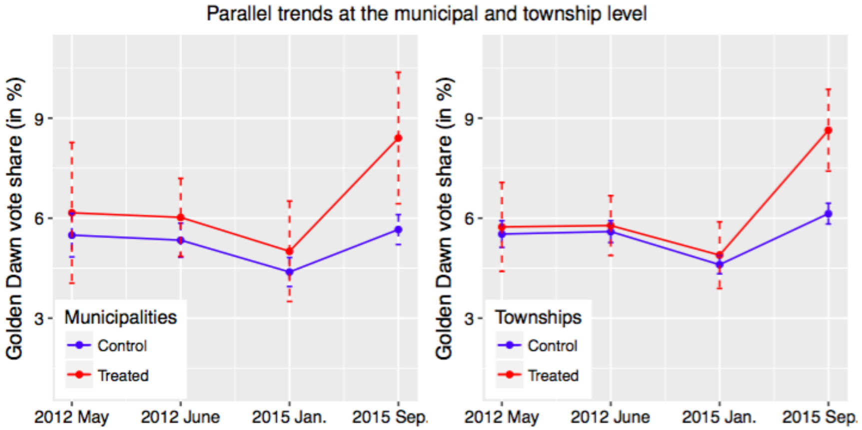
- Randomize treatment and take the DIGM
- Identify and control for confounding variables such that the CIA holds
- Identify an instrumental variable and use two-stage-least-squares to estimate average treatment effect for compliers
- Identify a situation in which the treatment depends on a cutoff
- Use observations at more than one point in time

Today: Generalizing the diff-in-diff.

Simplest diff-in-diff



Dinas et al on the Golden Dawn



Diff-in-diff with unit and time period dummies

Given **panel data**, you can run

```
lm(gdper ~ treatment + as.factor(election) + as.factor(muni))
```

to estimate coefficients of regression

$$\text{gdper}_{mt} = \beta_1 \text{treatment}_{mt} + \alpha_t + \gamma_m,$$

which **MM** would write as

$$\text{gdper}_{mt} = \beta_1 \text{treatment}_{mt} + \sum_{j=1}^{T} \alpha_j \text{Election}_{jt} + \sum_{k=1}^{M} \gamma_k \text{Municipality}_k .$$

Regression output (truncated):

```
Call:
lm(formula = gdper ~ treatment + as.factor(election) + as.factor(muni) -
    1, data = d[use, ])

Residuals:
    Min      1Q  Median      3Q     Max
-4.5855 -0.5236 -0.0003  0.4404  6.9990

Coefficients:
                                     Estimate Std. Error t value Pr(>|t|)
treatment                              2.0788     0.3948   5.265 2.79e-07 ***
as.factor(election)Sept15              7.7566     0.5635  13.764  < 2e-16 ***
as.factor(election)Jan15               6.4612     0.5624  11.488  < 2e-16 ***
as.factor(election)June12              7.4365     0.5624  13.222  < 2e-16 ***
as.factor(election)May12               7.5862     0.5624  13.489  < 2e-16 ***
as.factor(muni)Αγίου Βασιλείου        -3.9911     0.7829  -5.098 6.33e-07 ***
as.factor(muni)Αγίου Ευστρατίου       -2.1644     0.7829  -2.765 0.006078 **
as.factor(muni)Αγίου Νικολάου         -3.8906     0.7829  -4.969 1.17e-06 ***
as.factor(muni)Αγαθονησίου            -3.6954     0.7891  -4.683 4.41e-06 ***
```

Panel diff-in-diff: main idea

Given a simple diff-in-diff in panel data, we can run this regression:

$$Y_{it} = \beta_1 \text{treatment}_{it} + \alpha_t + \gamma_i$$

But in panel data we can run this regression for **any** type of treatment applied in **any** pattern.

Under what assumptions is β_1 an unbiased estimator of the ATT?
Two ways of putting it:

- **parallel trends**: time trends unrelated to treatment received; i.e., if treatment did not vary, treated and untreated units would follow common trends
- **no time-varying confounders**: any omitted variables related to treatment must be fixed over time

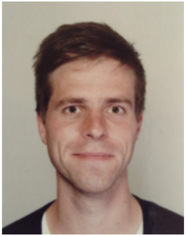
"English Bacon": research question

Does the UK government favor politically-aligned local councils when distributing targeted grants?

Consider assessing this with cross-sectional data (Ward & John, 1999).

- What covariates would you need?
- What about IV?
- What about RDD?

“English Bacon”: overview



Alex Fouirnaies

Hande Mutlu-Eren

- Assemble panel data for 1992-2012 with
  - partisan composition of local councils
  - grants allocated (per capita)
- Define treatment Copartisan$_{it}$ as: council i's majority and PM are copartisans in year t
- Regress grants on (lagged) treatment and
  - council dummies (council fixed effects)
  - year dummies (year fixed effects)
  - council-year interactions (council-specific linear time trends)
- Test for larger effects before elections, in swing councils, etc. (more next week on treatment effect heterogeneity)

"English Bacon": basic regression (no unit-specific time trends)

We might expect grants at t to depend on $\text{Copartisan}_{i,t-1}$.
We estimate

$$\text{LogOfGrantsPerCapita}_{it} = \beta_1 \text{Copartisan}_{i,t-1} + \alpha_t + \gamma_i$$

with this syntax

```
lm(lngrants ~ treatment_lag1 + as.factor(year) + as.factor(council) )
```

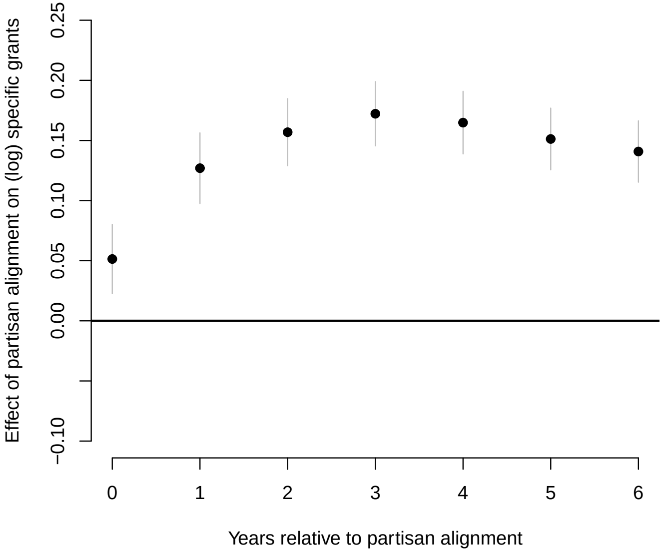
to estimate effect of alignment k years ago on grants now.

Regression output (truncated)

```
> summary(lm(lngrants ~ treatment_lag1 + as.factor(year) + as.factor(councilnumber), data = d[use,]))

Call:
lm(formula = lngrants ~ treatment_lag1 + as.factor(year) + as.factor(councilnumber),
    data = d[use, ])

Residuals:
    Min      1Q  Median      3Q     Max
-3.2089 -0.2575  0.0148  0.2418  4.3960

Coefficients:
                           Estimate Std. Error t value Pr(>|t|)
(Intercept)               0.4260079  0.0998185   4.268 2.00e-05 ***
treatment_lag1            0.1269693  0.0149935   8.468  < 2e-16 ***
as.factor(year)1993       0.1383544  0.0318947   4.338 1.46e-05 ***
as.factor(year)1994       0.1507899  0.0317807   4.745 2.14e-06 ***
as.factor(year)1995       0.0719591  0.0321439   2.239 0.025214 *
as.factor(year)1996       0.0982419  0.0319827   3.072 0.002138 **
as.factor(year)1997       0.0837433  0.0321113   2.608 0.009132 **
as.factor(year)1998       0.0833194  0.0318026   2.620 0.008818 **
as.factor(year)1999       0.1550595  0.0317998   4.876 1.11e-06 ***
as.factor(year)2000       0.2804133  0.0317496   8.832  < 2e-16 ***
as.factor(year)2001       0.4673901  0.0315067  14.835  < 2e-16 ***
as.factor(year)2002       0.6083286  0.0312453  19.469  < 2e-16 ***
as.factor(year)2003       1.1727693  0.0309422  37.902  < 2e-16 ***
as.factor(year)2004       1.3882406  0.0311179  44.612  < 2e-16 ***
as.factor(year)2005       1.5416901  0.0311378  49.512  < 2e-16 ***
as.factor(year)2006       2.1168448  0.0310975  68.071  < 2e-16 ***
as.factor(year)2007       2.2289501  0.0313889  71.011  < 2e-16 ***
as.factor(year)2008       2.2081314  0.0313613  70.409  < 2e-16 ***
as.factor(year)2009       2.3290924  0.0322764  72.161  < 2e-16 ***
as.factor(year)2010       2.3613410  0.0322684  73.178  < 2e-16 ***
as.factor(councilnumber)2 0.4049491  0.1336061   3.031 0.002448 **
as.factor(councilnumber)3 0.2732103  0.1393311   1.961 0.049940 *
```

Effect of partisan alignment at $t - k$ on log grants

For lags of $k = 0, 1, \ldots, 6$ years:



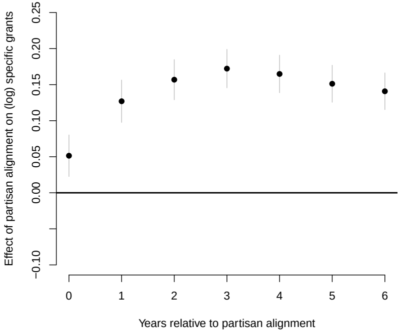
What could explain this finding?

Recall: regression equation was

$$\text{LogOfGrantsPerCapita}_{it} = \beta_1 \text{Copartisan}_{i,t-k} + \alpha_t + \gamma_i$$

Could we find positive β_1 because

- rural councils get fewer per-capita grants and tend to be Conservative; mostly Labour governments in 1992-2012?
- Labour governments gave more grants when they were in government, and there are more Labour councils in the data?



What else could explain it?

Explaining panel DiD findings

Suppose the **data generating process (DGP)** is

$$Y_{it} = \beta_1 D_{it} + \eta \mathbf{X}_t + \zeta \mathbf{U}_i + \psi \mathbf{V}_{it} + \omega_{it}$$

where

- $\mathbf{X}_t$ are time-specific variables that affect outcomes for all units the same way (e.g. budget for targeted grants),
- $\mathbf{U}_i$ are unit-specific variables that are constant over time (e.g. urban/rural character, presence of Roman ruins),
- $\mathbf{V}_{it}$ are variables that may vary within units over time (e.g. presence of ambitious council member, local economic situation), and
- ω_{it} is random noise.

In panel-DiD analysis where we estimate $Y_{it} = \beta_1 D_{it} + \alpha_t + \gamma_i + \epsilon_{it}$,

- time dummies (α_t) control for all $\mathbf{X}_t$
- unit dummies (γ_i) control for all $\mathbf{U}_i$

so the only possible confounders are $\mathbf{V}_{it}$.

Applying regression anatomy to a panel DiD regression

Think of a panel DiD regression this way:

1. Regress treatment on unit and time period fixed effects:

$$\text{Copartisan}_{i,t-k} = \alpha_t + \gamma_i$$

2. Regress outcome on the residuals from the above regression:

$$\text{LogOfGrants}_{it} = \beta_1 \left(\text{Copartisan}_{i,t-k} - \widehat{\text{Copartisan}}_{i,t-k} \right)$$

Key conclusions:

- All residuals will be zero for any unit that is always treated or never treated → no role in estimating β_1
- β_1 estimated based on **variation in treatment over time within units**
- the only relevant confounders **vary with treatment over time within units**

Panel DiD regression as the **“within”** estimator.

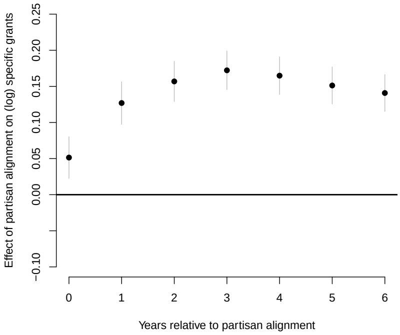
What could explain this finding? (2)

Recall: regression equation was

$$\text{LogOfGrantsPerCapita}_{it} = \beta_1 \text{Copartisan}_{i,t-k} + \alpha_t + \gamma_i$$

What confounders might vary with treatment over time within units?

- Labour councils had growing needs, Conservative councils shrinking needs?
- Labour councillors improving?
- others?



Relaxing the parallel trends assumption

Regression equation was

$$\text{LogOfGrantsPerCapita}_{it} = \beta_1 \text{Copartisan}_{i,t-k} + \alpha_t + \gamma_i$$

but consider adding unit-specific linear time trends:

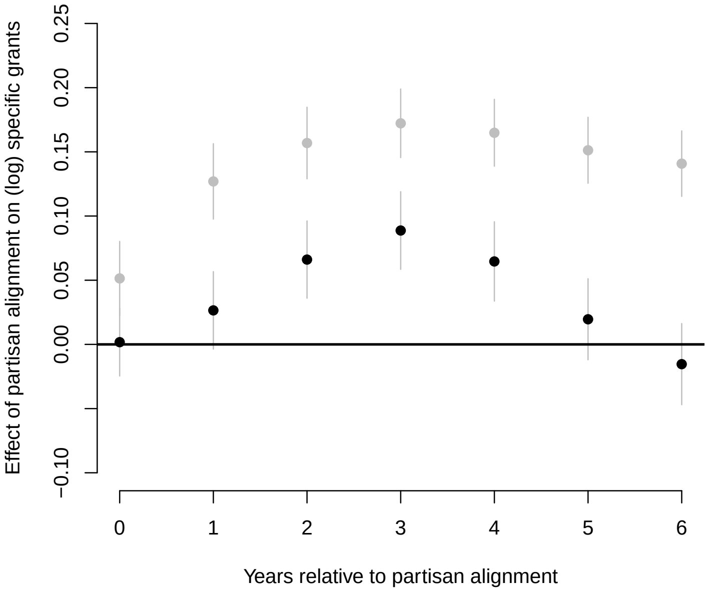
$$\text{LogOfGrantsPerCapita}_{it} = \beta_1 \text{Copartisan}_{i,t-k} + \alpha_t + \gamma_i + \gamma_i t$$

where t is the year. To implement (needs at least 3 years):

```
lm(lngrants ~ treatment_k + as.factor(year) + as.factor(council)*year )
```

(Could add $\texttt{year}^2$ or $\sqrt{\text{year}}$ or $\ln(\text{year})$ to make time trends non-linear.)

Effect over time, w. unit specific time trends



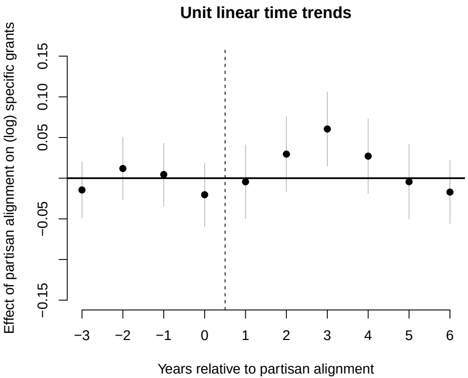
Testing assumptions in panel DiD

Unfortunately, no test as simple and transparent as the parallel trends plot.

The alternative:

$$\text{LogOfGrantsPerCapita}_{it} = \sum_{k=0}^{5} \beta_k \text{Copartisan}_{i,t-k} + \sum_{k=1}^{3} \theta_k \text{Copartisan}_{i,t+k} + \alpha_t + \gamma_i + \gamma_i t$$

i.e. include **lags** and **leads** of treatment in one regression.



Levitt on effects of campaign spending

Levitt (1994), "Using Repeat Challengers to Estimate the Effect of Campaign Spending on Election Outcomes in the U.S. House".

Question: What is the effect of campaign spending on election outcomes?

Consider running this cross-sectional regression:

$$\text{DemVoteShare}_i = \beta_0 + \beta_1(\text{DemSpend}_i - \text{RepSpend}_i) + \beta_2\text{DemPresVoteShare}_i + \epsilon_i$$

- Would you expect β_1 to be positive or negative?
- What assumption is necessary to interpret that coefficient causally?
- Why might this assumption be violated?

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Consider running this panel regression:

$$\text{DemVoteShare}_{it} = \beta_0 + \beta_1(\text{DemSpend}_{it} - \text{RepSpend}_{it}) + \alpha_t + \gamma_i + \epsilon_i$$

where γ_i is a dummy for each **candidate pair**.

- Would you expect β_1 to be positive or negative?
- What assumption is necessary to interpret that coefficient causally?
- Why might this assumption be violated?

Levitt and use of covariates

As noted above, the only relevant confounders are those that **change within units over time**.

In panel DiD you can control for observable covariate that change within units over time, e.g.:

$$\text{DemVoteShare}_{it} = \beta_0 + \beta_1(\text{DemSpend}_{it} - \text{RepSpend}_{it}) + \alpha_t + \gamma_i + \theta(\text{DemScandal}_{it} - \text{RepScandal}_{it}$$

Levitt controls for scandal and incumbency.

First differences approach

Suppose again the **data generating process (DGP)** is

$$Y_{it} = \beta_1 D_{it} + \alpha \mathbf{X}_t + \gamma \mathbf{U}_i + \psi \mathbf{V}_{it} + \omega_{it}.$$

We estimated β_1 via regression with unit and time-period dummies.

First differences approach: Generate first difference of each variable, e.g.

$$\Delta Y_{it} = Y_{it} - Y_{i,t-1}$$

and then estimate

$$\Delta Y_{it} = \beta_1^f \Delta D_{it} + \alpha_t,$$

i.e. regress differenced outcome on differenced treatment and year dummies (could add unit dummies for unit-specific linear time trends).

Generally gives similar results; **same** results if only two periods.

Ansell on effect of house prices on welfare attitudes

Ansell (2014), “The political economy of ownership: housing markets and the welfare state”

Question: How does variation in house prices affect homeowners? preferences regarding redistribution?

Consider running this cross-sectional regression:

$$\text{SupportForRedistribution}_i = \beta_0 + \beta_1 \text{PriceOfHome}_i + \beta_2 \text{Income}_i + \beta_3 \text{Age}_i + \epsilon_i.$$

- Would you expect β_1 to be positive or negative?
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$$\text{SupportForRedistribution}_{it} = \beta_1 \text{PriceOfHome}_{it} + \alpha_t + \gamma_i$$

or (Ansell’s actual basic specification – first differences)

$$\Delta\text{SupportForRedistribution}_{it} = \beta_1 \Delta\text{PriceOfHome}_{it} + \alpha_t$$

- Would you expect β_1 to be positive or negative?
- What assumption is necessary to interpret β_1 causally?
- Why might this assumption be violated?

Ansell's control strategy

Ansell (2014) controls for changes in

- home ownership
- household income
- party ID
- retired status

and controls for (i.e. allows time trends to vary by)

- age
- gender
- race

Adler on the "Waitrose effect"

Adler (2017 MPhil dissertation), "The other Waitrose effect"

Question: How does gentrification affect renters?

Consider running this cross-sectional regression:

$$\text{EvictionRate}_i = \beta_0 + \beta_1 \text{WaitroseNearby}_i + \beta_2 \text{UnemploymentRate}_i + \beta_3 \text{CrimeRate}_i + \epsilon_i.$$

- Would you expect β_1 to be positive or negative?
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