

The background of the slide is a photograph of a large, classical-style building with a prominent arched entrance and many windows. In the foreground, there are green leaves and branches of a tree, and a black lamppost. The sky is blue.

AME

Week 3: Random Effects

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Today's Plan

- Random Effects
- Hausman Test
- Your time to shine!

Random Effects Model

- Linear Panel Data Model

$$y_{it} = c_i + \mathbf{x}_{it}\boldsymbol{\beta} + u_{it} \quad (1)$$

- Let's assume no confounding time-invariant heterogeneity $E(c_i x_{it}) = 0$ and strict exogeneity $E(u_{it} x_{is}) = 0 \forall s, t \in T$ holds. Add to that assumptions FE.3 $E(\mathbf{u}_i \mathbf{u}_i') = \sigma_u^2 I_T \quad \forall i \in N$ and (new!) $E(\mathbf{c}_i \mathbf{c}_i') = \sigma_c^2 \mathbf{j}_T \mathbf{j}_T' \quad \forall i \in N$ where $\mathbf{j}_T = [1 \dots 1]'$ is a $T \times 1$ vector of ones.
- Is POLS consistent? Yes
- Is POLS efficient? Error terms need to be homoskedastic (IID)
only need contemp. effects to be uncorr.

RE Covariance Matrix

- The composite error covariance matrix has non-zero off-diagonals due to the time-invariant heterogeneity, c_i :

$$\begin{aligned} E(\mathbf{v}_i \mathbf{v}_i') &= \sigma_c^2 \mathbf{j}_T \mathbf{j}_T' + \sigma_u^2 \mathbf{I}_T \\ &= \begin{bmatrix} \sigma_c^2 + \sigma_u^2 & \sigma_c^2 & \dots & \sigma_c^2 \\ \sigma_c^2 & \sigma_c^2 + \sigma_u^2 & \dots & \sigma_c^2 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_c^2 & \sigma_c^2 & \dots & \sigma_c^2 + \sigma_u^2 \end{bmatrix}_{T \times T} \end{aligned} \quad (2)$$

- POLS is inefficient as the composite error term is **not homoskedastic**
- RE accounts for this feature of the panel data and efficiently weights the data to minimise the variance

RE Quasi Demeaning I

- RE is equivalent to POLS on "quasi-demeaned" data:

$$\check{y}_{it} = \check{\mathbf{x}}_{it}\beta + \check{v}_{it} \quad (3)$$

where $\check{y}_{it} = y_{it} - \hat{\lambda}\bar{y}_{it}$, $\check{\mathbf{x}}_{it} = \mathbf{x}_{it} - \hat{\lambda}\bar{\mathbf{x}}_{it}$ and $\check{v}_{it} = v_{it} - \hat{\lambda}\bar{v}_{it}$

- Quasi-demeaning subtracts means weighted by

$$\hat{\lambda} = 1 - \sqrt{\frac{\hat{\sigma}_u^2}{(\hat{\sigma}_u^2 + T\hat{\sigma}_c^2)}} \quad (4)$$

For $\lambda = 0$
 \rightarrow POLS

For $\lambda \rightarrow 1$:
 \rightarrow FE world,

- To estimate λ we need estimates of σ_u^2 and σ_c^2 .
 - "Between estimator" returns $\hat{\sigma}_v^2 = \hat{\sigma}_c^2 + \frac{1}{T}\hat{\sigma}_u^2$
 - Fixed Effects yields $\hat{\sigma}_u^2$
 - Combine these to obtain $\hat{\sigma}_c^2 = \hat{\sigma}_v^2 - \frac{1}{T}\hat{\sigma}_u^2$

RE Quasi Demeaning II

- Use perm function to quasi-demean the data. For this you'll need the matrix $\mathbf{C}_T = \mathbf{I}_T - \hat{\lambda}\mathbf{P}_T$ where $\mathbf{P}_T = [1/T \dots 1/T]'$
- Rearranging (4)

$$\hat{\lambda} = 1 - \sqrt{\frac{1}{(1 + T\hat{\sigma}_c^2/\hat{\sigma}_u^2)}}$$

we see that

$$\begin{aligned}\hat{\lambda} \rightarrow 1 \quad \text{for} \quad T\hat{\sigma}_c^2/\hat{\sigma}_u^2 \rightarrow \infty &\Rightarrow \hat{\beta}_{RE} \rightarrow \hat{\beta}_{FE} \\ \hat{\lambda} \rightarrow 0 \quad \text{for} \quad T\hat{\sigma}_c^2/\hat{\sigma}_u^2 \rightarrow 0 &\Rightarrow \hat{\beta}_{RE} \rightarrow \hat{\beta}_{POLS}\end{aligned}$$

- RE lies between POLS and FE estimators and puts more weight on observations for which there is more variation (e.g. if lots of within variation, σ_c^2 is large, efficient to be closer to FE)

RE Assumptions

- Random Effects Assumptions

$$RE.1a : \quad E(\mathbf{x}_{it} u_{is}) = 0 \quad \forall \quad i \in N \quad \text{and} \quad s, t \in T$$

$$RE.1b : \quad E(\mathbf{x}_{it} c_i) = 0 \quad \forall \quad i \in N \quad \text{and} \quad t \in T$$

$$RE.2 : \quad \text{rank}(E(\tilde{\mathbf{X}}' \tilde{\mathbf{X}})) = K \quad \forall \quad i \in N$$

$$RE.3 : \quad E(\mathbf{v}_i \mathbf{v}_i') = \sigma_u^2 \mathbf{I}_T + \sigma_c^2 \mathbf{j}_T \mathbf{j}_T' \quad \forall \quad i \in N$$

- We need both no confounding time-invariant heterogeneity (RE.1b) and strict exogeneity (RE.1a)
- The fact that RE tends to FE in one limit and POLS in another limit explains why we need "the worst of both worlds"
- RE in linear settings might seem silly but comes to shine in nonlinear settings :)

Hausman Test: RE vs FE

- Under assumptions RE.1a, RE.2 and RE.3 (and FE.2), we can test whether there are time invariant omitted variables i.e. whether $E(\mathbf{x}_{it}c_i) = 0$

- Hausman Test Statistic

$$H = (\hat{\beta}_{RE} - \hat{\beta}_{FE})'(\widehat{Avar}(\hat{\beta}_{FE}) - \widehat{Avar}(\hat{\beta}_{FE}))(\hat{\beta}_{RE} - \hat{\beta}_{FE}) \sim \chi_M^2$$

where $M \leq K$ is the number of coefficients

- Only include estimated coefficients $\hat{\beta}_{RE}$ on time varying regressors (since FE doesn't have the ones on time-variant regressors)

Your time to shine!

- Have a look at the toolbox `LinearModelsWeek3.py`
- Solve the problem set and use functions from the toolbox where necessary