Machine Learning for econometrics

Event studies: Causal methods for pannel data

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Motivation

A visual reminder on difference-in-differences

Difference-in-differences

- Introduced by
- A method to estimate the effect of a treatment on a treated unit
- The treatment effect is estimated by comparing the evolution of the treated unit to a control unit
- The difference between the two differences is the treatment effect

Target effect: Sample Average Treatment effect on the Treated, SATT

$$\tau_{\mathrm{SATT}} = \frac{1}{|\{i : D_i = 1\}|} \sum_{i : D_i = 1} \frac{1}{T - H} \sum_{t = H+1}^{T} Y_{it}(1) - Y_{it}(0)$$

DID estimator

$$\widehat{\tau_{\text{DID}}} = \frac{1}{|\{i:D_i=1\}|} \sum_{i:D_i=1} \left[\frac{1}{T-H} \sum_{t=H+1}^{T} Y_{it} - \frac{1}{H} \sum_{t=1}^{H} Y_{it}\right] - \frac{1}{|\{i:D_i=0\}|} \sum_{i:D_i=0} \left[\frac{1}{T-H} \sum_{t=H+1}^{T} Y_{it} - \frac{1}{H} \sum_{t=1}^{H} Y_{it}\right]$$

Temporal consistency assumption

No anticipation of the treatment (in practice, not always true)

Assumption

$$Y_{it}(0) = Y_{it}(1) \forall t = 1, ..., H.$$

Main and strong assumption of the DID method

Assumption

$$\mathbb{E}[Y_{it}(0,\infty) - Y_{i1}(0,\infty)] = \beta_t, t = 2, \ldots, T.$$

Parallel trend assumption

Under the temporal consistency and the parallel trend assumptions, the DID estimator is unbiased ie. $\mathbb{E}[\widehat{\tau_{\mathrm{DID}} - \tau}_{\mathrm{SATT}}] = 0$

See (Wager, 2024) for a clear proof.

Estimation: link with two way fixed effect

In practice, DID is estimated with a two-way fixed effect model (TWFE):

$$Y_{it} \sim \alpha_i + \beta_t + A_{it}\tau \text{ where } A_{it} = D_i * (t \leq H)$$

- α_i capture the individual fixed effect
- β_t capture the time fixed effect (under pararell trend)

This link can be seen with the parallel trend assumption: $\beta_t =$

Interrupted Time Series

Synthetic Controls

Synthetic Controls

Introduced in (Abadie & Gardeazabal, 2003) and (Abadie et al., 2010), well described in (Abadie, 2021)

- A method for estimating the effect of a treatment on a single unit
- The treatment unit is compared to a weighted average of control units
- The weights are chosen to minimize the difference between the treated unit and the synthetic control

Example for the effect of taxes on sugar-based product consumption in (Puig-Codina et al., 2021), review of usage in healthcare (Bouttell et al., 2018).

Time-series modelisation: other methods

State space models

Take-away

Python hands-on

To your notebooks 🧑‍💻 !

- url: https://github.com/strayMat/causal-ml-course/tree/main/notebooks

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