

pantarei: three-way decomposition of variability in longitudinal, time-series-cross-sections, and multilevel data

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XVIII Italian Stata Conference, Milan, September 25, 2025

The context I

Panel data (longitudinal and time-series-cross-sections) and multilevel data are widely used, the former in econometrics, the latter in *psychometrics* (psychology, sociology, education, criminology, biostatistics, etc., Bou and Satorra, 2017).

Different methodological approaches and aims emerge, reflecting the peculiarities of each field.

Different language, or different interpretation of the same language: fixed effects, random effects, multilevel models, mixed models.

We often deal with complex data and “social” structures, but these dataset can all be considered as grouped data:

- In econometrics, standard panel data have a structure with repeated observations over time nested in individuals, companies, countries.
- In psychometrics, multilevel models are used to analyse hierarchical data, such as *individual responses* (level-1 students or trees/plots) collected *within groups* (level-2 schools and background, species and ecological regions). Multilevel modelling also deals with cross-classifications or supergroups.
- Clustering and cross-classified effects tend to create dependencies between observations and imbalanced data structures: non-consecutive time periods or different number of units in each group.

The context II

A preliminary and crucial step of any empirical research is to study the nature and relevance of the components that influence the variability of the variables, particularly the dependent variable.

The study of variability at various levels is interesting in itself and can provide indications on the directions in which further investigation would be worthwhile.

Quantifying the unexplained variability with an unconditional (empty) model represents a preliminary step in assessing what we still do not understand about the differences in the values of the response variable between and within clusters.

Once explanatory variables have been introduced, we can obtain an indication of the progress made in explaining the variability of the response variable and the variability that remains unexplained.

Furthermore, quantifying the different types of variabilities in the response variable and the possible explanatory variables is a fundamental guide for the modelling and estimation strategies to be employed (Gibbons et al., 2014).

The context III

- The presence of a significant clustering excludes the possibility of implementing POLS:
 - The assumption of independent replications is violated (McNeish and Kelley, 2019; McNeish, 2023). Instead, the dependence of observations within clusters is of fundamental interest because it reflects essential aspects of the social world, such as the effect of attending the same school or living in the same area, working in the same company.
 - Each nesting level is associated with a variability that has a distinct interpretation. For example, the growth of trees is influenced by their individual characteristics but also by the characteristics of the species and the ecological regions).
 - Failure to distinguish between these different sources of variability would lead to incorrect conclusions due to logical errors such as:
 - ▶ The *ecological fallacy* (Robinson, 1950), which interprets associations at the higher level as pertaining to the lower level: conclusions about individuals are drawn on the basis of group-level data analysis, but the relationships observed at the group level are not necessarily valid at the individual level.
 - ▶ The *atomistic fallacy* (Alker, 1969), which instead interprets associations at the individual level as pertaining to the higher level.
 - ▶ In the “panel” jargon, the fallacy consists of confusing aggregate effects with individual effects, resulting from confounding the within-group (individuals) and between-group (higher level) effects.

The context IV

- The absence of within-cluster variability excludes the possibility of implementing an FE estimation, particularly if the interest is on measurable higher-level explanatory variables, such as the role of education, race or gender on the wages of workers inside different companies.
- Considerably different between and within variabilities may suggest avoiding the weighted average implemented by RE/GLS and instead estimating the between and within effects of explanatory variables on the dependent variable separately, exploiting the Mundlak (1978)'s approach (also useful for testing endogeneity because of heterogeneity).

The aim of the new command `l`

The new command `pantarei` has a name that derives from the ancient Greek expression πάντα ῥεῖ (Heraclitus of Ephesus, c. 535 – c. 475 BCE, pre-Socratic Greek philosopher?) to indicate that “everything flows”, in the sense that heterogeneity and variations are central and even the methodologies for analysing panel data are constantly changing.

It breaks down the total variability into:

- (1) The component due to level-2, individuals, cross-section or variability between clusters.
- (2) The component due to level-1 observations nested in level-2, the variability within clusters.

The within variability is further decomposed into:

- (2a) The residual variability once level-2 and level-1 heterogeneities have been taken into account, called within level-2-level-1 variability.
- (2b) The variability due to the level-1 effect, called between level-1 variability.

The aim of the new command II

- It is suitable for longitudinal, cross-sectional time-series and multilevel data.
- The standard panels investigated by the FE approach are the default ones; the `re` option exploits the GLS/RE approach; the `ml` option uses the ML and mixed model (hierarchical and with cross-effects).
- Two levels are considered, but it is possible to replicate the command on the same dataset by changing the levels considered, particularly in multilevel datasets.
- The joint tests on the statistical significance of the heterogeneities at the levels considered are reported.
- In the default FE setting, the levels are considered including dummy variables, and the F tests for the joint null hypothesis that all levels have the same mean are reported.
- In the GLS/RE case, levels are considered random and their variance parameters are tested using Breusch and Pagan's Lagrange multiplier tests; a mixed model is also implemented for level-1 effects which are estimated and tested as in the FE case.
- In the ML multilevel models, the levels are again considered random and tested using likelihood-ratio tests that compare the fitted models with and without random effects. A mixed model is also implemented for level-1 effects, which are estimated and tested as in FE case. In addition, a cross-effects specification is used whereby level-1 is not simply nested within level-2 clusters, but a single artificial level-3 super-cluster is assumed within which both level-2 and level-1 are nested (a trick from Rasbash and Goldstein, 1994; Goldstein, 1987).

The aim of the new command `lll`

- The dataset can be investigated with the `common` option, which computes the decomposition of variability for the subsample of non-missing observations of all variables.
- The default FE model has the `ur` option, which implements, for each variable, the Elliott et al. (1996) `dfgls` unit root test on the level-1 common factor that may drive all level-2 clusters. This is a proxy of the common correlated effect, CCE, which is both estimated from the residuals of each variable estimated against level-1 dummies and proxied by computing the level-1 averages (Pesaran, 2006; Brown et al., 2021). The longer the time span, the more relevant the stationarity feature of the common factor used to account for cross-sectional dependence becomes.
- A graph of the time series of the estimated and computed common factors for each variable is saved in the researcher's working directory as a file `UR_varname.gph`.
- The `ml` option predicts, from the cross-effects model, the empirical Bayes estimates (i.e. posterior, shrunken, or best linear unbiased predictions, BLUPs) of the effects together with their associated standard errors, and produces caterpillar plots of the effects, which are saved for each variable as files `pillaru03lev1_varname.gph` (level-1 effects) and `pillaru02lev2_varname.gph` (level-2 effects).

The aim of the new command IV

- The new command is flexible and extends the existing commands `xtsum`, which only works for datasets that can be sorted with `tsset` or `xtset` and does not consider the role of CCE inside the within variability, and `loneway`, which allows only one level at a time.
- It also simplifies the use of post-regression results available after `mixed`. For example, a similar reason led to the creation of `pisamixed.ado`, contained in the zipped file `PISA2022_Stata_PublicCodes` and available for download from the website <https://www.oecd.org/en/data/datasets/pisa-2022-database.html#data>, which assists in the use of `mixed` calibrated on PISA data.
- The variance decomposition performed by the new command is consistent across different approaches to data, as it calculates the percentages of variability for each level as the ratio of partial sums of squares, rather than as VPCs and ICCs given by variance ratios (which are not adequately comparable due to the different degrees of freedom used in the calculation of variances).

Where we would like to go I

A model for standard panel:

$$y_{it} = \alpha + \sum_{k=1}^K \beta_k x_{kit} + (\theta' \mathbf{w}_i) + \mu_i + \tau_t + \varepsilon_{it}$$

In the econometric literature, FE and RE denote two type of estimators of β in a model where the unobserved random variable, μ_i , varies across units. We select FE or RE depending on whether μ_i is allowed to correlate or not (at unit level) with the time varying variables $\mathbf{x}_{it}$.

Very often we have endogeneity because of heterogeneity, $\mathbb{E}(\mathbf{x}_{it}\mu_i) \neq 0$ and only FE provides unbiased estimates of β . However, the unbiased within transformation cannot provide estimates of θ for $\mathbf{w}_i$, the time-invariant/changing very little over time observables, when they are of prime theoretical interest.

The useful extension is Mundlak (1978) and Chamberlain (1980) discussed in the tribute to the live and work of Marc Nerlove (Baltagi and Mátyás, 2025) and Bellemare and Millimet (2025) is:

$$y_{it} = \beta' \mathbf{x}_{it} + \theta' \mathbf{w}_i + \tau_t + \pi'_x \bar{\mathbf{x}}_i + e_i + \varepsilon_{it}$$

where the “between” equation $\alpha + \mu_i = \alpha_i = \pi'_x \bar{\mathbf{x}}_i + e_i$ with $\bar{\mathbf{x}}_i = T_i^{-1} \sum_{t=1}^{T_i} \mathbf{x}_{it}$, is used to captures the sample variation across units.

Where we would like to go II

A multilevel hierarchical model (Goldstein, 2011; Bryk and Raudenbush, 2002; Hox and Roberts, 2011; Snijders and Bosker, 2012) with level-1 individuals $i = 1, \dots, n_j$ nested within level-2 groups $j = 1, \dots, J$ is:

$$y_{tij} = \beta_{0j} + \sum_{k=1}^K \beta_{kj} x_{tijk} + \sum_{s=1}^T \gamma_s D_{st} + \varepsilon_{tij}$$

$$\beta_{0j} = \beta_{00} + \beta'_{01} \mathbf{w}_j + u_{0j}$$

$$\beta_{kj} = \beta_{k0} + \beta'_{k1} \mathbf{w}_j + u_{kj} \quad \text{for } k = 1, \dots, K$$

- β_{00} is the grand mean of y across all groups j ; the mean of y for group j is $\beta_{00} + u_{0j}$ so that the distances between groups averages respect to the grand average β_{00} represent the between-group variability.
- β_{k0} is the grand mean slope across all groups, and $\beta_{k0} + u_{kj}$ is the role of group j on the effect of x_{tijk} . The target is understanding how effects vary.
- Different types of effects incorporated at different levels: u_{0j} and u_{kj} are considered as random while γ_s can be a fixed effect for D_{st} , the dummy for period s , which is the best choice when time is sparse and period effects are nuisance controls.
- β_{kj} slope for variable k in group j ; $\mathbf{x}_{tij} = (x_{tij1}, \dots, x_{tijK})'$ vector of unit- and time-varying covariates (usually centered).

Where we would like to go III

- The $\mathbf{w}_j$ vector of time-invariant group-level covariates (usually centered) can be included in β_{0j} and β_{kj} so that β_{01} and β_{k1} are the vectors of contextual effects induced by $\mathbf{w}_j$ on intercept and slope k , respectively.
- Multilevel models can also be integrated with the Mundlak (1978)'s approach.

Where do we start I

Unconditional "empty" models are:
FE/LSDV

$$y_{it} = \alpha + \underbrace{\sum_{j=1}^{N-1} \mu_j D_{ji}}_{\text{lev2 heterog.}} + \underbrace{\sum_{s=1}^{T-1} \tau_s \Theta_{st}}_{\text{lev1 heterog.}} + \varepsilon_{it}$$

The μ_i term is "unobserved heterogeneity" or unobserved "permanent/stable" effects specific to each level-2 cluster *i included in the sample* and nesting level-1 *t*.

Adding a dummy variable for each unit (minus one baseline) is equivalent to within-transform the data.

Within-transformation prevents the estimation of $\mathbf{w}_i$ time-invariant variables.

Unobserved "unstable" factors are in the error term ε_{it} , with $\mathbb{E}(\varepsilon_{it}) = 0$ and $\text{Var}(\varepsilon_{it}) = \sigma_\varepsilon^2$. Time dummies capture the role of CCE as a component of within-units variability, and it is equivalent to compute temporal averages.

RE/Random Intercept Model

$$y_{it} = \alpha + \sum_{s=1}^{T-1} \tau_s \Theta_{st} + \underbrace{\mu_i + \varepsilon_{it}}_{v_{it}}$$

The v_{it} two-way error term includes "unobserved heterogeneity" which is condensed by variability σ_μ^2 . The two components have

$\mathbb{E}(\varepsilon_{it}) = \mathbb{E}(\mu_i) = 0$, $\text{Var}(\varepsilon_{it}) = \sigma_\varepsilon^2$ and $\text{Cov}(\varepsilon_{it}, \mu_i) = 0$.

The μ_i is the result of a random draw from a distribution, with some units higher (lower) on y ; each draw, added to the grand mean of y , α , gives the observed intercept of unit *i*. The interest is *on the population* of clusters, beyond the specific clusters in the sample.

In this "random effects" framework, the $\mathbf{w}_i$ time-invariant variables can be estimated. Time effects can be considered as fixed or random as well.

Where do we start II

Two-level hierarchical model (Goldstein, 2011; Bryk and Raudenbush, 2002; Hox and Roberts, 2011; Snijders and Bosker, 2012) with level-1 units $i = 1, \dots, n_j$ nested within level-2 groups $j = 1, \dots, J$:

$$y_{ij} = \beta_{0j} + \varepsilon_{ij}$$

$$\beta_{0j} = \beta_{00} + u_{0j}$$

The term β_{00} is the grand mean of y_{ij} across all groups j ; the mean of y for group j is $\beta_{00} + u_{0j}$ so that the distances between groups averages respect to the grand average β_{00} represent the between-group variability.

The distances between each observation y_{ij} and the group mean represents the within-group between-individual variability.

Two-way cross-classified model (Goldstein, 2011; Rasbash and Goldstein, 1994; Rasbash and Browne, 2001; Rasbash and Browne, 2008; Beretvas, 2011) where level-1 units $i = 1, \dots, n_{(j_1, j_2)}$ are clustered in more that one level-2 classification and the classification units are not nested within each other. The cross-classified factors are $j_1 = 1, \dots, J_1$ and $j_2 = 1, \dots, J_2$ at the same level-2; the pair or combination (j_1, j_2) indexes the cells of the cross-classification:

$$y_{i(j_1, j_2)} = \beta_{0(j_1, j_2)} + \varepsilon_{i(j_1, j_2)}$$

$$\beta_{0(j_1, j_2)} = \beta_{000} + u_{0j_1} + u_{0j_2} + u_{00j_1 \times j_2}$$

The term β_{000} is the overall mean of $y_{i(j_1, j_2)}$ across all level-2 j_1 , all level-2 j_2 and units i .

Where do we start III

The random effects (with covariances typically assumed to be zero) are:

$u_{0j} \sim \mathcal{N}(0, \sigma_{u_0}^2)$ with $\sigma_{u_0}^2$ between-group variance.

$\varepsilon_{tij} \sim \mathcal{N}(0, \sigma_\varepsilon^2)$, with σ_ε^2 within-group between-units variance.

$u_{00j_1} \sim \mathcal{N}(0, \sigma_{u_{00j_1}}^2)$, with $\sigma_{u_{00j_1}}^2$ between level-2 j_1 variance having adjusted for differences between level-2 j_2 .

$u_{00j_2} \sim \mathcal{N}(0, \sigma_{u_{00j_2}}^2)$, with $\sigma_{u_{00j_2}}^2$ between level-2 j_2 variance having adjusted for differences between level-2 j_1 .

$\varepsilon_{i(j_1, j_2)} \sim \mathcal{N}(0, \sigma_\varepsilon^2)$, with σ_ε^2 level-1 variance within the cells defined by level-2 j_2 j_1 pairings.

$u_{00j_1 \times j_2} \sim \mathcal{N}(0, \sigma_{u_{00j_1 \times j_2}}^2)$ random interaction effect between the two cross-classified factors; without sufficiently large within-cell sample sizes, it is hard to separate the additive variances from the variance within the cells of the cross-classification and thus this last random effect is most typically set to zero.

Where do we start IV

FE/RE models can be estimated with ji instead of it . Multilevel models can be estimated with ti instead of ij .

FE/RE models are estimated by inverting the indices in ti , and multilevel models can be estimated by inverting the indices in ji to capture the variability at each level and test the significance of the effect of each level.

In multilevel models we can use a mixed specification in which i of ij and t of ti are considered fixed effects captured by a set of dummy variables, i.e., by $\sum_{n=1}^{n_j} \gamma_{un} D_{ni}$ for units within each cluster j and $\sum_{s=1}^T \gamma_{ms} D_{st}$ for measurement occasions t within each cluster i , respectively.

Of course, there are a huge number of possible model specifications if each coefficient can be either fixed or random. This number increases with the number of clusters (level-1, level-2, level-3, ...). Strategies change if the panel structure is hierarchical or cross-classified.

The new `pantarei` command presents the possible specifications for two-level models and considers the possibility that there are few units within groups or that temporal observations are few and scattered, so that dummy variables are just controls for noise and panel imbalance in a mixed framework.

The syntax I

`pantarei list of variables [,options]`

- options: the default is FE model; `ur` can be added to test for stationarity of CCE and obtain the plot of CCE. `re` implements the RE/GLS model; `ml` implements the multilevel and cross-classified models. `common` can be added to the default, `re` and `ml` to implement the models on the sub-sample of non missing values.
- list of variables must follow the order level-2, level-1, variables that we want to investigate.
- It is a good idea to generate level-2 and level-1 indices as progressive numbers (e.g. `egen lev2=(group) level-2-index, label`); this is not necessary for temporal level-1 index already in the form e.g. 2005, .., 2025 or 2020q1, .., 2025q4.
- The command can be executed under conditions by using the sequence `preserve` hence `if` or `in` condition hence `pantarei` hence `restore`.
- Time series operators (`l.` or `d.`) are not allowed, but lagged and first-differenced variables can be generated before implementing the `pantarei` command.

A macro panel I

pantarei id year tint dlpc

----- Level 2 (i): id Level 1 (t): year -----						
Hypothetical full sample, N x T: 209						
N: 11 T: 19						

Variable		Mean	Std.Dev.	% SS	Observations	Test

tint	Overall xit-x..	.09459	.03436		N x T 209	id effects:
	1-Between xi.-x..		.02169	36.41	N-min 11	F(10, 180) = 41.89
	2-Within xit-xi.		.02808	63.59	N-bar 11.00	Prob > F = 0.00
	----- of which: -----				N-max 11	year effects:
	2a-res xit-xi.-x.t+x..		.01461	15.64	T-min 19	F(18, 180) = 30.65
	2b-between x.t-x..		.02439	47.95	T-bar 19.00	Prob > F = 0.00
	(2b in % of 2)			(75.40)	T-max 19	Balancedness = 100.00

dlpc	Overall xit-x..	.04837	.04363		N x T 198	id effects:
	1-Between xi.-x..		.02583	32.02	N-min 11	F(10, 170) = 26.01
	2-Within xit-xi.		.03693	67.98	N-bar 11.00	Prob > F = 0.00
	----- of which: -----				N-max 11	year effects:
	2a-res xit-xi.-x.t+x..		.02149	20.93	T-min 18	F(17, 170) = 22.49
	2b-between x.t-x..		.03072	47.06	T-bar 18.00	Prob > F = 0.00
	(2b in % of 2)			(69.22)	T-max 18	Balancedness = 94.74

A macro panel II

pantarei id year tint dlpc, common ur

----- Level 2 (i): id Level 1 (t): year -----					
Hypothetical full sample, N x T: 209					
N: 11 T: 19					

Variable	Mean	Std.Dev.	% SS	Observations	Test

tint Overall xit-x..	.09329	.03421		N x T 198	id effects:
1-Between xi.-x..		.02137	35.66	N-min 11	F(10, 170) = 37.83
2-Within xit-xi.		.02816	64.34	N-bar 11.00	Prob > F = 0.00
----- of which: -----		-----		N-max 11	year effects:
2a-res xit-xi.-x.t+x..		.01474	16.03	T-min 18	F(17, 170) = 30.15
2b-between x.t-x.. (CF)		.0244	48.32	T-bar 18	Prob > F = 0.00
(2b in % of 2)			(75.09)	T-max 18.00	Balancedness = 94.74
Estimated CF x.t					H0: UR - pval = 0.47
Computed CF x.t					H0: UR - pval = 0.47

dlpc Overall xit-x..	.04837	.04363		N x T 198	id effects:
1-Between xi.-x..		.02583	32.02	N-min 11	F(10, 170) = 26.01
2-Within xit-xi.		.03693	67.98	N-bar 11.00	Prob > F = 0.00
----- of which: -----		-----		N-max 11	year effects:
2a-res xit-xi.-x.t+x..		.02149	20.93	T-min 18	F(17, 170) = 22.49
2b-between x.t-x.. (CF)		.03072	47.06	T-bar 18	Prob > F = 0.00
(2b in % of 2)			(69.22)	T-max 18.00	Balancedness = 94.74
Estimated CF x.t					H0: UR - pval = 0.08
Computed CF x.t					H0: UR - pval = 0.08

A macro panel III

```
g dtint=d.tint
g ddlpc=d.dlpc
pantarei id year dtint ddlpc, common ur
```

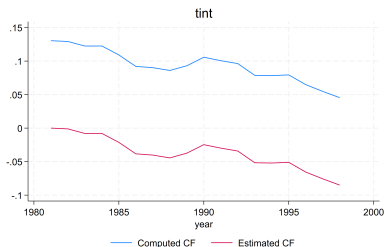
----- Level 2 (i): id Level 1 (t): year -----					
Hypothetical full sample, N x T: 209					
N: 11 T: 19					

Variable		Mean	Std.Dev.	% SS	Observations Test

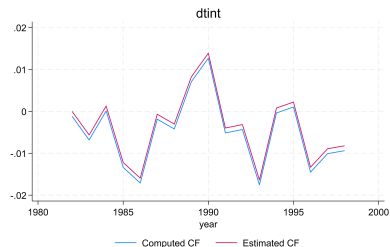
dtint	Overall xit-x..	-.005	.01157		N x T 187 id effects:
	1-Between xi.-x..		.001859	2.36	N-min 11 F(10, 160) = 0.76
	2-Within xit-xi.		.01175	97.64	N-bar 11.00 Prob > F = 0.67
	----- of which: -----				N-max 11 year effects:
	2a-res xit-xi.-x.t+x..		.008803	49.83	T-min 17 F(16, 160) = 9.59
	2b-between x.t-x.. (CF)		.008222	47.81	T-bar 17 Prob > F = 0.00
	(2b in % of 2)			(48.97)	T-max 17.00 Balancedness = 89.47
	Estimated CF x.t				H0: UR - pval = 0.01
	Computed CF x.t				H0: UR - pval = 0.01

ddlpc	Overall xit-x..	-.00584	.01455		N x T 187 id effects:
	1-Between xi.-x..		.002577	2.87	N-min 11 F(10, 160) = 0.82
	2-Within xit-xi.		.01474	97.13	N-bar 11.00 Prob > F = 0.61
	----- of which: -----				N-max 11 year effects:
	2a-res xit-xi.-x.t+x..		.01175	56.10	T-min 17 F(16, 160) = 7.31
	2b-between x.t-x.. (CF)		.009583	41.03	T-bar 17 Prob > F = 0.00
	(2b in % of 2)			(42.24)	T-max 17.00 Balancedness = 89.47
	Estimated CF x.t				H0: UR - pval = 0.03
	Computed CF x.t				H0: UR - pval = 0.03

A macro panel IV



CCE for the levels of the interest rate



CCE for the first differences of the interest rate

A macro panel V

pantarei id year tint dlpc, common re

----- Level 2 (j): id Level 1 (i): year -----					
Hypothetical full sample, Ni x Nj: 209					
Nj: 11 Ni: 19					
Variable	Mean	Std.Dev.	% SS	Observations	Test
tint Overall xij-x..	.09329	.03421		Ni x Nj 198	id effects:
1-Between xj-x..		.02278	40.54	Nj-min 11	Chi2(1) = 170.98
2-Within xij-xj		.02707	59.46	Nj-bar 11.00	Prob > Chi2 = 0.00
----- of which: -----				Nj-max 11	year effects:
2a-res xij-xj-xi+x..		.01474	16.03	Ni-min 18	Chi2(1) = 184.31
2b-between xi-x..		.02314	43.44	Ni-bar 18.00	Prob > Chi2 = 0.00
(2b in % of 2)			(73.05)	Ni-max 18	Balancedness = 94.74

-- year as fixed effects: --					
3-Between xj-x..		.02137	35.66		id effects:
4-Within xij-xj		.02816	64.34		Chi2(1) = 759.32
----- of which: -----					Prob > Chi2 = 0.00
4a-res xij-xj-xi+x..		.01474	16.03		year effects:
4b-between xi-x..		.0244	48.32		Chi2(17) = 512.54
(4b in % of 4)			(75.09)		Prob > Chi2 = 0.00

A macro panel VI

pantarei id year tint dlpc, common ml

----- Level 2 (j): id Level 1 (i): year -----						
Hypothetical full sample, Ni x Nj: 209						
Nj: 11 Ni: 19						

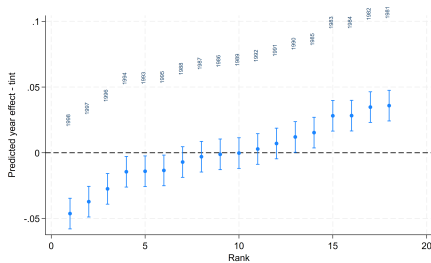
Variable		Mean	Std.Dev.	% SS	Observations	Test

tint	Overall xij-x..	.09329	.03421		Ni x Nj 198	id effects:
	1-Between xj-x..		.02392	44.68	Nj-min 11	Chi2(1) = 51.32
	2-Within xij-xj		.02611	55.32	Nj-bar 11.00	Prob > Chi2 = 0.00
	----- of which: -----				Nj-max 11	year effects:
	2a-res xij-xj-xi+x..		.01405	14.57	Ni-min 18	Chi2(1) = 71.58
	2b-between xi-x..		.02241	40.75	Ni-bar 18.00	Prob > Chi2 = 0.00
	(2b in % of 2)			(73.66)	Ni-max 18	Balancedness = 94.74

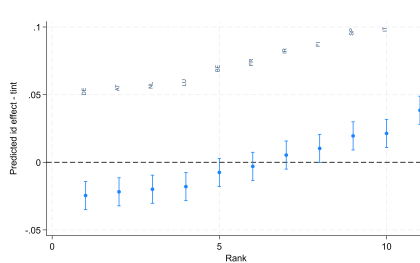
-- year as fixed effects: --						
	3-Between xj-x..		.02137	35.66		id effects:
	4-Within xij-xj		.02816	64.34		Chi2(1) = 180.57
	----- of which: -----					Prob > Chi2 = 0.00
	4a-res xij-xj-xi+x..		.01405	14.57		year effects:
	4b-between xi-x..		.02477	49.77		Chi2(17) = 563.80
	(4b in % of 4)			(77.36)		Prob > Chi2 = 0.00

-- year as crossed-effect: --						
	3-Between xj-x..		.0205	34.81		id effects:
	4-Within xij-xj		.02753	65.19		Chi2(1) = 163.35
	----- of which: -----					Prob > Chi2 = 0.00
	4a-res xij-xj-xi+x..		.01474	16.99		year effects:
	4b-between xi-x..		.02367	48.19		Chi2(1) = 71.58
	(4b in % of 4)			(73.93)		Prob > Chi2 = 0.00

A macro panel VII



Level-3 (cross-effects) pillar-plot for the interest rate



Level-2 pillar-plot for the interest rate

One of the most widely used longitudinal panels I

In abdata (Arellano and Bond, 1991; Blundell and Bond, 1998) there are no missing values, so we can skip the common option.

pantarei id year n w k

----- Level 2 (i): id Level 1 (t): year -----					
Hypothetical full sample, N x T: 1260					
N: 140 T: 9					

Variable	Mean	Std.Dev.	% SS	Observations	Test

n Overall xit-x..	1.056	1.342		N x T 1031	id effects:
1-Between xi.-x..		1.331	97.90	N-min 35	F(139, 883) = 428.33
2-Within xit-xi.		.2092	2.10	N-bar 114.56	Prob > F = 0.00
----- of which: -----				N-max 140	year effects:
2a-res xit-xi.-x.t+x..		.1731	1.43	T-min 7	F(8, 883) = 52.24
2b-between x.t-x..		.1169	0.68	T-bar 7.36	Prob > F = 0.00
(2b in % of 2)			(32.12)	T-max 9	Balancedness = 81.83

w Overall xit-x..	3.143	.263		N x T 1031	id effects:
1-Between xi.-x..		.2503	90.01	N-min 35	F(139, 883) = 75.38
2-Within xit-xi.		.08939	9.99	N-bar 114.56	Prob > F = 0.00
----- of which: -----				N-max 140	year effects:
2a-res xit-xi.-x.t+x..		.07837	7.61	T-min 7	F(8, 883) = 34.51
2b-between x.t-x..		.04302	2.38	T-bar 7.36	Prob > F = 0.00
(2b in % of 2)			(23.82)	T-max 9	Balancedness = 81.83

k Overall xit-x..	-.4416	1.514		N x T 1031	id effects:
1-Between xi.-x..		1.503	97.97	N-min 35	F(139, 883) = 396.39
2-Within xit-xi.		.2322	2.03	N-bar 114.56	Prob > F = 0.00
----- of which: -----				N-max 140	year effects:
2a-res xit-xi.-x.t+x..		.2037	1.55	T-min 7	F(8, 883) = 34.39
2b-between x.t-x..		.1116	0.48	T-bar 7.36	Prob > F = 0.00
(2b in % of 2)			(23.76)	T-max 9	Balancedness = 81.83

One of the most widely used longitudinal panels II

Option `ur` gives the error message

The lenght of time series could be not enough to compute UR test (at least 9 periods are required) Error code `r(127)` (or `r(2000)` or `r(498)`) `maxlag()` invalid - invalid number, missing not allowed

Anyway, we can produce the pillar-plots with the option `m1`

```
pantarei id year n w k, m1
```

One of the most widely used longitudinal panels III

		Level 2 (j): id		Level 1 (i): year			
		Hypothetical full sample, Ni x Nj: 1260					
		Nj: 140 Ni: 9					
Variable		Mean	Std.Dev.	% SS	Observations	Test	
n	Overall xij-x..	1.056	1.342		Ni x Nj 1031	id effects:	
	1-Between xj-x..		1.327	97.20	Nj-min 35	Chi2(1)	=3032.80
	2-Within xij-xj		.2412	2.80	Nj-bar 114.56	Prob > Chi2 =	0.00
	----- of which: -----				Nj-max 140	year effects:	
	2a-res xij-xj-xi+x..		.1724	1.42	Ni-min 7	Chi2(1)	= 2.50
	2b-between xi-x..		.1671	1.38	Ni-bar 7.36	Prob > Chi2 =	0.03
	(2b in % of 2)			(49.38)	Ni-max 9	Balancedness	= 81.83
-- year as fixed effects: --							
	3-Between xj-x..		1.331	97.90		id effects:	
	4-Within xij-xj		.2092	2.10		Chi2(1)	=3355.32
	----- of which: -----					Prob > Chi2 =	0.00
	4a-res xij-xj-xi+x..		.1724	1.42		year effects:	
	4b-between xi-x..		.118	0.69		Chi2(8)	= 422.78
	(4b in % of 4)			(32.73)		Prob > Chi2 =	0.00
-- year as crossed-effect: --							
	3-Between xj-x..		1.329	97.72		id effects:	
	4-Within xij-xj		.2175	2.28		Chi2(1)	=3335.63
	----- of which: -----					Prob > Chi2 =	0.00
	4a-res xij-xj-xi+x..		.1731	1.43		year effects:	
	4b-between xi-x..		.1308	0.85		Chi2(1)	= 2.50
	(4b in % of 4)			(37.20)		Prob > Chi2 =	0.03

One of the most widely used longitudinal panels IV

w	Overall xij-x..	3.143	.263		Ni x Nj	1031	id effects:	
	1-Between xj-x..		.2521	91.33	Nj-min	35	Chi2(1)	=1665.09
	2-Within xij-xj		.08329	8.67	Nj-bar	114.56	Prob > Chi2 =	0.00
	----- of which: -----				Nj-max	140	year effects:	
	2a-res xij-xj-xi+x..		.07801	7.54	Ni-min	7	Chi2(1)	= 4.25
	2b-between xi-x..		.02966	1.13	Ni-bar	7.36	Prob > Chi2 =	0.01
	(2b in % of 2)			(13.05)	Ni-max	9	Balancedness	= 81.83

--	year as fixed effects: --							
	3-Between xj-x..		.2503	90.01			id effects:	
	4-Within xij-xj		.08938	9.99			Chi2(1)	=1883.55
	----- of which: -----						Prob > Chi2 =	0.00
	4a-res xij-xj-xi+x..		.07801	7.54			year effects:	
	4b-between xi-x..		.04362	2.45			Chi2(8)	= 276.27
	(4b in % of 4)			(24.50)			Prob > Chi2 =	0.00

--	year as crossed-effect: --							
	3-Between xj-x..		.2438	89.12			id effects:	
	4-Within xij-xj		.09128	10.88			Chi2(1)	=1863.04
	----- of which: -----						Prob > Chi2 =	0.00
	4a-res xij-xj-xi+x..		.07838	7.95			year effects:	
	4b-between xi-x..		.04672	2.93			Chi2(1)	= 4.25
	(4b in % of 4)			(26.94)			Prob > Chi2 =	0.01

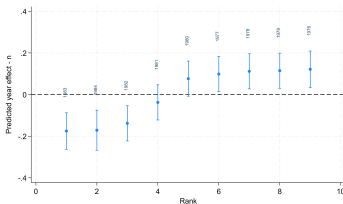
One of the most widely used longitudinal panels V

k	Overall xij-x..	-.4416	1.514		Ni x Nj	1031	id effects:	
	1-Between xj-x..		1.505	98.14	Nj-min	35	Chi2(1)	=3063.15
	2-Within xij-xj		.2217	1.86	Nj-bar	114.56	Prob > Chi2 =	0.00
	----- of which: -----				Nj-max	140	year effects:	
	2a-res xij-xj-xi+x..		.2028	1.54	Ni-min	7	Chi2(1)	= 0.23
	2b-between xi-x..		.0905	0.32	Ni-bar	7.36	Prob > Chi2 =	0.16
	(2b in % of 2)			(17.14)	Ni-max	9	Balancedness	= 81.83

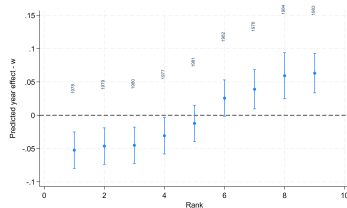
-- year as fixed effects: --								
	3-Between xj-x..		1.503	97.97			id effects:	
	4-Within xij-xj		.2322	2.03			Chi2(1)	=3288.44
	----- of which: -----						Prob > Chi2 =	0.00
	4a-res xij-xj-xi+x..		.2028	1.54			year effects:	
	4b-between xi-x..		.1132	0.50			Chi2(8)	= 278.52
	(4b in % of 4)			(24.44)			Prob > Chi2 =	0.00

-- year as crossed-effect: --								
	3-Between xj-x..		1.498	97.78			id effects:	
	4-Within xij-xj		.2422	2.22			Chi2(1)	=3267.04
	----- of which: -----						Prob > Chi2 =	0.00
	4a-res xij-xj-xi+x..		.2037	1.56			year effects:	
	4b-between xi-x..		.1306	0.67			Chi2(1)	= 0.23
	(4b in % of 4)			(29.91)			Prob > Chi2 =	0.16

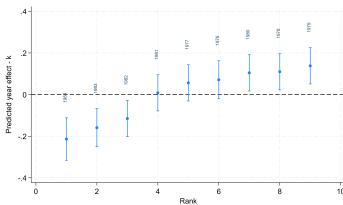
One of the most widely used longitudinal panels VI



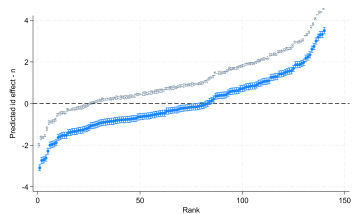
Level-3 (cross-effects) pillar-plot for log(employees)



Level-3 (crossed-effects) pillar-plot for log(wage)



Level-3 (cross-effects) pillar-plot for log(capital)



Level-2 pillar-plot for log(employees)

Considerations I

- Cross-classified multilevel models are applicable to macro panels, although the latter are usually considered hierarchical structures with periods nested within individuals in a balanced manner (all units measured over the same time span and all starting in the same period).
- In fact, it may be appropriate to consider a cross-classification of measurement occasions treated as random in order to capture events that can affect all units. This is an alternative way of considering CCEs induced by shocks to the international business cycle and different capacities to adapt to joint monetary policy choices (such as euro adoption).
- In a balanced macro long T panel, fixed time effects or cross-time effects are relevant and capable of capturing a broken trend that tends to be non-stationary for the interest rate (an $I(1)$ process).
- Also, cross-classified models allow us to assess the effects of panel imbalance, in the form of panel dropout or occasional non-measurement, as in abdata.
- Multilevel models show that in this longitudinal short T unbalanced panel, time considered as random is more relevant, particularly for variable wage w , capturing entries and exits of units from the sample as well as the role of inflation.
- Although the UR test requires at least 9 periods and cannot be implemented on abdata, pillar plots allow for some considerations, such as the tendency of employees n to decrease when wages w increase in 1983-1984, the decline in wages w as a consequence of the second oil shock in 1979-1980; a stable decrease of capital stock k over the period.

Very unbalanced micro panel I

Data from de Jong et al. (2011)

```
egen id=group(gvkey), label
```

```
tsset id yeara
```

```
Panel variable: id (unbalanced)
```

```
Time variable: yeara, 1986 to 2001, but with gaps
```

```
Delta: 1 unit
```

```
xtdes
```

```
id: 1, 2, ..., 5449
```

```
n = 5449
```

```
yeara: 1986, 1987, ..., 2001
```

```
T = 16
```

```
Delta(yeara) = 1 unit
```

```
Span(yeara) = 16 periods
```

```
(id*yeara uniquely identifies each observation)
```

```
Distribution of T_i:  min      5%      25%      50%      75%      95%      max
                   1         1         1         3         8        14        16
```

Freq.	Percent	Cum.	Pattern
384	7.05	7.05	1
176	3.23	10.28	1111111111111111
167	3.06	13.34	1.....
149	2.73	16.08	1.
136	2.50	18.57	11.....
132	2.42	20.99	1...
131	2.40	23.40	1..
113	2.07	25.47	111.....
98	1.80	27.27	1....
3963	72.73	100.00	(other patterns)
5449	100.00		XXXXXXXXXXXXXXXXXX

Very unbalanced micro panel II

pantarei id yeara bdr mdr, common ur

-----			Level 2 (i): id		Level 1 (t): yeara		-----	
			Hypothetical full sample, N x T: 87184					
			N: 5449		T: 16			

Variable			Mean	Std.Dev.	% SS	Observations	Test	

The lenght of time series could be not enough to compute UR test								
(at least 9 periods are required)								
Error code r(127) (or r(2000) or r(498))								
bdr	Overall xit-x..		.2608	.2139		N x T	27762	id effects:
1-Between xi.-x..			.1826	72.90		N-min	1528	F(5448, 22298)= 11.21
2-Within xit-xi.			.1242	27.10		N-bar	1735.12	Prob > F = 0.00
----- of which: -----						N-max	2056	yeara effects:
2a-res xit-xi.-x.t+x..			.123	26.56		T-min	1	F(15, 22298) = 30.50
2b-between x.t-x.. (CF)			.01631	0.54		T-bar	5	Prob > F = 0.00
(2b in % of 2)				(2.01)		T-max	16.00	Balancedness = 31.84
Estimated CF x.t								H0: UR - pval = 0.00
Computed CF x.t								H0: UR - pval = 0.04

The lenght of time series could be not enough to compute UR test

(at least 9 periods are required)

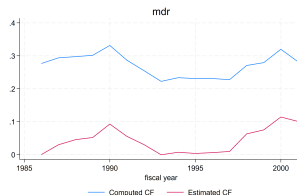
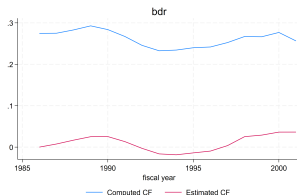
Error code r(127) (or r(2000) or r(498))

mdr	Overall xit-x..	.2689	.2459	N x T	27762 id effects:
1-Between xi.-x..		.2086	71.93	N-min	1528 F(5448, 22298)= 11.12
2-Within xit-xi.		.1453	28.07	N-bar	1735.12 Prob > F = 0.00
----- of which: -----				N-max	2056 yeara effects:
2a-res xit-xi.-x.t+x..		.141	26.40	T-min	1 F(15, 22298) = 93.99
2b-between x.t-x.. (CF)		.03282	1.67	T-bar	5 Prob > F = 0.00
(2b in % of 2)			(5.95)	T-max	16.00 Balancedness = 31.84
Estimated CF x.t					H0: UR - pval = 0.13
Computed CF x.t					H0: UR - pval = 0.09

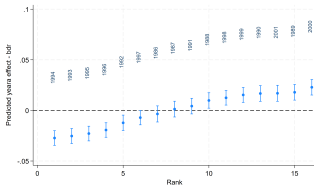
Very unbalanced micro panel III

```
pantarei id yeara bdr mdr, common ml
```

Very unbalanced micro panel IV

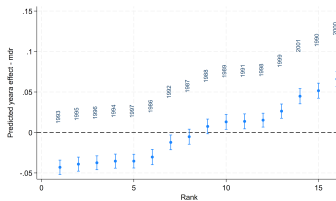


CCE for debt-ratio, book value



Level-3 (crossed-effects) pillar-plot for debt-ratio, book value

CCE for debt-ratio, market value



Level-3 (crossed-effects) pillar-plot for debt-ratio, market value

Very unbalanced micro panel V

The `ur` option provides a warning when the panel is unbalanced, but the test is implemented for those companies with more than 9 periods.

The debt-to-market value ratio is non-stationary.

Some breaks occurred: the oil shock (Iraq invaded Kuwait, causing an increase in the price of crude oil, which sparked fears of inflation) and the credit crisis (bankruptcy of hundreds of US credit institutions, more restrictive lending by banks, restrictive policy by the FED to curb inflation) in 1990, which caused the S&P 500 to fall by about 14% from July to October 1990.

In 2000 the dot-com bubble burst, with technology stocks being overvalued (the Nasdaq grew by almost 400% between 1995 and March 2000, driven largely by unprofitable internet companies), between June 1999 and May 2000, the FED raised the federal funds rate from 4.75% to 6.5% to cool the overheated economy, and companies overinvesting in IT systems before 2000, only to slow down their investments afterward. This caused the Nasdaq Composite to fall by around 50% and the S&P 500 to fall by 9%.

Quarterly data & micro panel I

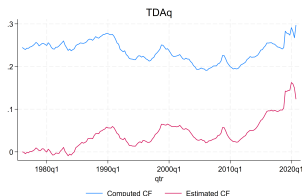
The `pantarei` command also works, e.g., with quarterly data. An example from COMPUSTAT data over the 1975q1-2020q4 (Bontempi and Bottazzi, 2025), again for debt ratios at book and market values.

```
pantarei id qtr TDAq TDMq, ur
```

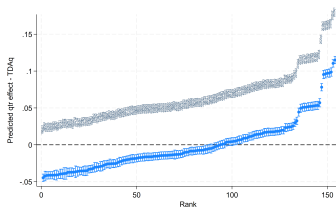
		Level 2 (i): id		Level 1 (t): qtr		-----	
		Hypothetical full sample, N x T: 2281140					
		N: 12673		T: 180			
Variable		Mean	Std.Dev.	% SS	Observations	Test	
-----		-----					
TDAq	Overall xit-x..	.2327	.211		N x T	436256	id effects:
	1-Between xi.-x..		.1681	63.48	N-min	483	F(12179, 423897)= 62.96
	2-Within xit-xi.		.1293	36.52	N-bar	2423.64	Prob > F = 0.00
	----- of which: -----				N-max	3812	qtr effects:
	2a-res xit-xi.-x.t+x..		.1269	35.14	T-min	1	F(179, 423897)= 93.59
	2b-between x.t-x.. (CF)		.02493	1.39	T-bar	36	Prob > F = 0.00
	(2b in % of 2)			(3.80)	T-max	180.00	Balancedness = 19.12
	Estimated CF x.t						H0: UR - pval = 0.81
	Computed CF x.t						H0: UR - pval = 0.22
-----		-----					
TDMq	Overall xit-x..	.2314	.2396		N x T	424603	id effects:
	1-Between xi.-x..		.1933	65.07	N-min	479	F(12146, 412277)= 65.32
	2-Within xit-xi.		.1437	34.93	N-bar	2358.91	Prob > F = 0.00
	----- of which: -----				N-max	3779	qtr effects:
	2a-res xit-xi.-x.t+x..		.1393	32.81	T-min	1	F(179, 412277)= 149.00
	2b-between x.t-x.. (CF)		.035	2.12	T-bar	35	Prob > F = 0.00
	(2b in % of 2)			(6.08)	T-max	180.00	Balancedness = 18.61
	Estimated CF x.t						H0: UR - pval = 0.00
	Computed CF x.t						H0: UR - pval = 0.28
-----		-----					

```
pantarei id qtr TDAq TDMq, common ml
```

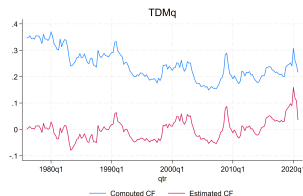
Quarterly data & micro panel II



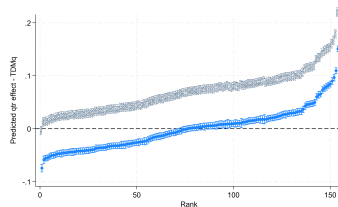
CCE for debt-ratio, book value quarterly



Level-3 (cross-effects) pillar-plot for debt-ratio, book value quarterly



CCE for debt-ratio, market value quarterly



Level-3 (cross-effects) pillar-plot for debt-ratio, market value quarterly

Another preliminar analysis I

Data taken from Bontempi and Kean (2025) Do efficient institutions discourage foreign direct investment (FDI) in developing countries rich in natural resources?

One of the main findings is that the emerging of democracy stimulates FDI regardless of the level of natural resources, provided that the host countries are already governed democratically to some extent.

Conversely, countries characterised by the risk of expropriation or long-standing governments (often associated with more autocratic regimes) do not discourage FDI aimed at exploiting natural resources.

Another preliminar analysis II

	CO2	FDI	DEM	RISK	GOV	FE	ME
between i	92.69	58.39	65.37	44.86	18.51	81.75	79.00
between t	0.84	0.44	9.15	28.66	43.86	0.59	0.84
residual within	6.47	41.17	25.48	26.49	37.63	17.55	20.16
UR	yes	yes	yes	yes	no	no	yes

Table: Managing pantarei results

Another preliminar analysis III



FDI



CO2 emissions



Fuels



Minerals



Democracy

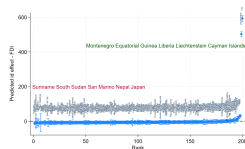


Gov. stability

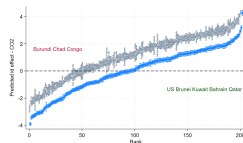


Risk of expropriation

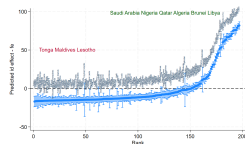
Another preliminar analysis IV



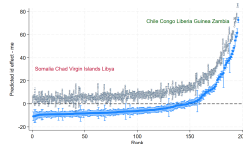
FDI



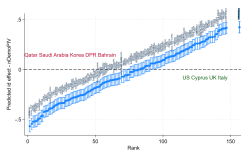
CO2 emissions



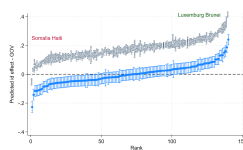
Fuels



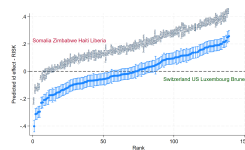
Minerals



Democracy



Gov. stability



Risk of expropriation

A classical multilevel dataset I

Data taken from Abrevaya (2006) studying the effect of smoking on the weight (in grams) of single newborns. Smoking status was determined by the answer to the question on the birth certificate regarding tobacco consumption during pregnancy. Smoking may vary from one pregnancy to another.

```
egen mom=group(momid)
```

```
pantarei mom idx birwt cigs smoke, common ml
```

A classical multilevel dataset II

----- Level 2 (j): mom Level 1 (i): idx -----					
Hypothetical full sample, Ni x Nj: 11934					
Nj: 3978 Ni: 3					
Variable	Mean	Std.Dev.	% SS	Observations	Test
birwt Overall xij-x..	3470	527.1		Ni x Nj 8604	mom effects:
1-Between xj-x..		448.4	72.35	Nj-min 648	Chi2(1) =1315.66
2-Within xij-xj		378	27.65	Nj-bar 2868.00	Prob > Chi2 = 0.00
----- of which: -----				Nj-max 3978	idx effects:
2a-res xij-xj-xi+x..		375.6	27.29	Ni-min 2	Chi2(1) = 22.99
2b-between xi-x..		38.84	0.36	Ni-bar 2.16	Prob > Chi2 = 0.00
(2b in % of 2)			(1.31)	Ni-max 3	Balancedness = 72.10

-- idx as fixed effects: --					
3-Between xj-x..		448.6	72.40		mom effects:
4-Within xij-xj		377.7	27.60		Chi2(1) =1336.67
----- of which: -----					Prob > Chi2 = 0.00
4a-res xij-xj-xi+x..		375.6	27.29		idx effects:
4b-between xi-x..		36.05	0.31		Chi2(2) = 55.14
(4b in % of 4)			(1.13)		Prob > Chi2 = 0.00

-- idx as crossed-effect: --					
3-Between xj-x..		369	63.97		mom effects:
4-Within xij-xj		377.7	36.03		Chi2(1) =1336.68
----- of which: -----					Prob > Chi2 = 0.00
4a-res xij-xj-xi+x..		375.7	35.63		idx effects:
4b-between xi-x..		35.57	0.40		Chi2(1) = 22.99
(4b in % of 4)			(1.10)		Prob > Chi2 = 0.00

A classical multilevel dataset III

smoke	Overall xij-x..		.1399	.3469		Ni x Nj	8604	mom effects:	
	1-Between xj-x..			.3188	84.43		Nj-min	648	Chi2(1) =3330.07
	2-Within xij-xj			.1867	15.57		Nj-bar	2868.00	Prob > Chi2 = 0.00
	----- of which: -----			-----			Nj-max	3978	idx effects:
	2a-res xij-xj-xi+x..			.1867	15.57		Ni-min	2	Chi2(1) = 0.00
	2b-between xi-x..			1.04e-09	0.00		Ni-bar	2.16	Prob > Chi2 = 0.50
	(2b in % of 2)				(0.00)		Ni-max	3	Balancedness = 72.10

-- idx as fixed effects: --									
	3-Between xj-x..			.3188	84.43			mom effects:	
	4-Within xij-xj			.1867	15.57			Chi2(1) =3325.32	
	----- of which: -----			-----				Prob > Chi2 = 0.00	
	4a-res xij-xj-xi+x..			.1867	15.57			idx effects:	
	4b-between xi-x..			.003505	0.01			Chi2(2) = 0.74	
	(4b in % of 4)				(0.04)			Prob > Chi2 = 0.69	

-- idx as crossed-effect: --									
	3-Between xj-x..			.2942	82.21			mom effects:	
	4-Within xij-xj			.1867	17.79			Chi2(1) =3330.07	
	----- of which: -----			-----				Prob > Chi2 = 0.00	
	4a-res xij-xj-xi+x..			.1867	17.79			idx effects:	
	4b-between xi-x..			2.32e-08	0.00			Chi2(1) = 0.00	
	(4b in % of 4)				(0.00)			Prob > Chi2 = 0.50	

A classical multilevel dataset IV

```
-----
cigs      Overall xij-x.. | 2.269   8.904       | Ni x Nj   8604 | mom effects:
      1-Between xj-x.. |           7.288   67.00 | Nj-min    648 | Chi2(1)      = 752.75
      2-Within xij-xj |           6.976   33.00 | Nj-bar  2868.00 | Prob > Chi2 =  0.00
      ----- of which: ----- |
      2a-res xij-xj-xi+x.. |           6.977   33.00 | Ni-min     2 | Chi2(1)      =  0.00
      2b-between xi-x.. |          4.77e-07   0.00 | Ni-bar    2.16 | Prob > Chi2 =  0.50
      (2b in % of 2) |                   (0.00) | Ni-max     3 | Balancedness = 72.10
-----

-- idx as fixed effects: -- |
      3-Between xj-x.. |           7.288   66.99 | mom effects:
      4-Within xij-xj |           6.977   33.01 | Chi2(1)      = 750.21
      ----- of which: ----- |
      4a-res xij-xj-xi+x.. |           6.977   33.00 | Prob > Chi2 =  0.00
      4b-between xi-x.. |           .1018   0.01 | idx effects:
      (4b in % of 4) |                   (0.03) | Chi2(2)      =  0.15
      Prob > Chi2 =  0.93
-----

-- idx as crossed-effect: -- |
      3-Between xj-x.. |           5.587   54.40 | mom effects:
      4-Within xij-xj |           6.975   45.60 | Chi2(1)      = 752.75
      ----- of which: ----- |
      4a-res xij-xj-xi+x.. |           6.977   45.60 | Prob > Chi2 =  0.00
      4b-between xi-x.. |          .0000403   0.00 | idx effects:
      (4b in % of 4) |                   (0.00) | Chi2(1)      =  0.00
      Prob > Chi2 =  0.50
-----
```

A classical multilevel dataset V

Results similar to Rabe-Hesketh and Skrondal (2012). There is an average of 2.16 births per mother.

The random intercept or level-2 residual (a mother-specific error component which remains constant across births) represents the combined effects of omitted mother characteristics or unobserved heterogeneity at the mother level and ranges from 64 to 72%. This also represents the estimated intraclass correlation capturing the correlation (equal to 0.72) between the birth weights of siblings or tells us that 72% of the variance in birth weight is shared between siblings.

Birth weight and smoking vary more between mothers (clusters of mothers as units of analysis) than within mothers (level-1 newborns as units of analysis).

As the mother effect is shared by all responses by the same mother, it induces a within-mother dependence of 28-36% in birth weight and 16-18% in smoking behaviour (among the residuals). This indicates that birth weight and smoking behaviour are not stable across pregnancies and that weight is less stable than smoking behaviour.

The between level-1 variability of weight is very low (0.4) (the between level-1 variability of smoking is zero). This indicates that weight and smoking behaviour are not related to birth order (firstborn, secondborn and thirdborn).

A cross-classified multilevel dataset I

A typical cross-classified data structure is the conifer system investigated by Ols et al. (2020) and Bontempi, Mairesse, et al. (2025), based on 10.643 trees sampled across the systematic grid of the continuous French national forest inventory (NFI) over the 2006–2016 period.

A national $1 \text{ km} \times 1 \text{ km}$ grid is used; every year, one tenth of the grid is inventoried and 5,442 plots classified as forests by the photo interpretation of aerial images are visited in the field in order to deliver fully renewed information on forests. Sampling plots are temporary, specie-homogeneous and consist in 25-m radius circles within which two dominants trees, chosen within the main tree species encountered on the plot, are measured (241 plots, 4% of the total, have only one tree). The panel is not a strict three-level hierarchy. Rather it is a cross-classified multilevel model where trees are nested within the cells formed by the cross-classification of species-by-ecological regions.

Therefore, the growth of tree-plots (measured by radial increment or diameter in metres and logs) can be influenced by both species and ecological regions, which are both sources of variation when considering tree-plots nested in the cross-classification of both species and ecological regions.

Hence, there are two separate two-level hierarchies which cross one another:

- (1) a tree-plot-within-specie hierarchy, and
- (2) a tree-plot-within-ecological-region hierarchy.

A cross-classified multilevel dataset II

Table: Distribution of Tree Species by Ecological regions

	1-Crystalline Oceanic West	2-Semi-Oceanic Central North	3-Semi-Continental East	4-Vosges	5-Oceanic South West	6-Massif Central	7-Alps	8-Mediterranean	Total
Douglas fir	0	551 (A) (48.7)	0	0	0	1,145 (A) (35.9)	0	0	1,696 (15.9)
Norway spruce	0	0	337 (A) (100)	303 (47.8)	0	730 (A) (22.9)	279 (19.3)	0	1,649 (15.5)
European larch	0	0	0	0	0	0	341 (23.6)	0	341 (3.2)
Aleppo pine	0	0	0	0	0	0	0	455 (100)	455 (4.3)
Corsican pine	482 (A) (44.5)	0	0	0	0	0	0	0	482 (4.5)
Maritime pine	602 (A) (55.5)	0	0	0	2,366 (A) (100)	0	0	0	2,968 (27.9)
Scots pine	0	581 (A) (51.3)	0	0	0	725 (22.7)	826 (57.1)	0	2,132 (20.0)
Silver fir	0	0	0	331 (52.2)	0	589 (18.5)	0	0	920 (8.6)
Total	1,084 (10.19)	1,132 (10.64)	337 (3.17)	634 (5.96)	2,366 (22.23)	3,189 (29.96)	1,446 (13.59)	455 (4.28)	10,643 (100)

Note: (A) for afforested trees.

A cross-classified multilevel dataset III

```
egen treespid=group(treesp), label  
egen ecoregid=group(ecoreg), label  
pantarei ecoregid treespid ri1 diameter13 lri1 ldiam, ml
```

A cross-classified multilevel dataset IV

----- Level 2 (j): ecoreg Level 1 (i): treesp -----					
Hypothetical full sample, Ni x Nj: 9464952					
Nj: 2968 Ni: 3189					

Variable	Mean	Std.Dev.	% SS	Observations	Test

ri1 Overall xj-x..	.00285	.002085		Ni x Nj 10643	ecoreg effects:
1-Between xj-x..		.0004631	4.31	Nj-min 341	Chi2(1) =1393.53
2-Within xij-xj		.002041	95.69	Nj-bar 1330.38	Prob > Chi2 = 0.00
----- of which: -----				Nj-max 2968	treesp effects:
2a-res xij-xj-xi+x..		.001851	78.67	Ni-min 337	Chi2(1) =2232.66
2b-between xi-x..		.0009197	17.02	Ni-bar 1330.38	Prob > Chi2 = 0.00
(2b in % of 2)			(17.79)	Ni-max 3189	Balancedness = 0.11

-- treesp as fixed effects: --					
3-Between xj-x..		.0007936	12.67		ecoreg effects:
4-Within xij-xj		.001949	87.33		Chi2(1) = 224.55
----- of which: -----					Prob > Chi2 = 0.00
4a-res xij-xj-xi+x..		.001851	78.67		treesp effects:
4b-between xi-x..		.000656	8.66		Chi2(7) =1191.27
(4b in % of 4)			(9.92)		Prob > Chi2 = 0.00

-- treesp as crossed-effect: --					
3-Between xj-x..		.0004482	4.34		ecoreg effects:
4-Within xij-xj		.001969	95.66		Chi2(1) = 240.59
----- of which: -----					Prob > Chi2 = 0.00
4a-res xij-xj-xi+x..		.001851	84.49		treesp effects:
4b-between xi-x..		.0007192	11.17		Chi2(1) =2232.66
(4b in % of 4)			(11.68)		Prob > Chi2 = 0.00

A cross-classified multilevel dataset V

```
-----
diame-13 Overall xij-x.. | .3329 .1364 | Ni x Nj 10643 | ecoreg effects:
-- treesp as fixed effects: --| | | |
  3-Between xj-x.. | .03751 6.62 | | ecoreg effects:
  4-Within xij-xj | .1319 93.38 | | Chi2(1) = 223.72
  ----- of which: -----| | Prob > Chi2 = 0.00
  4a-res xij-xj-xi+x.. | .1259 85.02 | | treesp effects:
  4b-between xi-x.. | .04216 8.36 | | Chi2(7) =1042.74
  (4b in % of 4) | (8.95) | | Prob > Chi2 = 0.00
-----

-- treesp as crossed-effect: --| | | |
  3-Between xj-x.. | .03676 5.81 | | ecoreg effects:
  4-Within xij-xj | .1385 94.19 | | Chi2(1) = 236.12
  ----- of which: -----| | Prob > Chi2 = 0.00
  4a-res xij-xj-xi+x.. | .1259 77.78 | | treesp effects:
  4b-between xi-x.. | .06179 16.42 | | Chi2(1) =1404.65
  (4b in % of 4) | (17.43)| | Prob > Chi2 = 0.00
-----
```

A cross-classified multilevel dataset VI

```

----- Level 2 (j): ecoreg   Level 1 (i): treesp -----
Hypothetical full sample, Ni x Nj: 9464952
Nj: 2968   Ni: 3189
-----
Variable |      Mean   Std.Dev.  % SS | Observations | Test
-----+-----+-----+-----+-----+-----
lri1      Overall xj-x.. |    -6.151     .825      | Ni x Nj   10643 | ecoreg effects:
      1-Between xj-x.. |      .2522     8.18      | Nj-min    341 | Chi2(1)      =2414.64
      2-Within xij-xj   |      .7908    91.82      | Nj-bar   1330.38 | Prob > Chi2 =  0.00
      ----- of which: ----- | ----- | Nj-max    2968 | treesp effects:
      2a-res xij-xj-xi+x.. |      .6796    67.78      | Ni-min    337 | Chi2(1)      =3370.56
      2b-between xi-x.. |      .4324    24.04      | Ni-bar   1330.38 | Prob > Chi2 =  0.00
      (2b in % of 2)   |              (26.18) | Ni-max    3189 | Balancedness =  0.11
-----+-----+-----+-----+-----+-----
-- treesp as fixed effects: -- | | | |
      3-Between xj-x.. |      .4012    20.70      | | | | ecoreg effects:
      4-Within xij-xj   |      .7349    79.30      | | | | Chi2(1)      = 660.74
      ----- of which: ----- | | | | Prob > Chi2 =  0.00
      4a-res xij-xj-xi+x.. |      .6796    67.78      | | | | treesp effects:
      4b-between xi-x.. |      .2994    11.52      | | | | Chi2(7)      =1818.63
      (4b in % of 4)   |              (14.53) | | | | Prob > Chi2 =  0.00
-----+-----+-----+-----+-----+-----
-- treesp as crossed-effect: -- | | | |
      3-Between xj-x.. |      .2575     9.60      | | | | ecoreg effects:
      4-Within xij-xj   |      .7393    90.40      | | | | Chi2(1)      = 680.28
      ----- of which: ----- | | | | Prob > Chi2 =  0.00
      4a-res xij-xj-xi+x.. |      .6798    76.38      | | | | treesp effects:
      4b-between xi-x.. |      .3112    14.02      | | | | Chi2(1)      =3370.56
      (4b in % of 4)   |              (15.51) | | | | Prob > Chi2 =  0.00
-----+-----+-----+-----+-----+-----

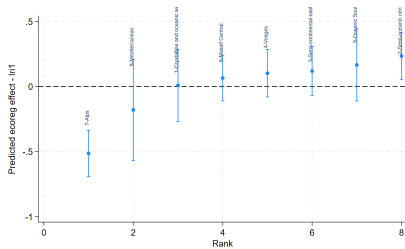
```

A cross-classified multilevel dataset VII

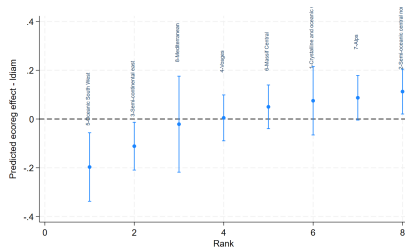
```
-----
ldiam Overall xij-x.. | -1.196 .4623 | Ni x Nj 10643 | ecogreg effects:
-- treesp as fixed effects: --| | |
3-Between xj-x.. | .1261 6.51 | | ecogreg effects:
4-Within xij-xj | .4471 93.49 | | Chi2(1) = 219.08
----- of which: -----| | Prob > Chi2 = 0.00
4a-res xij-xj-xi+x.. | .4322 87.30 | | treesp effects:
4b-between xi-x.. | .1229 6.19 | | Chi2(7) = 750.28
(4b in % of 4) | (6.62) | | Prob > Chi2 = 0.00
-----

-- treesp as crossed-effect: --| | |
3-Between xj-x.. | .1181 5.30 | | ecogreg effects:
4-Within xij-xj | .4672 94.70 | | Chi2(1) = 230.75
----- of which: -----| | Prob > Chi2 = 0.00
4a-res xij-xj-xi+x.. | .4323 81.02 | | treesp effects:
4b-between xi-x.. | .1898 13.68 | | Chi2(1) = 1130.98
(4b in % of 4) | (14.45) | | Prob > Chi2 = 0.00
-----
```

A cross-classified multilevel dataset VIII

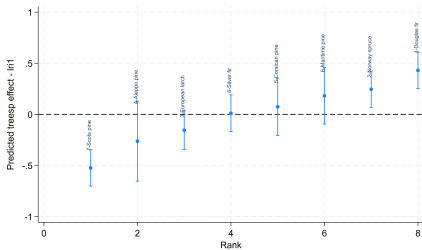


Ecological regions for radial increment in logs

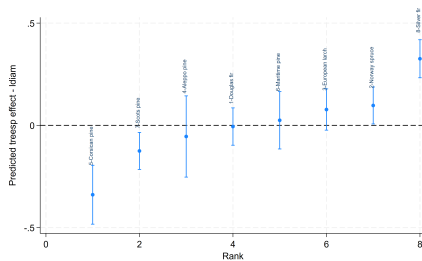


Ecological regions for diameter in logs

A cross-classified multilevel dataset IX



Species for radial increment in logs



Species for diameter in logs

A cross-classified multilevel dataset X

A different picture emerges when we compare **radial increment** and diameter (in logs). Diameter can be affected by measurement errors (inaccuracy) because the bark is also included, but this does not grow in the same way as wood (rings).

We see that **14.02**-13.68% of the variation in growth lies between species, while **9.60**-5.30% lies between ecological regions, and **76.38**-81.02% lies between tree-plots. Thus, there are stronger growth disparities across the 8 species than there are across the 8 ecoregs. This finding is surprising given that the number of ecoregs in the data is equal to the number of species.

In terms of ICCs, we note that homogeneity or correlation in growth at the species level is greater than at the ecological region level (here coincide with VPCs). The greatest homogeneity is found in trees of the same species living in the same ecological region, computed as **23.62**-18.98%.

These results guide the modelling of conditional models, in which adjusted ICCs are based on the residuals of the conditional model rather than on the observations of the dependent variable alone, allowing us to assess how the addition of explanatory variables can modify the unexplained variability and similarity between and within the various clusters.

Thank you for your attention!

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