

GSERM - Oslo 2019

Panel/TSCS Data + Unit Effects

January 7, 2019 (morning session)

- Instructor: Prof. Christopher Zorn (zorn@psu.edu).
- Class: January 7-11, 2019, 9:30-3:00 CET, at the Norwegian Business School.
- The course outline / syllabus is here.
- More important: Slides, readings, code, etc. are on the course github repo
(<https://github.com/PrisonRodeo/GSERM-Oslo-2019-git>).


PrisonRodeo / **GSERM-Oslo-2018-git**

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R

- All examples, plots, etc.
- Current version is 3.5.2
- Packages you'll use (see the econometrics and survival analysis task views for more):
 - plm
 - lme4
 - gee
 - survival (nearly everything you need)
 - eha
 - timereg

Stata

- Current version is 15.1
- Mostly use the `-xt-` and `-st-` series of commands (for “cross-sectional time series” and “survival time”)

- “Longitudinal” \neq “Time Series”
- Terminology:
 - “Unit” / “Units” / “Units of observation” / “Panels” = Things we observe repeatedly
 - “Observations” = Each (one) measurement of a unit
 - “Time points” = When each observation on a unit is made
 - $i \in \{1 \dots N\}$ indexes units
 - $t \in \{1 \dots T\}$ or $\{1 \dots T_i\}$ indexes observations / time points
 - If $T_i = T \forall i$ then we have “balanced” panels / units
 - NT = Total number of observations (if balanced)
- Averages:
 - Y_{it} indicates a variable that varies over both units and time,
 - $\bar{Y}_i = \frac{1}{T} \sum_{t=1}^T Y_{it}$ = the over-time mean of Y ,
 - $\bar{Y}_t = \frac{1}{N} \sum_{i=1}^N Y_{it}$ = the across-unit mean of Y , and
 - $\bar{Y} = \frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T Y_{it}$ = the grand mean of Y .

- $N \gg T \rightarrow$ “panel” data
 - (American) National Election Study panel studies ($N = 2000, T = 3$)
 - (U.S.) Panel Study of Income Dynamics ($N = \text{large}, T \approx 12$)
- $T \gg N$ or $T \approx N \rightarrow$ “time-series cross-sectional” (“TSCS”) data
- $N = 1 \rightarrow$ “time series” data

Panel/TSCS Data Structure

id	t	Y	X_1	...
1	1	250	3.4	...
1	2	290	3.3	...
\vdots	\vdots	\vdots	\vdots	...
2	1	160	4.7	...
2	2	150	4.9	...
\vdots	\vdots	\vdots	\vdots	...

Variation: A Tiny (Fake) Example

id	year	gender	pres	pid	approve
1	1998	female	clinton	dem	3
1	2000	female	clinton	dem	3
1	2002	female	bush	dem	5
1	2004	female	bush	dem	3
2	1998	male	clinton	gop	2
2	2000	male	clinton	gop	1
2	2002	male	bush	gop	4
2	2004	male	bush	gop	3
3	1998	male	clinton	gop	2
3	2000	male	clinton	gop	2
3	2002	male	bush	gop	4
3	2004	male	bush	dem	1

Aggregation: Cross-Sectional

id	gender	pres	pid	approve
1	female	?	dem	3.50
2	male	?	gop	2.50
3	male	?	?	2.25

Aggregation: Temporal

year	female	pres	pid	approve
1998	0.33	clinton	0.66(?)	2.33
2000	0.33	clinton	0.66(?)	2.00
2002	0.33	bush	0.66(?)	4.33
2004	0.33	bush	0.33(?)	2.33

Aggregation:

- Loses information
- Distorts relationships
- Forces arbitrary decisions

If you have variation in multiple dimensions, use it.

Within- and Between-Unit Variation

Define:

$$\bar{Y}_i = \frac{1}{T_i} \sum_{t=1}^{T_i} Y_{it}$$

Then:

$$Y_{it} = \bar{Y}_i + (Y_{it} - \bar{Y}_i).$$

- The *total* variation in Y_{it} can be decomposed into
- The *between-unit* variation in the \bar{Y}_i s, and
- The *within-unit* variation around \bar{Y}_i (that is, $Y_{it} - \bar{Y}_i$).

Variation (U.S. Supreme Court Tenure)

"Total" Variation:

```
> with(scotus, describe(service))
vars    n mean   sd median trimmed mad min max range skew kurtosis
X1      1 1765 11.74 8.34     10   10.93 8.9   1  37    36 0.73   -0.28
se
X1 0.2
```

"Between" Variation:

```
> scmeans <- ddply(scotus,.(justice),summarise,
+                 service = mean(service))
> with(scmeans, describe(service))
vars    n mean   sd median trimmed  mad min max range skew kurtosis
X1      1 107 8.87 4.99     8.5    8.59 5.93 1.5  21   19.5 0.4   -0.92
se
X1 0.48
```

"Within" Variation:

```
> scotus <- ddply(scotus,.(justice), mutate,
+                 servmean = mean(service))
> scotus$within <- with(scotus, service-servmean)
> with(scotus, describe(within))
vars    n mean   sd median trimmed  mad min max range skew kurtosis
X1      1 1765   0 6.92     0     0 6.67 -18  18    36   0   -0.36
se
X1 0.16
```

Model

$$Y_i = \beta_0 + \beta_1 X_i + u_i$$

assumes:

- All the usual OLS assumptions, plus
- $\beta_{0i} = \beta_0 \forall i$ s
- $\beta_{1i} = \beta_1 \forall i$ s

$$Y_{it} = \beta_0 + \beta_1 X_{it} + u_{it}$$

(same)

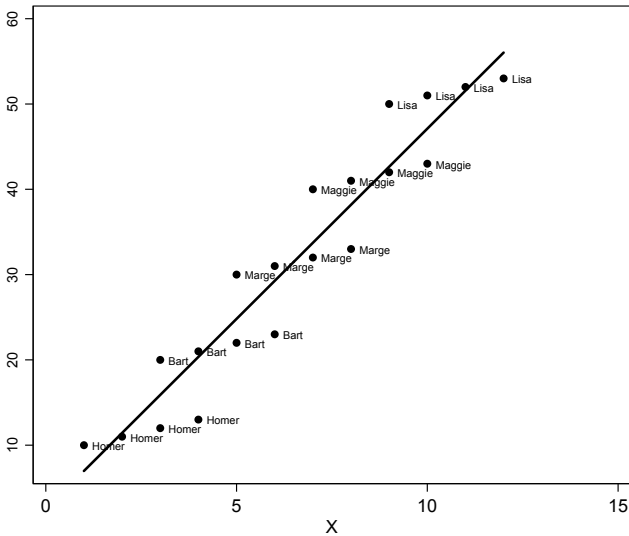
Variable Intercepts

$$Y_{it} = \beta_{0i} + \beta_1 X_{it} + u_{it}$$

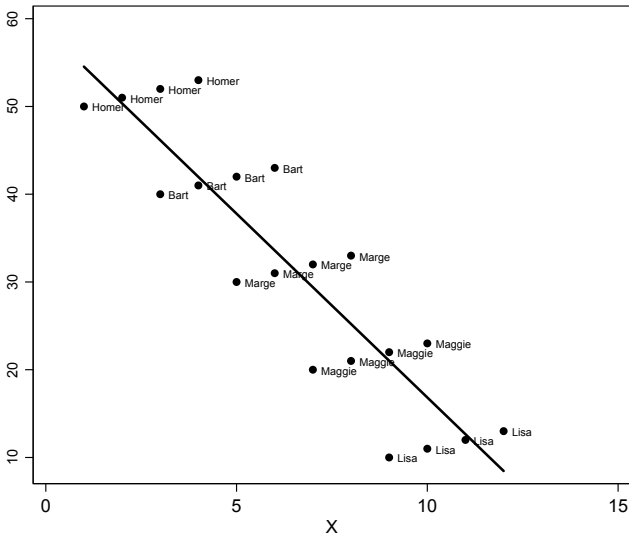
$$Y_{it} = \beta_{0t} + \beta_1 X_{it} + u_{it}$$

$$Y_{it} = \beta_{0it} + \beta_1 X_{it} + u_{it}$$

Varying Intercepts



Varying Intercepts



Varying Slopes (+ Intercepts)

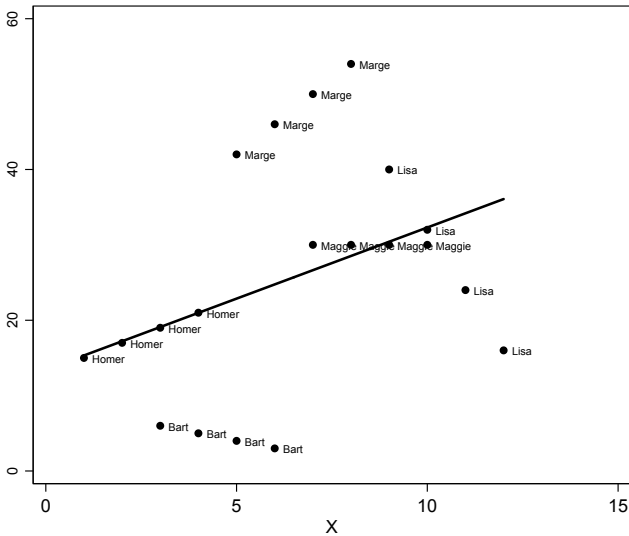
$$Y_{it} = \beta_0 + \beta_{1i}X_{it} + u_{it}$$

$$Y_{it} = \beta_{0i} + \beta_{1i}X_{it} + u_{it}$$

$$Y_{it} = \beta_{0t} + \beta_{1t}X_{it} + u_{it}$$

$$Y_{it} = \beta_{0it} + \beta_{1it}X_{it} + u_{it}$$

Varying Slopes + Intercepts



$$u_{it} \sim \text{i.i.d.} N(0, \sigma^2) \forall i, t$$

$$\text{Var}(u_{it}) = \text{Var}(u_{jt}) \forall i \neq j \text{ (i.e., no cross-unit heteroscedasticity)}$$

$$\text{Var}(u_{it}) = \text{Var}(u_{is}) \forall t \neq s \text{ (i.e., no temporal heteroscedasticity)}$$

$$\text{Cov}(u_{it}, u_{js}) = 0 \forall i \neq j, \forall t \neq s \text{ (i.e., no auto- or spatial correlation)}$$

- Adds data
- Generalizability

$$Y_{it} = \beta_0 + \beta_1 X_{it} + u_{it}$$

Implies

- that the process governing the relationship between X and Y is exactly the same for each i ,
- that the process governing the relationship between X and Y is the same for all t ,
- that the process governing the us is the same $\forall i$ and t as well.

“Partial” Pooling (Bartels 1996)

Two regimes:

$$Y_A = \beta'_A \mathbf{X}_A + u_A$$

$$Y_B = \beta'_B \mathbf{X}_B + u_B$$

with $\sigma_A^2 = \sigma_B^2$, and $\text{Cov}(u_A, u_B) = 0$.

Estimators:

$$\hat{\beta}_{A,B} = (\mathbf{X}'_{A,B} \mathbf{X}_{A,B})^{-1} \mathbf{X}'_{A,B} Y_{A,B}$$

and

$$\widehat{\text{Var}}(\hat{\beta}_{A,B}) = \hat{\sigma}_{A,B}^2 (\mathbf{X}'_{A,B} \mathbf{X}_{A,B})^{-1},$$

A Pooled Estimator

$$\begin{aligned}\hat{\beta}_P &= (\mathbf{X}'_A \mathbf{X}_A + \mathbf{X}'_B \mathbf{X}_B)^{-1} (\mathbf{X}'_A Y_A + \mathbf{X}'_B Y_B) \\ &= (\mathbf{X}'_A \mathbf{X}_A + \mathbf{X}'_B \mathbf{X}_B)^{-1} [\beta_A (\mathbf{X}'_A \mathbf{X}_A) + \beta_B (\mathbf{X}'_B \mathbf{X}_B)],\end{aligned}$$

$$\begin{aligned}E(\hat{\beta}_P) &= \beta_A + (\mathbf{X}'_A \mathbf{X}_A + \mathbf{X}'_B \mathbf{X}_B)^{-1} \mathbf{X}'_B \mathbf{X}_B (\beta_B - \beta_A) \\ &= \beta_B + (\mathbf{X}'_A \mathbf{X}_A + \mathbf{X}'_B \mathbf{X}_B)^{-1} \mathbf{X}'_A \mathbf{X}_A (\beta_A - \beta_B)\end{aligned}$$

$$F = \frac{\frac{\hat{\mathbf{u}}_P' \hat{\mathbf{u}}_P - (\hat{\mathbf{u}}_A' \hat{\mathbf{u}}_A + \hat{\mathbf{u}}_B' \hat{\mathbf{u}}_B)}{K}}{\frac{(\hat{\mathbf{u}}_A' \hat{\mathbf{u}}_A + \hat{\mathbf{u}}_B' \hat{\mathbf{u}}_B)}{(N_A + N_B - 2K)}} \sim F_{[K, (N_A + N_B - 2K)]}$$

$$\hat{\beta}_{\lambda} = (\lambda^2 \mathbf{X}'_A \mathbf{X}_A + \mathbf{X}'_B \mathbf{X}_B)^{-1} (\lambda^2 \mathbf{X}'_A Y_A + \mathbf{X}'_B Y_B)$$

with $\lambda \in [0, 1]$:

- $\lambda = 0 \rightarrow$ separate estimators for $\hat{\beta}_A$ and $\hat{\beta}_B$,
- $\lambda = 1 \rightarrow$ “fully pooled” estimator $\hat{\beta}_P$,
- $0 < \lambda < 1 \rightarrow$ a regression where data in regime A are given some “partial” weighting in their contribution towards an estimate of β .

“(R)oughly speaking, it makes sense to pool disparate observations if the underlying parameters governing those observations are sufficiently similar, but not otherwise.”

- Bartels (1996)

“Unit Effects”

One- and Two-Way Unit Effects

Two-way variation:

$$Y_{it} = \mathbf{X}_{it}\beta + \gamma V_i + \delta W_t + u_{it}$$

→ two-way effects:

$$Y_{it} = \mathbf{X}_{it}\beta + \alpha_i + \eta_t + u_{it}$$

One-way effects:

$$Y_{it} = \mathbf{X}_{it}\beta + \eta_t + u_{it} \quad (\text{time})$$

$$Y_{it} = \mathbf{X}_{it}\beta + \alpha_i + u_{it} \quad (\text{units})$$

“Brute force” model:

$$\begin{aligned}Y_{it} &= \mathbf{X}_{it}\boldsymbol{\beta} + \alpha_i + u_{it} \\ &= \mathbf{X}_{it}\boldsymbol{\beta} + \alpha_1 I(i=1)_i + \alpha_2 I(i=2)_i + \dots + u_{it}\end{aligned}$$

Alternatively:

$$\bar{X}_i = \frac{\sum_{N_i} X_{it}}{N_i}$$

and

$$\tilde{X}_{it} = X_{it} - \bar{X}_i.$$

Yields:

$$Y_{it} = \bar{\mathbf{X}}_i \boldsymbol{\beta}_B + (\mathbf{X}_{it} - \bar{\mathbf{X}}_i) \boldsymbol{\beta}_W + \alpha_i + u_{it}$$

Means that:

$$\begin{aligned} Y_{it}^* &= Y_{it} - \bar{Y}_i \\ \mathbf{X}_{it}^* &= \mathbf{X}_{it} - \bar{\mathbf{X}}_i \end{aligned}$$

$$Y_{it}^* = \beta_{FE} \mathbf{X}_{it}^* + u_{it}.$$

≡ “Within-Effects” Model.

Standard F -test for

$$H_0 : \alpha_i = \alpha_j \forall i \neq j$$

versus

$$H_A : \alpha_i \neq \alpha_j \text{ for some } i \neq j$$

is $\sim F_{N-1, NT-(N-1)}$.

An Example: Refugee Flows in Africa, 1992-2001

Data:

- 50 African countries $\rightarrow (50 \times 49 =)$ 2450 directed dyads
- Ten years
- i indexes directed dyads, t indexes years

Model:

$$\ln(\text{Refugees})_{A \rightarrow Bt} = \beta_0 + \beta_1 \text{Population Difference}_{ABt} + \beta_2 \text{Distance}_{AB} + \beta_3 \text{POLITY Difference}_{ABt} + \beta_4 \text{War Difference}_{ABt} + u_{ABt}$$

Data: Refugee Flows in Africa, 1992-2001

```
> summary(Refugees)
  dirdyadID      year      ln_ref_flow      pop_diff
Min.   :404411  Min.   :1992  Min.   :-0.6931  Min.   :-0.117949
1st Qu.:451461  1st Qu.:1994  1st Qu.: -0.6931  1st Qu.: -0.008848
Median :510520  Median :1996  Median : -0.6931  Median : 0.000000
Mean   :512160  Mean   :1996  Mean   : -0.6011  Mean   : 0.000000
3rd Qu.:565553  3rd Qu.:1999  3rd Qu.: -0.6931  3rd Qu.: 0.008848
Max.   :651625  Max.   :2001  Max.   :14.1343  Max.   : 0.117949

  distance  regimedif  wardiff  pop_between
Min.   :0.000  Min.   :-1.00  Min.   :-4  Min.   :-0.109517
1st Qu.:1.299  1st Qu.: -0.25  1st Qu.: 0  1st Qu.: -0.008833
Median :2.169  Median : 0.00  Median : 0  Median : 0.000000
Mean   :2.200  Mean   : 0.00  Mean   : 0  Mean   : 0.000000
3rd Qu.:3.066  3rd Qu.: 0.25  3rd Qu.: 0  3rd Qu.: 0.008833
Max.   :5.652  Max.   : 1.00  Max.   : 4  Max.   : 0.109517

  pop_within  regime_between  regime_within  war_between
Min.   :-0.0088492  Min.   :-0.955  Min.   :-1.180  Min.   :-2.3
1st Qu.: -0.0004707  1st Qu.: -0.225  1st Qu.: -0.085  1st Qu.: -0.4
Median : 0.0000000  Median : 0.000  Median : 0.000  Median : 0.0
Mean   : 0.0000000  Mean   : 0.000  Mean   : 0.000  Mean   : 0.0
3rd Qu.: 0.0004707  3rd Qu.: 0.225  3rd Qu.: 0.085  3rd Qu.: 0.4
Max.   : 0.0088492  Max.   : 0.955  Max.   : 1.180  Max.   : 2.3

  war_within
Min.   :-2.5
1st Qu.: -0.3
Median : 0.0
Mean   : 0.0
3rd Qu.: 0.3
Max.   : 2.5
```

An Example: Refugee Flows in Africa, 1992-2001

Pooled OLS:

```
> RefOLS<-lm(ln_ref_flow~pop_diff+distance+regimedif+wardiff, data=Refugees)
> summary(RefOLS)
```

Residuals:

Min	1Q	Median	3Q	Max
-0.6114	-0.2109	-0.0857	0.0335	14.3756

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.3224073	0.0119195	-27.049	<2e-16 ***
pop_diff	-0.1732934	0.2166658	-0.800	0.424
distance	-0.1266528	0.0047016	-26.938	<2e-16 ***
regimedif	-0.0002476	0.0157962	-0.016	0.987
wardiff	0.0743220	0.0068169	10.903	<2e-16 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9097 on 23613 degrees of freedom

Multiple R-squared: 0.03467, Adjusted R-squared: 0.03451

F-statistic: 212 on 4 and 23613 DF, p-value: < 2.2e-16

An Example: Refugee Flows in Africa, 1992-2001

“Fixed” effects:

```
> library(plm)
> RefFE<-plm(ln_ref_flow~pop_diff+distance+regimedif+wardiff,
  data=Refugees, effect="individual", model="within")
> summary(RefFE)
Oneway (individual) effect Within Model
```

Unbalanced Panel: n=2450, T=1-10, N=23618

Residuals :

Min.	1st Qu.	Median	3rd Qu.	Max.
-9.03e+00	-5.74e-03	-9.18e-06	5.72e-03	1.14e+01

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t)
pop_diff	6.8642028	2.5516636	2.6901	0.007149 **
regimedif	0.0050497	0.0223160	0.2263	0.820984
wardiff	0.0104144	0.0073673	1.4136	0.157493

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 8149.6

Residual Sum of Squares: 8146

R-Squared : 0.00043949

Adj. R-Squared : 0.00039385

F-statistic: 3.102 on 3 and 21165 DF, p-value: 0.025509

An Example: Refugee Flows in Africa, 1992-2001

Models of Refugees in Africa		
Variable	OLS	Fixed Effects
Constant	-0.32 (0.01)	-
Population Difference	-0.17 (0.22)	6.86 (2.55)
Distance	-0.13 (0.005)	(dropped)
POLITY Difference	-0.0002 (0.016)	0.005 (0.022)
War Difference	0.074 (0.007)	0.010 (0.007)
$\hat{\rho}$	-	0.61
Note: $NT = 23618$ ($N = 2450$, $\bar{T} = 9.6$)		

Issues (?) with “Fixed” Effects

Pros:

- Specification Bias
- Intuitive
- Widely Used/Understood

Cons:

- Can't Estimate β_B
- Slowly-Changing \mathbf{X} s
- (In)Efficiency / Inconsistency (“Incidental Parameters”)

“Between” Effects

From:

$$Y_{it} = \bar{\mathbf{X}}_i \beta_B + (\mathbf{X}_{it} - \bar{\mathbf{X}}_i) \beta_W + \alpha_i + u_{it}.$$

“Between” effects:

$$\bar{Y}_i = \bar{\mathbf{X}}_i \beta_B + u_{it}$$

- Essentially cross-sectional
- Based on N observations

Refugee Flows in Africa, 1992-2001

“Between” effects:

```
> RefBE<-plm(ln_ref_flow~pop_diff+distance+regimedif+wardiff, data=Refugees,
  effect="individual", model="between")
> summary(RefBE)
Oneway (individual) effect Between Model
```

Unbalanced Panel: n=2450, T=1-10, N=23618

Residuals :

	Min.	1st Qu.	Median	3rd Qu.	Max.
	-0.5850	-0.2200	-0.0840	0.0534	9.6500

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t)
(Intercept)	-0.299703	0.029741	-10.0771	< 2.2e-16 ***
pop_diff	-0.246861	0.525232	-0.4700	0.6384
distance	-0.134874	0.011755	-11.4742	< 2.2e-16 ***
regimedif	0.010709	0.045117	0.2374	0.8124
wardiff	0.124185	0.022004	5.6439	1.855e-08 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 1383.9

Residual Sum of Squares: 1296.7

R-Squared : 0.063042

Adj. R-Squared : 0.062913

F-statistic: 41.1269 on 4 and 2445 DF, p-value: < 2.22e-16

Refugee Example Redux

Variable	OLS	Fixed (“Within”) Effects	Between Effects
Constant	-0.32 (0.01)	-	-0.30 (0.03)
Population Difference	-0.17 (0.22)	6.86 (2.55)	-0.25 (0.53)
Distance	-0.13 (0.005)	(dropped)	-0.13 (0.01)
POLITY Difference	-0.0002 (0.016)	0.005 (0.022)	0.01 (0.05)
War Difference	0.074 (0.007)	0.010 (0.007)	0.12 (0.02)
$\hat{\rho}$	-	0.61	-

Note: $NT = 23618$ ($N = 2450$, $\bar{T} = 9.6$).

“Random” Effects

Model:

$$Y_{it} = \mathbf{X}_{it}\boldsymbol{\beta} + u_{it}$$

with:

$$u_{it} = \alpha_i + \lambda_t + \eta_{it}$$

and

$$\begin{aligned} E(\alpha_i) = E(\lambda_t) = E(\eta_{it}) &= 0, \\ E(\alpha_i \lambda_t) = E(\alpha_i \eta_{it}) = E(\lambda_t \eta_{it}) &= 0, \\ E(\alpha_i \alpha_j) &= \sigma_\alpha^2 \text{ if } i = j, \text{ 0 otherwise,} \\ E(\lambda_t \lambda_s) &= \sigma_\lambda^2 \text{ if } t = s, \text{ 0 otherwise,} \\ E(\eta_{it} \eta_{js}) &= \sigma_\eta^2 \text{ if } i = j, \text{ } t = s, \text{ 0 otherwise,} \\ E(\alpha_i \mathbf{X}_{it}) = E(\lambda_t \mathbf{X}_{it}) = E(\eta_{it} \mathbf{X}_{it}) &= 0. \end{aligned}$$

“Variance Components”:

$$\text{Var}(Y_{it}|\mathbf{X}_{it}) = \sigma_{\alpha}^2 + \sigma_{\lambda}^2 + \sigma_{\eta}^2$$

If we assume $\lambda_t = 0$, then we get a model like:

$$Y_{it} = \mathbf{X}_{it}\beta + \alpha_i + \eta_{it}$$

with total error variance:

$$\sigma_u^2 = \sigma_{\alpha}^2 + \sigma_{\eta}^2.$$

“Random” Effects: Estimation

$$\begin{aligned} E(\mathbf{u}_i \mathbf{u}_i') \equiv \mathbf{\Sigma}_i &= \sigma_\eta^2 \mathbf{I}_T + \sigma_\alpha^2 \mathbf{i} \mathbf{i}' \\ &= \begin{pmatrix} \sigma_\eta^2 + \sigma_\alpha^2 & \sigma_\alpha^2 & \cdots & \sigma_\alpha^2 \\ \sigma_\alpha^2 & \sigma_\eta^2 + \sigma_\alpha^2 & \cdots & \sigma_\alpha^2 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_\alpha^2 & \sigma_\alpha^2 & \cdots & \sigma_\eta^2 + \sigma_\alpha^2 \end{pmatrix} \end{aligned}$$

$$\text{Var}(\mathbf{u}) \equiv \mathbf{\Omega} = \begin{pmatrix} \mathbf{\Sigma}_1 & 0 & \cdots & 0 \\ 0 & \mathbf{\Sigma}_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathbf{\Sigma}_N \end{pmatrix}$$

“Random” Effects: Estimation

Can estimate:

$$\Sigma^{-1/2} = \frac{1}{\sigma_\eta} \left[\mathbf{I}_T - \left(\frac{\theta}{T} \mathbf{\bar{y}} \mathbf{\bar{y}}' \right) \right]$$

where

$$\theta = 1 - \sqrt{\frac{\sigma_\eta^2}{T\sigma_\alpha^2 + \sigma_\eta^2}}.$$

With $\hat{\theta}$, calculate:

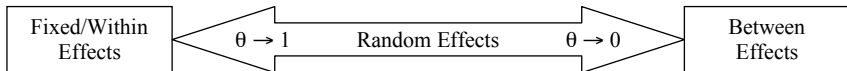
$$\begin{aligned} Y_{it}^* &= Y_{it} - \hat{\theta} \bar{Y}_i \\ X_{it}^* &= X_{it} - \hat{\theta} \bar{X}_i, \end{aligned}$$

estimate:

$$Y_{it}^* = (1 - \hat{\theta})\alpha + X_{it}^* \beta_{RE} + [(1 - \hat{\theta})\alpha_i + (\eta_{it} - \hat{\theta} \bar{\eta}_i)]$$

and iterate...

“Random” Effects: An Alternative View



Refugees Redux

```
> RefRE<-plm(ln_ref_flow~pop_diff+distance+regimedif+wardiff, data=Refugees,
  effect="individual", model="random")
> summary(RefRE)
Oneway (individual) effect Random Effect Model
  (Swamy-Arora's transformation)
```

Unbalanced Panel: n=2450, T=1-10, N=23618

Effects:

	var	std.dev	share
idiosyncratic	0.3849	0.6204	0.466
individual	0.4416	0.6645	0.534

theta :

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.3176	0.7168	0.7168	0.7141	0.7168	0.7168

Coefficients :

	Estimate	Std. Error	t-value	Pr(> t)
(Intercept)	-0.3063941	0.0285299	-10.7394	< 2.2e-16 ***
pop_diff	0.0638665	0.4974613	0.1284	0.897845
distance	-0.1324536	0.0112685	-11.7544	< 2.2e-16 ***
regimedif	0.0005633	0.0198580	0.0284	0.977370
wardiff	0.0228523	0.0069775	3.2751	0.001058 **

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Total Sum of Squares: 9216.6

Residual Sum of Squares: 9158.9

R-Squared : 0.0062699

Adj. R-Squared : 0.0062686

F-statistic: 37.177 on 4 and 23613 DF, p-value: < 2.22e-16

Refugees Redux, Remix

```
> library(lme4)

> AltRefRE<-lmer(ln_ref_flow~pop_diff+distance+regimedif+wardiff+(1|dirtyadID), data=Refugees)
> summary(AltRefRE)
Linear mixed model fit by REML
Formula: ln_ref_flow ~ pop_diff + distance + regimedif + wardiff + (1 | dirtyadID)
Data: Refugees
    AIC   BIC logLik deviance REMLdev
50733 50790 -25360   50692   50719
Random effects:
Groups      Name      Variance Std.Dev.
dirtyadID (Intercept) 0.46653   0.68303
Residual              0.38592   0.62123
Number of obs: 23618, groups: dirtyadID, 2450

Fixed effects:
              Estimate Std. Error t value
(Intercept) -0.3061471   0.0291477 -10.503
pop_diff     0.0758989   0.5075942   0.150
distance     -0.1325429   0.0115127 -11.513
regimedif    0.0007138   0.0199078   0.036
wardiff      0.0223476   0.0069779   3.203

Correlation of Fixed Effects:
              (Intr) pp_dff distnc regmdf
pop_diff     0.000
distance     -0.869  0.000
regimedif    0.000  0.036  0.000
wardiff      0.000 -0.004  0.000  0.109
```

Variable	OLS	Fixed Effects	Between Effects	Random Effects
Constant	-0.32 (0.01)	-	-0.30 (0.03)	-0.31 (0.03)
Population Difference	-0.17 (0.22)	6.86 (2.55)	-0.25 (0.53)	0.09 (0.52)
Distance	-0.13 (0.005)	(dropped)	-0.13 (0.01)	-0.13 (0.01)
POLITY Difference	-0.0002 (0.016)	0.005 (0.022)	0.01 (0.05)	0.0005 (0.0199)
War Difference	0.074 (0.007)	0.010 (0.007)	0.12 (0.02)	0.023 (0.007)
$\hat{\rho}$	-	0.61	-	0.56

Note: $NT = 23618$ ($N = 2450$, $\bar{T} = 9.6$).

“Random” Effects: Testing

Hausman test (FE vs. RE):

$$\hat{W} = (\hat{\beta}_{\text{FE}} - \hat{\beta}_{\text{RE}})'(\hat{\mathbf{V}}_{\text{FE}} - \hat{\mathbf{V}}_{\text{RE}})^{-1}(\hat{\beta}_{\text{FE}} - \hat{\beta}_{\text{RE}})$$

$$W \sim \chi_k^2$$

Issues:

- Asymptotic
- No guarantee $(\hat{\mathbf{V}}_{\text{FE}} - \hat{\mathbf{V}}_{\text{RE}})^{-1}$ is positive definite
- A general specification test...

Hausman test (FE vs. RE):

```
> phptest(RefFE, AltRefRE)
```

Hausman Test

```
data: ln_ref_flow ~ pop_diff + distance + regimedif + wardiff  
chisq = 34.712, df = 3, p-value = 0.0000001401  
alternative hypothesis: one model is inconsistent
```

Practical “Fixed” vs. “Random” Effects

- “Panel” vs. “TSCS” Data
- Data-Generating Process
- Covariate Effects

Separating Within and Between Effects

$$Y_{it} = \bar{\mathbf{X}}_i \boldsymbol{\beta}_B + (\mathbf{X}_{it} - \bar{\mathbf{X}}_i) \boldsymbol{\beta}_W + u_{it}$$

- Simple...
- Easy interpretation
- Easy to test $\hat{\boldsymbol{\beta}}_B = \hat{\boldsymbol{\beta}}_W$

Again With The Refugees...

Variable	Estimate
Constant	-0.32 (0.01)
Distance	-0.13 (0.004)
Between (Mean) Population Difference	-0.22 (0.22)
Within Population Difference	6.86 (3.74)
Between (Mean) POLITY Difference	0.01 (0.02)
Within POLITY Difference	0.005 (0.032)
Between (Mean) War Difference	0.12 (0.01)
Within War Difference	0.01 (0.01)

Note: $NT = 23618$ ($N = 2450$, $\bar{T} = 9.6$).

R :

- the `lme4` package; command is `lmer`
- the `plm` package; `plm` command
- the `nlme` package; command `lme`

Stata : `xtreg`

- the `re` (the default) = random effects
- the `fe` = fixed (within) effects
- the `be` = between-effects