Causal Data Analysis

Chapter 24: Appropriate Control Groups for Panel Data

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What is the appropriate control group in panel data?

- Diff-in-diff, FD, FE estimation methods
- $x = \{0, 1\} \Rightarrow$ all observations with $x = 0$ are in the control group
  - BUT: some control observations are very different from treated observations
  - BUT: in some periods $x = 1$ for very few, or no observations

- Can we improve the estimation if only a subset of untreated observations are used as controls?
  - We want to make the control group more similar to the treated group
  - We've been here before: matching

Event-time analysis

How to apply Diff-in-diff, FE, FD methods if the treatment is staggered in time?

- Same as if it took place in the same time
- **Intervention analysis** method (event study method)
  - An extension of Diff-in-diff, FE, FD

Define *intervention time*

- τ_{is}, where $s \in \{-s_{min}, ..., s_{max}\}$
- τ_{i0} – time of treatment
  - It is possible that τ_{i0} belongs to the treatment

Regression equation

Simple case

- Only treated subjects, no controls
- FD estimation (same for FE)

$$\Delta y_{it}^{E} = \alpha + \sum_{s_{min}}^{1} \gamma_s D_{i(-s)} + \sum_{0}^{s_{max}} \beta_s D_{is} \tag{1}$$

- $D_{is} = 1$ if $\tau_{is} = s$
  - E.g., $D_{i1} = 1$ if subject i is one year after the treatment
  - E.g., $D_{i(-3)} = 1$ if subject i is three years before the treatment
- β_1 – the effect of the treatment one year after the treatement
- γ_3 – the effect of the treatment three years before the treatment
- Can add controls to the regression

Control group

How to construct a control group?

- Look for subjects which are similar to the treated group **before treatment**
- Intervention time may (artificially) be constructed for the controls
- Treatment: an interaction term between treatment and the intervention time

Regression equation

$$\Delta y_{it}^{E} = \alpha + \sum_{0}^{s_{max}} \beta_s D_{is} + \sum_{s_{min}}^{1} \gamma_s D_{i(-s)} \\ + \eta \cdot treated_i + \sum_{0}^{s_{max}} \delta_s \cdot treated_i \times D_{is} + \sum_{s_{min}}^{1} \phi_s \cdot treated_i \cdot D_{i(-s)} \tag{2}$$

Regression equation

$$\Delta y_{it}^{E} = \alpha + \sum_{0}^{s_{max}} \beta_s D_{is} + \sum_{s_{min}}^{1} \gamma_s D_{i(-s)} + \eta \cdot treated_i + \sum_{0}^{s_{max}} \delta_s \cdot treated_i \times D_{is} + \sum_{s_{min}}^{1} \phi_s \cdot treated_i \cdot D_{i(-s)} \tag{2}$$

- α/η – average trend in control/treated groups
- β – average post-treatment trend in the control group
- δ – average post-treatment trend in the treated group, relative to the control group
- PTA – all Φ_s coefficients are small and not significant statistically

Case study: the effect of soccer managers

What is the effect of manager's replacement on soccer team performance?

- If performance declines, managers are often replaced
  - The effect of managers is interesting in general (companies, NGOs,...)
- Sports are a good environment to study this question
  - Good performance measure
- We can also infer the effect of managers on performance in general (not only the change)
  - It is hard (impossible) to measure causality in cross section, that's why we use changes (panel)

Thought experiment

- Choose a group of underperforming teams
- Replace the manager in half of them
- Perform a diff-in-diff estimation

Features of the analysis

1: Subjects selected non-randomly (bad performers)
  - This suits the question

2: Need employable managers
  - It is not certain that good managers are available ⇒ need to take into account when interpreting the results

3: Managers replaced during championship
  - As little change in the environment as possible (e.g., same players)

Potential mechanisms

- The new manager wants to prove his/her quality $\Rightarrow$ **positive effect**
- Getting results takes time $\Rightarrow$ **no effect** in the short run
- Statistical regularity: after every storm comes a calm $\Rightarrow$ **positive effect, but not causal**
  - Regression to the mean
- The new manager is less efficient than the old one $\Rightarrow$ **negative effect**

Replacement of the manager

Who replaces the manager?

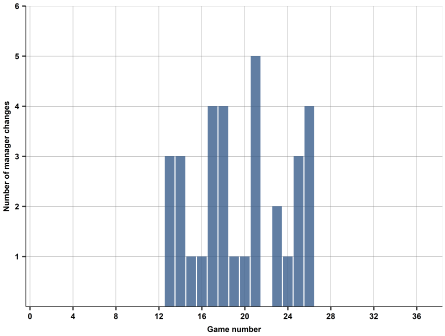
- Unsuccessful teams $\Rightarrow$ effect endogenous, because results are autocorrelated
- The club with lots of conflicts between the manager and other stakeholders (bad match) $\Rightarrow$ likely to be endogenous
- The club which finds a new manager $\Rightarrow$ exogenous

Data

Observational data: English Premier League Football dataset, 11 tournaments (2008/09 – 2018/19)

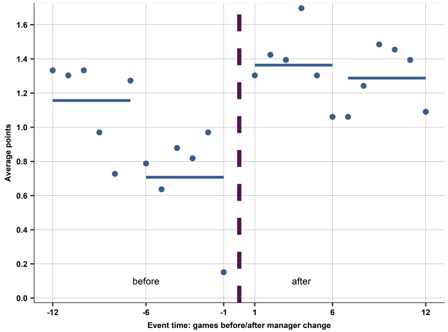
- Subject: team-game (each game included twice)
- Variables
  - Team
  - Tournament
  - Game
  - Manager
  - Score (0 – lost, 1 – draw, 3 – win)

Managerial replacement



- Replacement by the week of the tournament
  - At least 12 weeks before/after
- N=33 replacements

Intervention time and the outcome variable



- Treated clubs
- Intervention time: ± 12 relative to the week of replacement (0 not included)
- Average points
- 6-week averages added
- N=792

Patterns

How do points change around managerial replacement?

- 7-12 weeks before results worse than average (average = 1.38)
- 6-1 weeks before very bad results (0.71)
- 1 week before dreadful results (0.15)
  - **Ashenfelter's dip**: decline of the outcome before intervention
- Afterwards the results return to average

Conclusions

- Results improve after the replacement of the manager
- Very strong selection effects: poorly performing clubs replace the manager

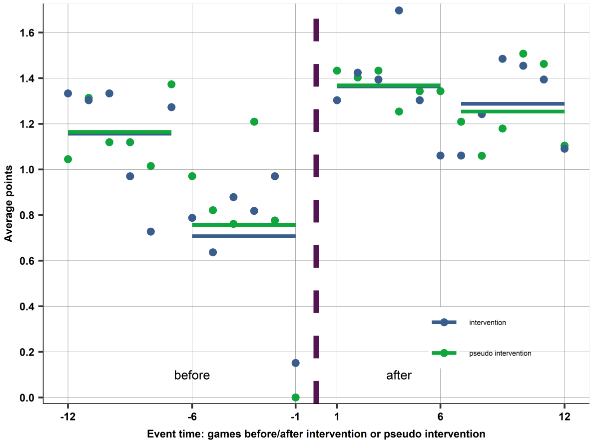
Control group

Best controls: clubs that did not replace the manager and they are similar to treated clubs pre-treatment

- Average points 7 – 12 weeks before intervention: 5 – 8
- Average points 1 – 6 weeks before intervention:: 1 – 8
- Lost game 1 week before the intervention

132 clubs, 24 time windows $\Rightarrow$ 67 pseudo interventions

Pseudo intervention



Regression

- Collapse games (2 data points before/after)
- Regression on the treated group ($N = 33 \times 3 = 99$)
- Regression on the control group: ($N = 67 \times 3 = 201$)
- Regression on the two groups together
  - *treated* – club-tournament with managerial replacement
  - $post_{1-6}$, $post_{7-12}$ – intervention time

$$\Delta y_{it}^{E} = \beta_0 + \beta_1 post_{1-6} + \beta_2 post_{7-12} + \beta_3 treat + \beta_4 treat \times post_{1-6} + \beta_5 treat \times post_{7-12} \quad (3)$$

The effect of managerial replacement (FD regression)

Variables	(1) treatment	(2) control	(3) treatment+control
$post_{1-6}$	1.11**	1.06**	1.06**
	(0.19)	(0.09)	(0.09)
$post_{7-12}$	0.37*	0.34**	0.34**
	(0.16)	(0.09)	(0.09)
$treated$			-0.00
			(0.10)
$treated \times post_{1-6}$			0.04
			(0.20)
$treated \times post_{7-12}$			0.04
			(0.18)
Constant	-0.45**	-0.45**	-0.45**
	(0.10)	(0.03)	(0.03)
Observations	99	201	300
R-squared	0.33	0.42	0.39

Comparative case study

Only one subject is treated? We still want to know the effect of the intervention

- Case study: one treated subject (country, region)
- Comparative: we want to produce a counterfactual to estimate a treatment effect

How to choose the control group?

Method of synthetic controls

For the single treated subject **create one control observation artificially**

⇒ Control, because it is used to estimate a counterfactual

⇒ Synthetic, because it is not an existing subject, but we create it from potential controls

  - The synthetic control and the treated subject should be very similar before treatment

Problems

- Self-selection
- How to do statistical inference with two subjects?
- How to draw general conclusions? ⇒ External validity is credible only if the environment is similar

Estimation

Diff-in-diff

- The average change of y of the treated subject before and after the treatment
- The average change of y of the synthetic control subject before and after the treatment
  - This is the counterfactual: how would have behaved the treated subject had it not been treated?

Finding the synthetic control

How to create the best possible control?

- Take all potential controls
  - They are called "donors"
- Mix them to we get the synthetic control subject
  - Using all, or part of the potential controls
- Find the best combination of the potential controls
  - Aim: the synthetic control's treated and control variables should resemble the treated subject's variables as much as possible in the pre-treatment period

Method

The synthetic control is a weighted average

- Take all the n potential j controls

$$\hat{Y}(0) = \sum_{j=2}^{n} w_j Y_j$$

- w_j – optimized weights
  - May equal 0
  - Do not change in time (same value before and after the treatment)

Example: the effect of the tax levied on tobacco in California

In 1988, the tax on tobacco was increased and smoking banned in public spaces

- Tobacco sales decline after 1988
  - But they had a negative trend even before 1988
- Synthetic controls: all American states
- Variables: $y =$ cigarette sales, controls: GDP/cap, tobacco price, beer consumption/cap
- Synthetic weights
  - $W > 0$: Colorado, Connecticut, Montana, Nevada, Utah
  - $W = 0$ for all other states

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Result: Δ cigarette purchases/cap 26 packs lower in real California relative to synthetic California

Estimation of the synthetic weights

Most important part of the method

- Uses all the variables from the pre-treatment period
- Estimates weights for the control subjects, which minimize the following distance (0–control; 1–treated)

$$\|X_1 - X_0 W\| \rightarrow min \tag{4}$$

- Aim: PTA – the pre-treatment trend before treatment be similar for the treated subject and the synthetic control

Remarks

The synthetic control method...

- ...can be generalized for the case of multiple treated subjects
- ...is a new method
  - Can be used to answer lots of questions
  - Statistical properties not completely understood yet

Case study: the effect of the earthquake on Haiti's GDP

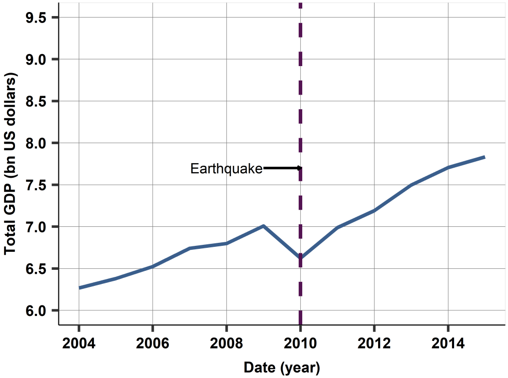
Big earthquake in January 2010

- 100,000 people died (pop: 10 million)
- Poor country: GDP/Cap = 710 USD ($GDP/Cap_{Hu,2010}$ = USD 13,200)

What was the effect of the disaster on Haiti's GDP? ⇒ Did the country got back to its natural growth trajectory?

- Smaller working age population
  - Deaths
  - Migration
  - Diseases, plaques, malnutrition
- Part of infrastructure ruined

GDP of Haiti



- Total GDP (bill. USD, 2010 prices)
- Source: Haiti-earthquake dataset

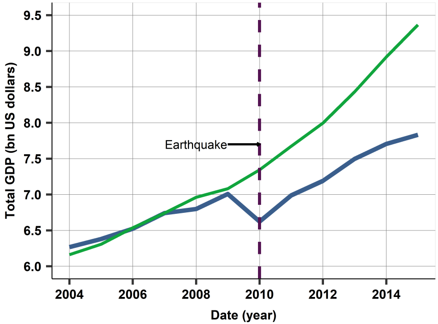
Haiti's synthetic control

We don't know, what would have been Haiti's GDP in absence of the earthquake

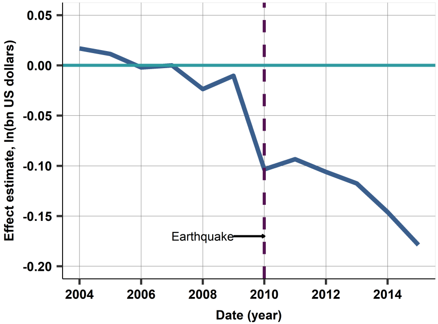
- Pre-treatment period: 2004-2009
- Potential controls: countries with GDP/Cap $<$ USD 4,000 in 2009 (22 countries)
- Variables: GDP/Cap, size, export, import, consumption, capital accumulation, inflation rate
- We use the average values of the variables to get the synthetic weights, except for GDP/Cap, which we use in three years separately

$W > 0$: 23% Burundi, 21% Kamerun, 0.2% Liberia, 9% Moldova, 47% Togo

Case study - The effect of the 2010 earthquake on the total GDP of Haiti. Synthetic control estimate



Total GDP in Haiti and synthetic Haiti



Log GDP difference between Haiti and synthetic Haiti

The effect of the earthquake

The eartquake decreased Haiti's GDP in the long run

- Approx 10% decline in 2010
- Diff. between Haiti and the synthetic control did not change until 2012
- Diff. increased after 2012

PTA

- Not completely satisfied – in the pre-treatment period Haiti's GDP grew somewhat slower than of the synthetic control's
- But this difference is much smaller than the post-treatment difference

External validity

- No Caribbean country among the countries used for the synthetic control