

Consider the panel LRM

$$y_{it} = \mathbf{x}'_{it}\boldsymbol{\beta} + \mu_i + \nu_{it}.$$

y_{it} : an observation for individual i at time t .

\mathbf{x}'_{it} : K independent variables for individual i at time t . $1 \times K$. A variable can be time-varying or time-invariant.

$\boldsymbol{\beta}$: vector of true coefficients. $K \times 1$.

GLM, FGLS, econometric application: RE estimator

$$y_{it} = \mathbf{x}'_{it}\beta + \mu_i + \nu_{it}.$$

μ_i : time-invariant error, specific to i . $\mu_i \sim N(0, \sigma_\mu^2)$, and hence it is a random effect. Hence, the model is called the random effects model. μ_i captures individual heterogeneity. μ_i is assumed to be uncorrelated with \mathbf{x}_{it} which is a strong assumption. μ_i are uncorrelated among individuals.

ν_{it} : time-variant error. $\nu_{it} \sim N(0, \sigma_\nu^2)$. ν_{it} is uncorrelated with X_{it} . ν_{it} are uncorrelated among individuals, but also within individuals.

ε_{it} : define it as $\mu_i + \nu_{it}$. It is the composite error of the model. μ_i and ν_{it} are independent.

GLM, FGLS, econometric application: RE estimator

Derive the variance-covariance matrix of ε_{it} . That is, derive $E[\varepsilon\varepsilon' \mid \mathbf{X}]$.

GLM, FGLS, econometric application: RE estimator

The variance for i , at a given t :

$$E [\varepsilon_{it}\varepsilon_{it} \mid \mathbf{x}'_{it}] = \sigma_{\mu}^2 + \sigma_{\nu}^2.$$

The covariance for i , across t : ε_{it} are **correlated within an individual**, due to the time-invariant μ_i . Serial correlation! That is, for every i , and $t \neq s$,

$$E [\varepsilon_{it}\varepsilon_{is} \mid \mathbf{x}'_{it}] = \sigma_{\mu}^2.$$

The covariance for i and j , across t : ε_{it} are **not correlated across individuals**. That is, for every $i \neq j$,

$$E [\varepsilon_{it}\varepsilon_{js} \mid \mathbf{x}'_{it}] = 0.$$

GLM, FGLS, econometric application: RE estimator

How does $E[\varepsilon\varepsilon' \mid \mathbf{X}]$ look like?

GLM, FGLS, econometric application: RE estimator

For T errors of individual i , stored in ε_i ,

$$E[\varepsilon_i \varepsilon_i' | \mathbf{X}_i'] = \begin{bmatrix} \sigma_\mu^2 + \sigma_\nu^2 & \sigma_\mu^2 & \dots & \sigma_\mu^2 & \dots & \sigma_\mu^2 \\ \sigma_\mu^2 & \sigma_\nu^2 + \sigma_\nu^2 & \dots & \sigma_\mu^2 & \dots & \sigma_\mu^2 \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \sigma_\mu^2 & \sigma_\mu^2 & \dots & \sigma_\mu^2 + \sigma_\nu^2 & \dots & \sigma_\mu^2 \\ \vdots & \vdots & \dots & \vdots & \ddots & \vdots \\ \sigma_\mu^2 & \sigma_\mu^2 & \dots & \sigma_\mu^2 & \dots & \sigma_\mu^2 + \sigma_\nu^2 \end{bmatrix}_{T \times T}$$

$$\equiv \omega_i$$

ε_{it} are serially correlated within an individual!

GLM, FGLS, econometric application: RE estimator

For T errors of N individuals, stored in ε ,

$$E[\varepsilon\varepsilon' \mid \mathbf{X}] = \Omega = \begin{bmatrix} \omega_1 & \mathbf{0} & \dots & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \omega_2 & \dots & \mathbf{0} & \dots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \omega_n & \dots & \mathbf{0} \\ \vdots & \vdots & \dots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{0} & \dots & \omega_N \end{bmatrix}_{NT \times NT}$$

GLM, FGLS, econometric application: RE estimator

Example $\mathbf{\Omega}$ for $N = 2, T = 2$,

$$E[\varepsilon\varepsilon' | \mathbf{X}] = \mathbf{\Omega} = \begin{bmatrix} \sigma_{\mu}^2 + \sigma_{\nu}^2 & \sigma_{\mu}^2 & 0 & 0 \\ \sigma_{\mu}^2 & \sigma_{\mu}^2 + \sigma_{\nu}^2 & 0 & 0 \\ 0 & 0 & \sigma_{\mu}^2 + \sigma_{\nu}^2 & \sigma_{\mu}^2 \\ 0 & 0 & \sigma_{\mu}^2 & \sigma_{\mu}^2 + \sigma_{\nu}^2 \end{bmatrix}_{4 \times 4}$$

GLM, FGLS, econometric application: RE estimator

ε_{it} are serially correlated within individuals. We cannot estimate β efficiently using OLS! What can we do?

We have constructed

$$\Omega.$$

It includes the unknown σ_μ^2 and σ_ν^2 . There are different ways to estimate them. We do not cover this. Use these estimates to obtain

$$\hat{\Omega}.$$

Now GLS estimation is **feasible**. Then obtain

$$\hat{\Omega}^{-1} = \hat{P}'\hat{P}.$$

$\hat{P}\epsilon$ is serially uncorrelated within individuals!

GLM, FGLS, econometric application: RE estimator

Obtain $\hat{\mathbf{P}}\mathbf{y}$ and $\hat{\mathbf{P}}\mathbf{X}$. Applying the OLS on them,

$$\begin{aligned}\mathbf{b}_{FGLS} &= \underbrace{((\hat{\mathbf{P}}\mathbf{X})')}_{\mathbf{X}^{*'}} \underbrace{(\hat{\mathbf{P}}\mathbf{X})}_{\mathbf{X}^*}^{-1} \underbrace{(\hat{\mathbf{P}}\mathbf{X})'}_{\mathbf{X}^{*'}} \underbrace{\hat{\mathbf{P}}\mathbf{y}}_{\mathbf{y}^{*'}} \\ &= \mathbf{b}_{RE}\end{aligned}$$

The feasible generalised least squares estimator is the random effects estimator!

GLM, RE estimator, example

Example in MATLAB, where we check how the \hat{P} matrix looks like.

GLM, RE estimator, example

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Editor - /Users/Tunga/Library/Mobile Documents/com~apple~CloudDocs/Academic/Te
exerciseparttwo.m  exerciseparttwofunctionbgs.m  exerciseparttwofunctionfes.m
1      % The RE estimator as the FGLS estimator
2
3      % 1. Load the data
4 -    clear;
5 -    filename = 'C:\Users\username\Desktop\exercise.csv';
6 -    delimiterIn = ',';
7 -    headerlinesIn = 1;
8 -    exercisedata = importdata(filename,delimiterIn,headerlinesIn);
9
10     % 2. Create the systematic component of the regression
11 -    y = exercisedata.data(:,1);
12 -    N = length(y);
13 -    X = [ones(N,1) exercisedata.data(:,2:end)];
14
15     % 3. Create additional variables
16 -    T = 8;
17 -    M = N/T;
18 -    P_D = kron(eye(M),ones(T,T).*(1/T));
19
20     % 4. Obtain the RE coefficient estimates as FGLS coefficient estimates
21 -    fes = exerciseparttwofunctionfes(y,X,M,P_D,N);
22 -    bgs = exerciseparttwofunctionbgs(y,X,M,P_D,T);
23 -    s2_m = fes.s2_hat;
24 -    s2_v = bgs.s2_hat-s2_m/T;
25 -    L = 1-(T*s2_v/s2_m+1)^(-1/2);
26 -    P_hat = eye(N)-L*P_D;
27 -    y_t = P_hat*y;
28 -    X_t = P_hat*X;
29 -    B_hat = (X_t'*X_t)\(X_t'*y_t);
```

GLM, RE estimator, example

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Variables – X_t

X_t

4360x10 double

	1	2	3	4	5	6	7	8	9
1	0.3634	0	-0.0796	0	0	5.0875	-1.8647	-15.2334	0
2	0.3634	0	0.9204	0	0	5.0875	-0.8647	-12.2334	0
3	0.3634	0	-0.0796	0	0	5.0875	0.1353	-7.2334	0
4	0.3634	0	-0.0796	0	0	5.0875	1.1353	-0.2334	0
5	0.3634	0	-0.0796	0	0	5.0875	2.1353	8.7666	0
6	0.3634	0	-0.0796	0	0	5.0875	3.1353	19.7666	0
7	0.3634	0	-0.0796	0	0	5.0875	4.1353	32.7666	0
8	0.3634	0	-0.0796	0	0	5.0875	5.1353	47.7666	0
9	0.3634	0	0	0	0	4.7241	-0.7745	-23.1512	0
10	0.3634	0	0	0	0	4.7241	0.2255	-14.1512	0
11	0.3634	0	0	0	0	4.7241	1.2255	-3.1512	0
12	0.3634	0	0	0	0	4.7241	2.2255	9.8488	0
13	0.3634	0	0	0	0	4.7241	3.2255	24.8488	0
14	0.3634	0	0	0	0	4.7241	4.2255	41.8488	0
15	0.3634	0	0	0	0	4.7241	5.2255	60.8488	0
16	0.3634	0	0	0	0	4.7241	6.2255	81.8488	0
17	0.3634	0	0	0.3634	0	4.3607	-0.7745	-23.1512	0
18	0.3634	0	0	0.3634	0	4.3607	0.2255	-14.1512	0
19	0.3634	0	0	0.3634	0	4.3607	1.2255	-3.1512	0
20	0.3634	0	0	0.3634	0	4.3607	2.2255	9.8488	0
21	0.3634	0	0	0.3634	0	4.3607	3.2255	24.8488	0
22	0.3634	0	0	0.3634	0	4.3607	4.2255	41.8488	0
23	0.3634	0	0	0.3634	0	4.3607	5.2255	60.8488	0
24	0.3634	0	0	0.3634	0	4.3607	6.2255	81.8488	0

GLM, RE estimator, example

[illegible]