

Advanced Econometrics

Take-home exam

Gerdie Everaert



2023-2024

Main theme: dynamic panel data models

- 0. To warm up: OLS estimation
- 1. Fixed Effects (FE) estimation
 - ► Implement the FE estimator in R/Matlab
 - Simulate its properties in a dynamic setting
 - Use simulation methods for bias correction and inference
- 2. Generalized Method of Moments (GMM) estimation
 - ▶ Implement the GMM function in R/Matlab
 - Simulate its properties in a dynamic setting

To warm up: OLS estimation

- ► Sample R and Matlab **functions** implementing the basic OLS estimator are available on Ufora
 - inputs: y and X
 - output: OLS coefs, se, t-stats, p-values
- Replicate the OLS results (see next slide) for the following cigarette demand model (Baltagi, 2008)

$$\ln C_{it} = \alpha + \rho \ln C_{i,t-1} + \beta_1 \ln P_{it} + \beta_2 \ln P_{it} + \beta_3 \ln Y_{it} + \mu_{it}$$

with C_{it} the number of packs of cigarettes sold per person in state i in year t, P_{it} the price per pack, Y_{it} disposable income and Pn_{it} the minimum price found in neighboring states

 data for 46 states over the period 1963-92 are available on Ufora ('Data_Baltagi.xlsx')

Table 8.1 Pooled Estimation Results.* Cigarette Demand Equation 1963–92

	$\ln C_{i,t-1}$	$\ln P_{it}$	$\ln Pn_{it}$	$\ln Y_{it}$
OLS	0.97	-0.090	0.024	-0.03
	(157.7)	(6.2)	(1.8)	(5.1)
Within	0.83	-0.299	0.034	0.10
	(66.3)	(12.7)	(1.2)	(4.2)
2SLS	0.85	-0.205	0.052	-0.02
	(25.3)	(5.8)	(3.1)	(2.2)
2SLS-KR	0.71	-0.311	0.071	-0.02
	(22.7)	(13.9)	(3.7)	(1.5)
Within-2SLS	0.60	-0.496	-0.016	0.19
	(17.0)	(13.0)	(0.5)	(6.4)
FD-2SLS	0.51	-0.348	0.112	0.10
	(9.5)	(12.3)	(3.5)	(2.9)
FD-2SLS-KR	0.49	-0.348	0.095	0.13
	(18.7)	(18.0)	(4.7)	(9.0)
GMM-two-step	0.70	-0.396	-0.105	0.13
	(10.2)	(6.0)	(1.3)	(3.5)
System GMM	0.70	-0.415	-0.003	0.09
	(8.8)	(4.3)	(0.1)	(3.4)

^{*} Numbers in parentheses are *t*-statistics. All regressions except OLS and 2SLS include time dummies. *Source:* Some of the results in this table are reported in Baltagi, Griffin and Xiong (2000).

Implementing the FE estimator

- Write a Matlab/R function that implements the FE estimator
 - ▶ inputs: y and X
 - output: FE coefs, se, t-stats (p-values)
- Note that it may be (computationally) convenient to
 - ▶ set up y as a $(T \times N)$ matrix and X as a $(T \times N \times K)$ matrix
 - ▶ loop over the *N*-dimension to compute

$$X'M_DX = \sum_{i=1}^{N} X'_i M_d X_i, \qquad X'M_D y = \sum_{i=1}^{N} X'_i M_d y_i$$

with y_i and X_i the data for cross-sectional unit i and $M_d = I_T - T^{-1} \iota_T \iota_T'$

 Replicate the FE results reported by Baltagi (you can add time effects using dummies)

Simulating the properties of the FE estimator

Set up a Monte Carlo experiment to numerically illustrate the properties of the FE estimator in a dynamic setting

- ▶ Generate data from $y_{it} = \rho y_{i,t-1} + \varepsilon_{it}$ with $\varepsilon_{it} \sim N(0,1)$
 - use a burn-in of 25 periods (i.e., initialize $y_{i,-25} = 0$, generate y_{it} for $t = -24, \ldots, 0, 1, \ldots T$ and discard the first 25 draws)
 - by using $y_{i,0}, \dots, y_{i,T}$ and after taking a lag, this implies that you have T effective observations
 - use 3 different values of $\rho = 0, 0.5, 0.9$
 - use all combinations of T = 4, 10, 20, 50 and N = 10, 100
- ▶ Evaluate the properties of the FE estimator $\widehat{\rho}_{FE}$ in the model $y_{it} = \alpha_i + \rho y_{i,t-1} + \varepsilon_{it}$
 - \blacktriangleright compare the mean of $\widehat{\rho}_{\mathit{FE}}$ to the population parameter ρ
 - ▶ compare the mean of the estimated standard error $\widehat{se}(\widehat{\rho}_{FE})$ to the true standard error $se(\widehat{\rho}_{FE})$

Use simulation methods for bias correction and inference

- ▶ Implement a half-panel jackknife bias-corrected FE estimator $\widehat{\rho}_{\mathit{FEj}}$
 - use the above Monte Carlo setup to compare the mean of $\widehat{\rho}_{\mathit{FEj}}$ to the population parameter ρ
- Implement a bootstrap to compute standard errors for the jackknife FE estimator
 - think about an appropriate resampling scheme
 - compare the mean of the bootstrapped standard error $\widehat{se}^b(\widehat{\rho}_{FEi})$ to the true standard error $se(\widehat{\rho}_{FEi})$
 - compute the size of a t-test for ρ based on both the analytical and the bootstrapped standard errors