Synthetic controls and general panel data methods

EC420 MSU

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Last class(es)

Difference-in-differences

- Control for unobserved heterogeneity in i and And for overall time trends in t
- Develop a counterfactual: $E[Y_0|D=1]$
- Constructed with *treatment* and *control* groups
- Regression specification to get "*DiD Estimtor*"
- **Parallel trends assumption**

Today

- Past the *parallel trends* assumption
- Synthetic Counterfactual Method (SCM)

Recall that DiD's *identifying assumption* is that:

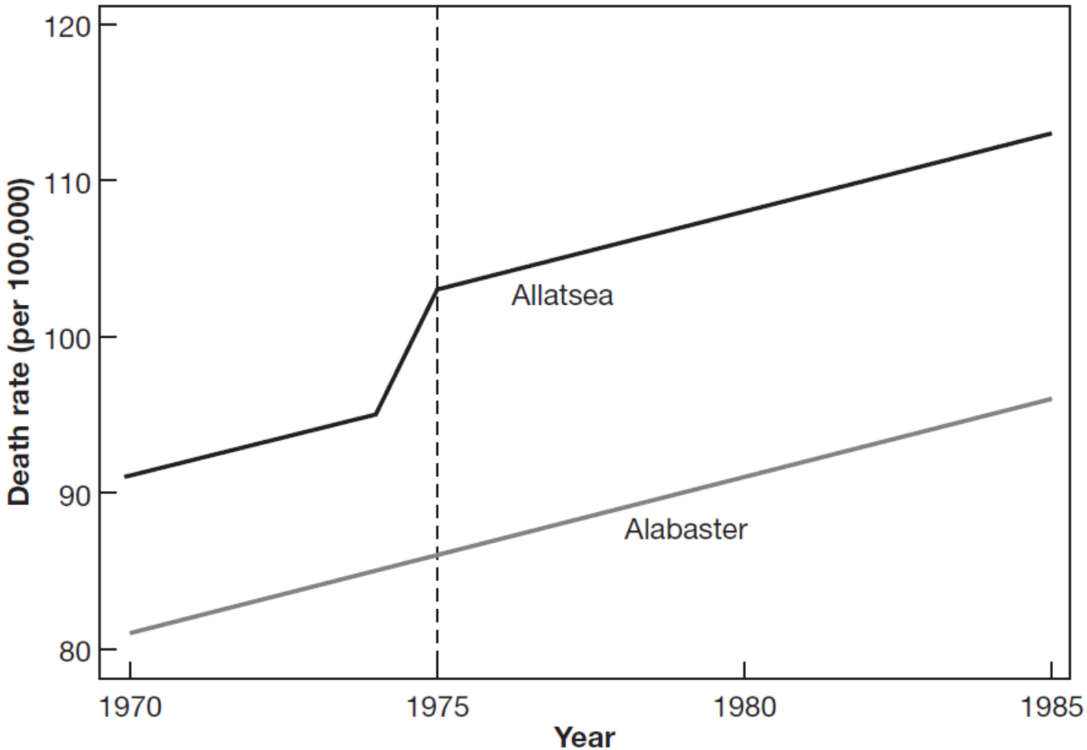
> In the absence of treatment, the trends in both groups would have been the same.

And recall that we can't directly test this

- We can look at pre-treatment trends
- But we would need to see the actual $E[Y_0|D=1]$ in order to ensure that it follows the same trend as $E[Y_0|D=0]$, the untreated group.

We saw examples where that seemed like a pretty safe assumption:

FIGURE 5.4
An MLDA effect in states with parallel trends



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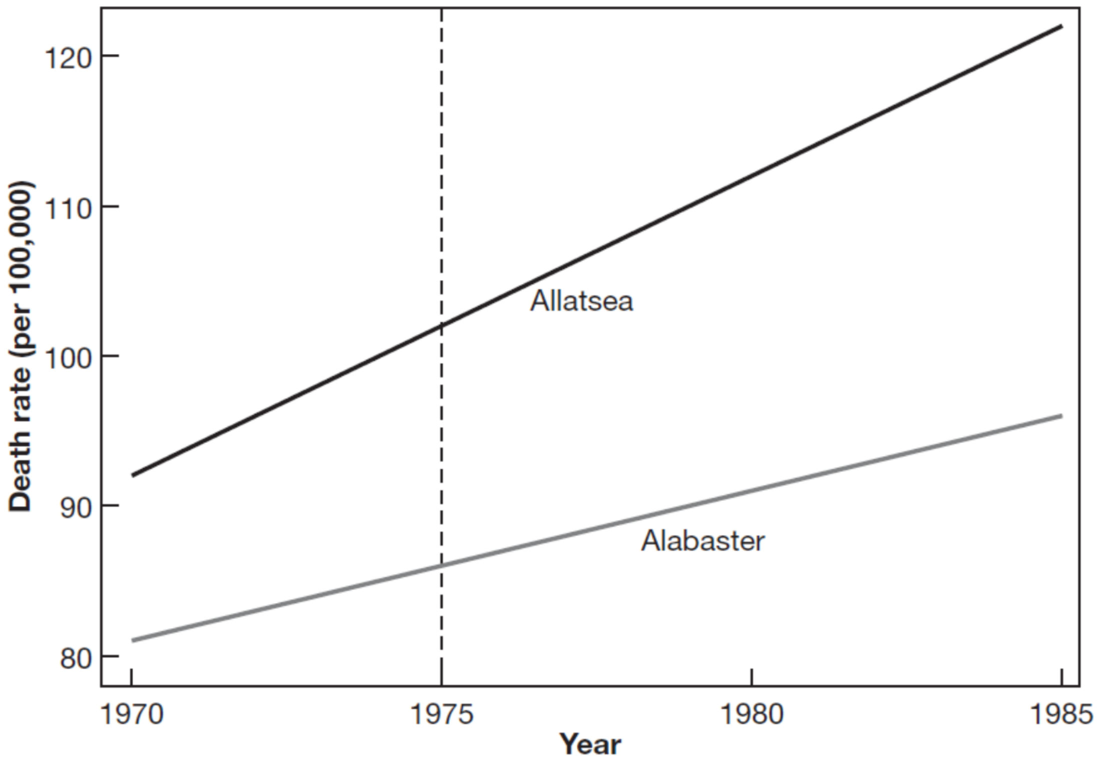
And some where it didn't necessarily hold

FIGURE 5.5
A spurious MLDA effect in states where trends are not parallel



What are we really after?

- We want a good $E[Y_0|D=1]$, the counterfactual for the treated group.

DiD gets us this by making that link between $E[Y_0|D=0]$ and $E[Y_0|D=1]$

So what if we are a little more flexible on how that link is made...?

Let's start with a DiD specification, but with i individual fixed effects:

$$y_{it} = \beta_0 + \phi_i + \beta_2 POST_t + \beta_3 TREAT_i * POST_t + u_{it}$$

Our assumption here is that, once we condition on the ϕ_i - that is, once we let each i have its own intercept, the *trends* are going to be the same.

But what drives those trends...? What moves all i together? And what if there were things that moved, say, 1/2 of the i's?

Let's say we're looking at city-level unemployment rates over different cities across the US

We want to know the effect of worker safety regulations on unemployment.

Let's pretend there is one observed thing and *one unobserved thing* that drives the trends:

- **Observed**: national unemployment rate.
- **Unobserved**: Price of canned tomatos.

Why *price of canned tomatoes*?

- Some i have tomato processing facilities in them, and some don't!
- We don't observe this.
- Treatment may be correlated (tomato processing is particularly dangerous for workers?)

Would you agree that:

- If the price of tomatoes is very high, there will likely be more employment in tomato-processing facilities?
- And thus, unemployment would be lower (better) in those cities with tomato-processing facilities?

And would you agree that:

- If our treatment is somehow correlated with the presence of tomato-processing facilities, we could be in trouble with our "parallel trends" assumption?
- Treatment may be endogenous (more worker safety rules when more dangerous employment)
- The effect may just be confounded by changes in tomato prices

What would "tomato prices" do as a confounder?

- If tomato prices go up, **some** i's (the ones with unobserved tomato processing facilities) will have lower unemployment
- So the *parallel trends* assumption is broken:
  - In the absence of treatment, a tomato-processing city would **not** follow the same trend as an untreated non-tomato-processing city.

A "factor loading" model:

- Let $\lambda_i^{tomato} = \mathbf{1}(\text{has tomato facility})$
- Let p_t^{tomato} be the national price of tomatos.

$$y_{it} = \beta_0 + \beta_1(\lambda_i^{tomato} * p_t^{tomato}) + \beta_2 D_{it} + \phi_i + \delta_t + u_{it}$$

This is just a model of unemployment y as a function of i specific traits, t specific trends in national unemployment rates, and *the effect of tomato prices on unemployment in tomato-processing cities*.

If $\lambda_i^{tomato} = 0$, then price of tomatos has no effect. If $\lambda_i^{tomato} = 1$, then the price of tomatos does have an effect (β_1).

A "factor loading" model:

$$y_{it} = \beta_0 + \beta_1(\lambda_i^{tomato} * p_t^{tomato}) + \beta_2 D_{it} + \phi_i + \delta_t + u_{it}$$

Parallel trends will not hold between a $\lambda_i^{tomato} = 1$ city and a $\lambda_i^{tomato} = 0$ city.

If we observed λ_i^{tomato}, we'd be fine

We would just control for it (include it in our X's)

But...we don't.

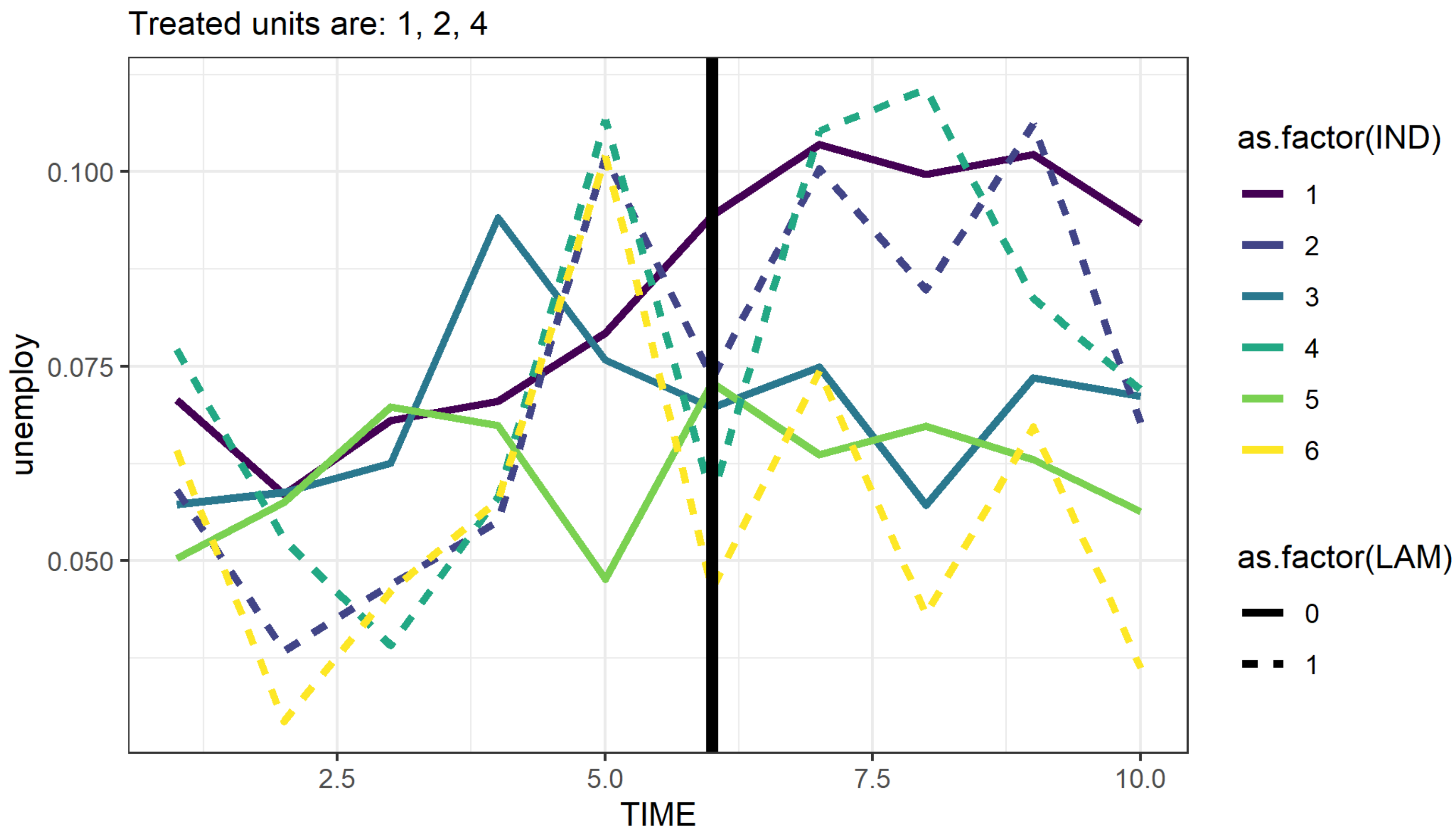
The Synthetic Counterfactual does its best to account for these unobserved factors

- Even without observing tomato processing facilities or the price of tomatos, we **would** expect that pre-treatment unemployment in tomato processing cities **would look like other tomato processing cities**.

- That is, since the tomato processing cities are subject to the same price of tomatos, then all of them will be a little higher on unemployment when tomato prices are low.

- The Synthetic Counterfactual Method looks for similarity in the pre-treatment trend and develops the counterfactual for i using all j's that have similar pre-treatment "paths".

Synthetic Counterfactual



The intuition is that parallel trends assumption is best met by choosing a control pool that...follows parallel trends!

All the SCM does is find the controls that

- Are not treated
- But have similar pre-treatment trends

Since it's straightforward to have parallel trends for **one** treatment unit and some selection of potential controls, the SCM only handles one single treatment unit

- Great for comparative policy analysis
- Some methods for combining results from many SCM's

Implementation

- Usually with a pre-packaged routine in R - `Synth`
- Requires panel data

User specifies:

- **One** treatment unit
- **Many** potential control units (untreated)
- A treatment start time

The Synthetic is estimated by finding weights w that are used to combine all of the un-treated units in the control group.

Implementation

- R makes a guess at w, weights on each of the control units
  - Let's say the guess is that the weights are $(.5, .5, 0, \cdots, 0)$
  - That is, the first two untreated i's are weighted at .5 and .5, the rest are 0.
- The pre-treatment "synthetic" outcome at any pre-treatment time t is:
  - $y_t^{synth} = .5 \times y_{1,t} + .5 \times y_{2,t} + 0 \times y_{3,t} + \cdots$

Implementation con't.

- The distance between y_t^{synth} and y_t^{actual} is checked. Much like OLS, synth sums the squared difference:
    - $(y_t^{synth} - y_t^{actual})^2 + (y_{t-1}^{synth} - y_{t-1}^{actual})^2 + \cdots)$ over the pre-treatment period
    - Obviously, post-treatment, we think there will be a difference. Comparing pre-treatment lets us match up tomato-processing cities!
- R *guesses* at the weights over and over again until the smalled squared sum of errors is found. Observed covariates can be included as well.
- Those weights define the Synthetic Counterfactual in both the pre-treatment period *and* in the post-treatment.

Synthetic Control

If we get a very good match between y_t^{synth} and y_t^{actual} for all t in the pre-treatment, we would naturally think we have controlled for the unobserved factors (the tomato plants, etc.).

- If we have controlled for these confounders, *even the unobserved ones*, then we can claim that treatment is "as good as exogenous".
  - $(Y_{0it}, Y_{1it}) \perp D$
- Thus, the difference between Y_t^{synth} and Y_t^{actual} **in the post-treatment periods** is the ATE
  - $E[Y_0|D=1] = E[Y_0^{synth}]$, and the latter is observed.

Let's pull up the Kirkpatrick and Bennear paper and look at the synth implementation there.

We'll focus on the intuition of the method - how do we claim that we are identifying a *causal* effect of PACE?