(Macro-)Panel Data Analysis with LIS data

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This session covers…

- Concepts & use of panel/TSCS data
- Some issues with pooled TSCS data
- Fixed/random effect models
- Hybrid models
- Use of dynamic specifications
- Error Correction Models
- Link with Causal Inference

→ Focus on assumptions, interpretation, pros & cons

What is panel/TSCS data?

- What is the actual difference?
- “Repeated observation of same cross-section units” vs “pooled time-series of multiple units”
- Different terminology depending on large-N or long-T structure, discipline-specific use
  - Large N, short T vs. small N, long T
  - Micro vs **macro** (country, state, region…) data
  - Microeconomics/sociology vs comparative political economy
- Different structure require different modelling strategies (cf. asymptotic properties)

Is LIS/LWS a Panel Dataset?

- No, it's not
- But it is possible to construct a pseudo-panel or TSCS structure by deriving group means
  - Pseudo panel: repeated cross-section of cohorts instead of tracking individuals (Deaton 1985; Verbeek 2008)
- E.g. Employment rate, mean wage, poverty risk, group-specific Gini Index
- Country-level indicators are often available from public databases (OECD, World Bank, ILO…)
- Using LIS microdata, we can further focus on specific groups within countries (education level, gender, cohort)

Examples of macro-panel/TSCS analysis

- Democracy and economic growth (Helliwell, 1994; Acemoglu et al., 2019)
- Political/Institutional determinants of welfare state development (Huber & Stephens, 1993); Wage inequality (Rueda & Pontusson, 2000; Iversen & Wren, 1998)
- Union power and macro-economic performance (Hicks, 1994; Boreham & Compton, 1992)
- Trade with China and labour regulation (Adolph et al., 2017)
- Active labour market policy and (un)employment (Benda et al., 2020)

Reasons to use macro-panel/TSCS

- Interest on the role of institutions, policies, macro-economic situations across countries (or states)
- Larger samples size N*T (=statistical power, more variables)
  - This can be also Group*T (gender/education groups within countries) → even larger N*T
- External validity: effects vary over time & space
- Using panel data helps control some of the important omitted variables
  - Omitted variables almost always exist
  - In non-experimental settings, addressing omitted variables bias is crucial

Some issues with TSCS data (1)

- Effects are averaged across different countries & years
  - *Between-country* effect: “Sweden’s unemployment rate is lower than Germany because of higher ALMP spending”
  - *Within-country* effect: “Germany’s unemployment rate declined because of an increase in ALMP spending”
  - Different modelling strategies tend to estimate different weighted average of the two effects
- Using constant coefficient implicitly assumes that the effects of X on Y is uniform across countries & over time
  - Effects tend to vary over time & space
  - You can model heterogeneous effects flexibly, but then parameters may be too many relative to sample size

Some issues with TSCS data (2)

- TSCS data by nature accompanies selection problems
  - "We use data from 18 advanced welfare states..."
  - Economic cycles / climate cycles
- Classic assumptions of OLS (iid)
  - Unit heteroskedasticity: Unemployment rate fluctuations in Germany & Sweden
  - Contemporaneous correlation: Economic shocks; Policy development in Germany & Austria; between Nordic countries
  - Serial correlation: Unemployment rate in the UK in 2022 & 2021

Fixed Effects Models

- Workhorse model in panel data analysis across social sciences
- Least-square dummy variables: include N-1 country-specific dummy variables (or N dummies without intercept)
- Within-groups estimation: subtract group-specific means (of IVs and DVs) from all observations.
- Removes omitted variables bias from unobserved 'time-invariant' variables: geographical characteristics, entrenched culture
  - Reasonable in TSCS analysis, as many country-specific characteristics are time-constant
- "Two-way" fixed effects: adding time dummies
  - Controls unobserved effects that varies over time but uniform across countries
  - Economic crisis, pandemic effects (not observed as variables)

Fixed Effects Models: Issues (1)

- You are only using within-country variations ΔX → ΔY: averaged across countries
  - If you are interested in between-country institutional effects, FE is not suitable!!
- No substantive meaning in the dummy coefficient: "Luxembourg is different because it's Luxembourg"
- Cannot include any substantive time-invariant variables
  - You are dumping all time-invariant characteristics into one dummy variable → controlling OVB has its cost
  - Ex) Welfare regime types, political institutions
  - But they can still be included as an interaction term (without independent terms)

Fixed Effects Models: Issues (2)

- Assuming that unobserved characteristics (omitted variables) are time-invariant → is that true?
  - Ex) Effects of women's education on family policy development: are gender norms time-constant?
  - Reverse causality (simultaneity or feedback effect)
- Not always useful when your main explanatory variables have little variations over time (e.g. effects of democracy on growth)
- Huge loss of DoF if you have short T (e.g. N=50, T=4)
- You are not just loosing DoF: FE models discard the information of "levels", only using changes within countries (e.g. unemployment in Italy and the US)

Random Effect Models

- RE models use both within- and between-country effects
  - Not discarding the ‘level’ information
  - More efficient than FE models (= smaller variance and less uncertainty)
- Useful when FE is too costly (e.g. N=50, T=4)
- Including time-invariant explanatory variable (“level-2”) is also possible
- RE models treat unobserved unit-specific characteristics (ui) as random errors (not fixed) that has a distribution
- Estimated through generalised least square (FGLS) or maximum likelihood (ML) approach
- Estimates are in between naive OLS and FE models

Random Effects Models: Issues

- Strong assumption: unobserved characteristics are uncorrelated with explanatory variables, cov(Xit, Ui) = 0
  - Almost always not true: estimates are mostly biased
  - Unobserved cultural characteristics, longstanding institutions usually shape policy/politics
- The problem here is whether the bias is substantially large to scrap the whole approach
- Hausmann Test: checking whether FE and RE coefficients are similar → most likely reject RE
- Better in prediction than causal inference
  - When you can allow some bias but want to include time-invariant variables (gender, race, regimes…), gain better predictive power & more efficient estimates
  - Economics (FE) vs sociology, political science (RE/FE)

Still the constant-coefficient issue hasn't been solved…

Hybrid Model

- Combining within- & between-unit (country) effects within the random effects framework (Allison, 2009; Schunck, 2013, 2017)
- $y_{it} = \beta_0 + \beta_1(X_{it} - \bar{X}_i) + \beta_2\bar{X}_i + \beta_3 C_i + u_i + \varepsilon_{it}$
- β_1 (within-country effect) is identical to the fixed-effect estimates (unbiased if no time-varying omitted variables)
- Country-specific means (levels) become one of level-2 (time-invariant) variables in multilevel modelling → between-country effect
- You can also include other time-invariant variables (C_i)
- If WE=BE, the model is identical to random-effects (intercept) model

Haapanala et al. (2022) “Decent Wage Floors in Europe: Does the Minimum Wage Directive Get it Right?”

Table 1. Results from random effects within-between (REWB) regression models.

	DV: share of workers on <60% median wage			DV: effective wage floor (P5 in PPS)		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Within: CBC	0.021	0.015	0.015	0.002	0.000	0.000
	(0.017)	(0.017)	(0.017)	(0.005)	(0.005)	(0.005)
Within: SMW dummy	3.250	3.009	3.010	-2.310***	-1.958**	-2.104**
	(3.040)	(3.109)	(3.109)	(0.887)	(0.916)	(0.915)
Within: SMW PPS	-0.462	-0.462	-0.462	0.318***	0.270***	0.285***
	(0.321)	(0.330)	(0.330)	(0.094)	(0.097)	(0.097)
Between: CBC	-0.123***	-0.128***	-0.129**	0.011	0.005	0.035***
	(0.030)	(0.029)	(0.063)	(0.009)	(0.007)	(0.013)
Between: SMW dumm	-5.599**	-11.027***	-11.031***	-5.302***	-1.767**	-1.525**
	(2.792)	(3.670)	(3.688)	(0.866)	(0.873)	(0.764)
Between: CBC*SMW dummy			0.001			-0.039***
			(0.069)			(0.014)
Between: SMW PPS	0.518	0.955*	0.953*	0.977***	0.637***	0.711***
	(0.385)	(0.515)	(0.532)	(0.118)	(0.122)	(0.111)
Constant	16.195***	20.086***	20.094***	8.970***	6.415***	5.990***
	(2.093)	(2.695)	(2.789)	(0.656)	(0.643)	(0.579)
Year FE	X	X	X	X	X	X
Controls		X	X		X	X

Hybrid Model: Issues

- But hybrid model is still bound to the RE assumption
- Unobserved country characteristics should not be correlated with $\overline{X}_i$ to get unbiased between-effect (or other time-invariant effect)

→ Otherwise between-effects would be biased

- Small-sample bias: another reason why the between-country effect is often unreliable (Bryan & Jenkins, 2016)
  - You need 25-30 countries for a simple model with single level-2 variable
- Using smaller N (<20) and for more complex modelling, Bayesian models often perform better (Stegmueller, 2013; Elff et al. 2021)

Modelling Dynamics

Use of Dynamic Specifications

- Use of lagged dependent variables (LDV) as an explanatory variable: ($Yit = \alpha * Yi,t\text{-}1 + \beta * Xit + ui + eit$)
  - Serial correlation: interesting aspect to 'model', not an estimation nuisance
  - Ex) Current employment rate is explained by previous employment rate
- OLS with LDV: bias of β very small, as much of the endogeneity (time-varying & invariant characteristics) is correlated with LDV
  - Panel-corrected standard error (PCSE: Beck & Katz, 1995): allows contemporaneous correlation & heteroskedasticity across countries

Dynamic Specifications: Issues (1)

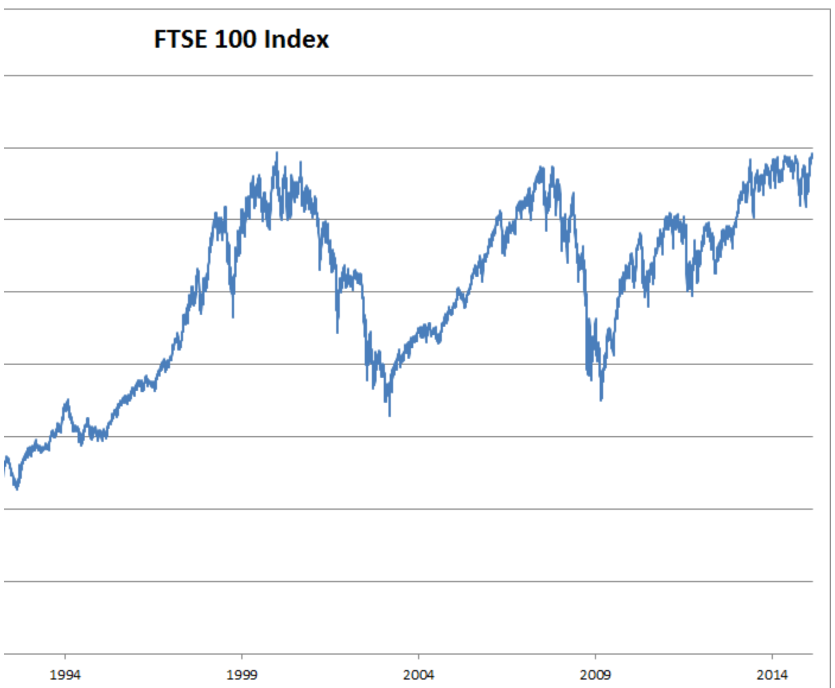
- But using LDV with FE introduces another type of bias (Nickell, 1981)
  - LDV is necessarily correlated with country-specific characteristics (ui)
  - Creates downward bias on LDV coefficient (thus affecting the size of Beta coefficient)
  - Bias wanes with longer T → not so much concern when T is very long

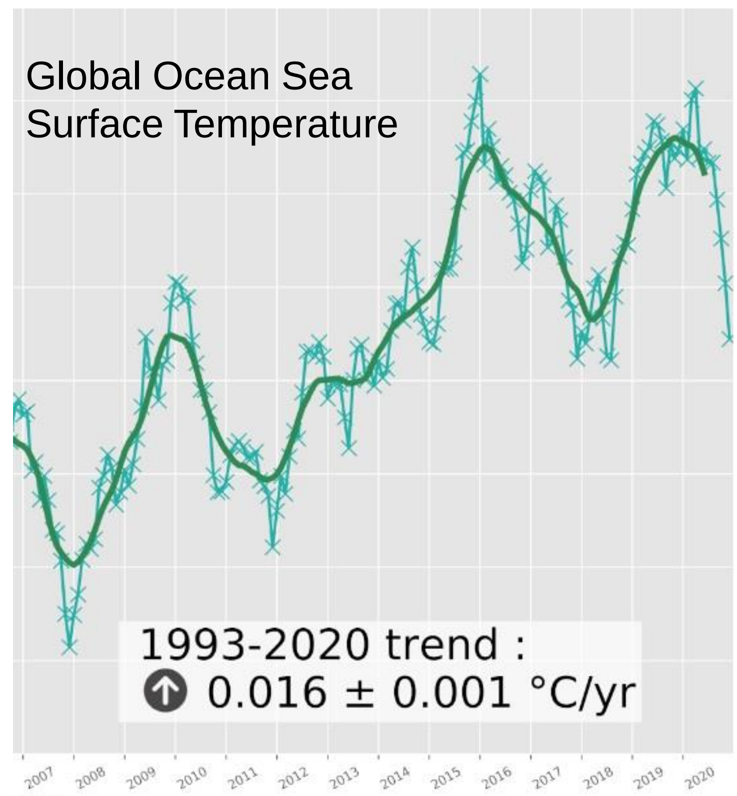
Dynamic Specifications: Issues (2)

- The substantive meaning of the coefficient changes: “Given the previous level of Y, one-unit change X increases/decreases Y by the size of β…”
  - Coefficient indicates a short-term, year-by-year response rather than a full effect

  → Short-term impulse of X on Y (there are delayed effects!)
  - Interpretation of long-run, full effect: $\beta/(1-\alpha)$ (* α: Coefficient of LDV)
- Most of the DV’s variation may be captured by LDV (thus very large R2)
  - Now, effects of X can be underestimated, even appear non-significant

Spurious Correlations in Time-Series Data





Error Correction Models

- Addresses spurious correlations in unit root processes
  - When you LDV coef. is near one
- Most commonly used is Engle & Granger (1987) two-step method
- $\Delta y_{it} = \beta_1 \Delta X_{it} + \beta_2 \left(y_{i,t-1} - \beta_3 X_{i,t-1} \right) + \varepsilon_{it}$
  where $\Delta X_{it} = X_{it}$ - $X_{i,t-1}$
- This can be rearranged to,
- $y_{it} = \alpha\, y_{i,t-1} + \beta_1 \Delta X_{it} + \beta_2 X_{i,t-1} + \varepsilon_{it}$
- Include levels & differences in a single dynamic model
  - Avoids non-stationarity & estimates short/long-term effects
- Core assumption: X and Y has a long-run equilibrium relationship (= residuals from the lagged-level model follow a stationary process)

Link with Causal Inference

- Contemporary causal inference literature is dominated by potential outcomes approach
  - This kind of approach is mostly not feasible with TSCS datasets
- Panel GMM estimation: way to combine unit-fixed effects with LDV (esp. in large-N, short-T settings)
  - Difference GMM (Arellano & Bond 1991): using lagged level ($Y_{i,t-2}$) as instruments
  - System GMM (Arellano & Bover 1995; Blundell & Bond 1998): using lagged difference ($\Delta Y_{i,t-2}$) as instruments
  - Very sensitive to small-sample bias (Roodman, 2009)
- Matching methods for TSCS (Imai et al., 2023)
- DiD with multiple time periods (Callaway & Sant'Anna 2021; Sun & Abraham, 2021; de Chaisematin & d'Haultfoeuille 2020)

Other issues to think about

- Cross-sectional dependence: "Are policy changes in Germany and France independent?"
  - Use of time dummies, panel-corrected standard error (Beck & Katz 1995)
  - Use of spatial models: modelling diffusion process
- Heterogeneous effects across time & space
  - Hypothetically, effect of X in the first half of the period is -0.5, and the second half is +0.5 → zero pooled effect
  - Same in cross-country aggregation: ex) Effects of ALMP may differ in Sweden and the UK
- Use of interaction effects: but you cannot include interactions with all countries or all time points! (use theory to group countries & times)

Summary & Conclusion

- Fixed-effects models give you within-country effects (often unbiased) but at (sometimes large) costs
- Random-effects models give you efficient but often biased estimates
- Hybrid models can separately estimate within- and between-country effects but they are still random-effects models
- Using LDVs can further address time-varying omitted variables but the interpretation is different
- Spurious correlations should also be considered (feat. error correction model)
- Panel GMM allows combining LDV with FE but is sensitive to biases in small N, long T setting

"All models are wrong, but some are useful“

“Since all models are wrong the scientist must be alert to what is importantly wrong”

George Box (1976), "Science and statistics", *Journal of the American Statistical Association*, 71 (356): 791–799.

Every method has its assumptions, pros & cons.

No one-size-fits-all solution

Need to choose carefully - which one would be the “least worrying” model, given your data structure, modelling assumptions & research questions.

Now, let's apply these models to LIS data

Thank you!
Q & A