

Day 3: Random-intercept models

Introduction to Multilevel Models
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Reliability

- ▶ Each overall error consists of the two error components ζ_j and ϵ_{ij} :

$$\xi_{ij} \equiv \zeta_j + \epsilon_{ij}$$

- ▶ The error components are independent, so it can be shown that the total variance is the sum of the between-subject and within-subject variances:

$$\begin{aligned}\text{Var}(y_{ij}) &= \text{Var}(\beta + \zeta_j + \epsilon_{ij}) \\ &= \text{Var}(\beta) + \text{Var}(\zeta_j + \epsilon_{ij}) \\ &= (0) + \psi + \theta\end{aligned}$$

- ▶ We can express the proportion of the total variance that is between subjects as:

$$\rho = \frac{\text{Var}(\zeta_j)}{\text{Var}(y_{ij})} = \frac{\psi}{\psi + \theta}$$

- ▶ ρ can also be thought of as **reliability** of measurements for the same subjects j . It is also analogous to R^2 in that it represents the proportion of the total variance that is “explained” by subjects

Intraclass correlation

- ▶ ρ can also be interpreted as the marginal correlation between measurements on two occasions i and i' for the same subject
- ▶ So ρ also represents within-cluster correlation
- ▶ We estimate the ICC using parameter estimates for ψ and θ :

$$\hat{\rho} = \frac{\hat{\psi}}{\hat{\psi} + \hat{\theta}}$$

- ▶ Can contrast the ICC with Pearson's r as:

$$r = \frac{\frac{1}{J-1} \sum_{j=1}^J (y_{ij} - \bar{y}_{i\cdot})(y_{i'j} - \bar{y}_{i'\cdot})}{s_{y_i} s_{y_{i'}}$$

- ▶ Pearson's r provides a measure of *relative agreement*, based on deviations of each i from their respective means
- ▶ ICC provides a measure of absolute agreement – and is therefore affected by linear transformations of the measurements

Fixed v. random effects

- ▶ The model we have called “random intercepts” is also a **one-way random-effects ANOVA model**, written as:

$$y_{ij} = \beta + \zeta_j + \epsilon_{ij} \quad \epsilon_{ij} | \zeta_j \sim N(0, \theta) \quad \zeta_j \sim N(0, \psi)$$

where ζ_j is a random intercept

- ▶ An alternative is the **one-way fixed-effects ANOVA model**:

$$y_{ij} = \beta + \alpha_j + \epsilon_{ij} \quad \epsilon_{ij} \sim N(0, \theta) \quad \sum_{j=1}^J \alpha_j = 0$$

where α_j is an unknown cluster-specific parameter

Fixed v. random effects: which to choose?

- ▶ Question: are we concerned about the *population* of clusters, or instead the particular clusters in the *sample*?
 - ▶ If we are interested in the variance ψ for the population of clusters, or inference for β when clusters and units are sampled from respective population, then use a random effects approach
 - ▶ If we are interested in the sample-specific “effects” α_j and inferences regarding β only when units (and not clusters) are considered randomly sampled, then use a fixed effects approach
- ▶ The choice mostly affects the standard error of $\hat{\beta}$ but also can affect $\hat{\beta}$ itself

Stata example using HSB data (xtreg)

```
. xtreg mathach, i(schoolid) mle nolog
```

```
Random-effects ML regression           Number of obs   =       7185
Group variable: schoolid              Number of groups =        160

Random effects u_i ~ Gaussian         Obs per group:  min =        14
                                       avg =       44.9
                                       max =        67

Log likelihood = -23557.905           Wald chi2(0)    =        0.00
                                       Prob > chi2     =          .
```

```
-----+-----
      mathach |          Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      _cons |    12.63707    .2436216    51.87   0.000    12.15958    13.11456
-----+-----
      /sigma_u |    2.924631    .1826925             2.587612    3.305544
      /sigma_e |    6.256868    .0527937             6.154245    6.361202
           rho |    .1793109    .0185934             .1452078    .2180551
-----+-----
Likelihood-ratio test of sigma_u=0:  chibar2(01)= 983.92 Prob>=chibar2 = 0.000
```

`_cons` overall population mean $\hat{\beta}$: 12.63707

`/sigma_u` between-subject standard deviation $\sqrt{\hat{\psi}}$ of ζ_j : 2.924631

`/sigma_e` within-subject SD $\sqrt{\hat{\theta}}$: 6.256868

`rho` intraclass correlation ρ , also computed as:

$$\hat{\rho} = \frac{\hat{\psi}}{\hat{\psi} + \hat{\theta}} = \frac{2.92^2}{6.26^2 + 2.92^2} = .18$$

Stata example using HSB data (xtmixed)

```
. xtmixed mathach || schoolid:, mle nolog
```

```
Mixed-effects ML regression  
Group variable: schoolid
```

```
Number of obs      =      7185  
Number of groups   =      160  
  
Obs per group: min =       14  
                avg  =      44.9  
                max  =       67
```

```
Log likelihood = -23557.905  
Wald chi2(0)    =          .  
Prob > chi2     =          .
```

```
-----  
mathach |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]  
-----+-----  
_cons |   12.63707   .2436173    51.87  0.000    12.15959    13.11455  
-----
```

```
-----  
Random-effects Parameters |      Estimate   Std. Err.     [95% Conf. Interval]  
-----+-----  
schoolid: Identity  
sd(_cons) |   2.924632   .1826955    2.587608    3.305552  
-----+-----  
sd(Residual) |   6.256868   .0527937    6.154245    6.361202  
-----
```

```
LR test vs. linear regression: chibar2(01) = 983.92 Prob >= chibar2 = 0.0000
```

Day 3 focus: random intercept models

- ▶ One way to look at this is that we are reparameterizing β from the models introduced earlier, by adding explanatory variables X (covariates)
- ▶ This allows us to model directly the distinction between the effects of X that are *within-cluster* from those that are *between-cluster*
- ▶ Another way to look at it: we are extending the CLRM by adding random intercepts ζ_j
- ▶ We also discuss the measures of variation explained by X , and the coefficients of determination (R^2 equivalents) for random intercept models

Sample variances at different levels

- ▶ **Overall standard deviation** measured in deviations from overall mean $\bar{x}_{..}$:

$$s_{xO}^2 = \frac{1}{N-1} \sum_{j=1}^J \sum_{i=1}^{n_j} (x_{ij} - \bar{x}_{..})^2$$

- ▶ **Between standard deviation** measured in deviations of cluster (level 2) means $\bar{x}_{.j}$ from overall means:

$$s_{xB}^2 = \frac{1}{J-1} \sum_{j=1}^J (\bar{x}_{.j} - \bar{x}_{..})^2$$

- ▶ **Within standard deviation** measured in deviations of observations (level 1) x_{ij} from the cluster means:

$$s_{xW}^2 = \frac{1}{N-1} \sum_{j=1}^J \sum_{i=1}^{n_j} (x_{ij} - \bar{x}_{.j})^2$$

Example using HSB dataset

```
. use http://www.stata-press.com/data/mlmus2/hsb.dta, clear  
. xtsum mathach ses sector, i(schoolid)
```

Variable		Mean	Std. Dev.	Min	Max	Observations
mathach	overall	12.74785	6.878246	-2.832	24.993	N = 7185
	between		3.117651	4.239781	19.71914	n = 160
	within		6.186706	-6.926784	30.71674	T-bar = 44.9063
ses	overall	.0001434	.7793552	-3.758	2.692	N = 7185
	between		.4139706	-1.193946	.8249825	n = 160
	within		.660588	-3.650597	2.856222	T-bar = 44.9063
sector	overall	.4931106	.4999873	0	1	N = 7185
	between		.4976359	0	1	n = 160
	within		0	.4931106	.4931106	T-bar = 44.9063

- ▶ T-bar is the mean number of students per school (measured for each variable – same here because no missing)
- ▶ No within variance for sector because this is a level-2 only variable

Specification for random-intercept model

- ▶ Standard CLRM model with covariates:

$$y_{ij} = \beta_1 + \beta_2 x_{2ij} + \cdots + \beta_p x_{pij} + \xi_{ij}$$

- ▶ Error term: $\xi_{ij} \equiv \zeta_j + \epsilon_{ij}$
- ▶ Linear random-intercept model with covariates:

$$\begin{aligned} y_{ij} &= \beta_1 + \beta_2 x_{2ij} + \cdots + \beta_p x_{pij} + \zeta_j + \epsilon_{ij} \\ &= (\beta_1 + \zeta_j) + \beta_2 x_{2ij} + \cdots + \beta_p x_{pij} + \epsilon_{ij} \end{aligned}$$

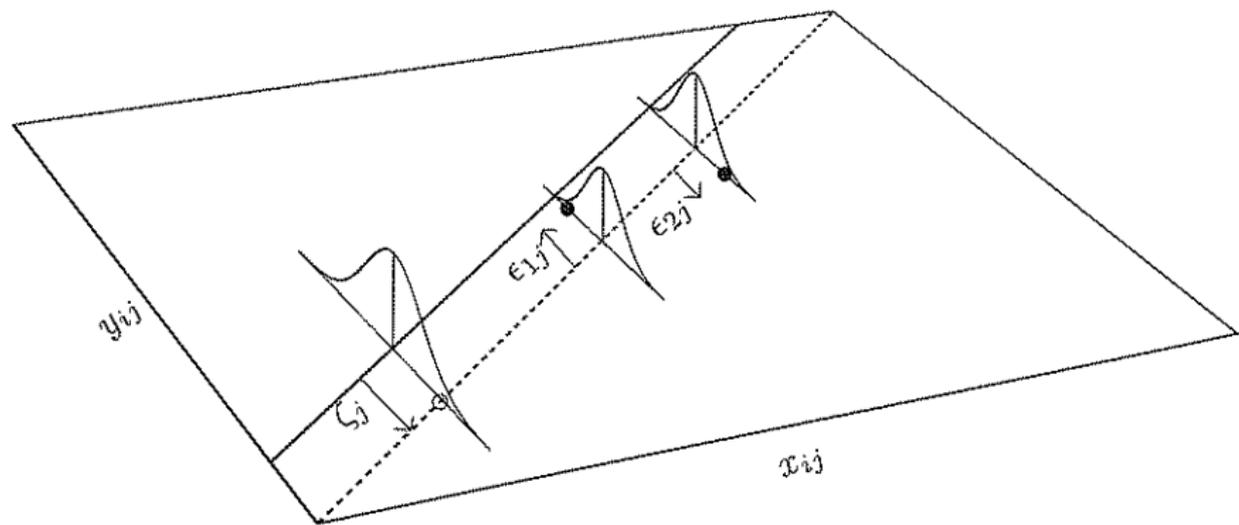
- ▶ Error assumptions (exogeneity):

$$\zeta_j | \mathbf{x}_{ij} \sim N(0, \psi)$$

and

$$\epsilon_{ij} | \mathbf{x}_{ij}, \zeta_j \sim N(0, \theta)$$

Illustration of random intercept model for one J group



Smoking and birth weight example from text: xtreg

```
. xtreg birwt smoke male mage hsgrad somecoll collgrad married black kessner2
> kessner3 novisit pretri2 pretri3, i(momid) mle

Random-effects ML regression                Number of obs   =    8604
Group variable: momid                      Number of groups  =    3978
Random effects u_i ~ Gaussian              Obs per group:   min =     2
                                           avg   =    2.2
                                           max   =     3

                                           LR chi2(13)     =    659.47
                                           Prob > chi2     =    0.0000

Log likelihood = -65145.752
```

birwt	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
smoke	-218.3289	18.20988	-11.99	0.000	-254.0196	-182.6382
male	120.9375	9.558721	12.65	0.000	102.2027	139.6722
mage	8.100548	1.347266	6.01	0.000	5.459956	10.74114
hsgrad	56.84715	25.03538	2.27	0.023	7.778705	105.9156
somecoll	80.68607	27.30914	2.95	0.003	27.16115	134.211
collgrad	90.83273	27.99598	3.24	0.001	35.96162	145.7038
married	49.9202	25.50319	1.96	0.050	-.0651368	99.90554
black	-211.4138	28.27818	-7.48	0.000	-266.838	-155.9896
kessner2	-92.91883	19.92624	-4.66	0.000	-131.9736	-53.86411
kessner3	-150.8759	40.83414	-3.69	0.000	-230.9093	-70.84246
novisit	-30.03035	65.69213	-0.46	0.648	-158.7846	98.72387
pretri2	92.8579	23.19258	4.00	0.000	47.40127	138.3145
pretri3	178.7295	51.64145	3.46	0.001	77.51416	279.9449
_cons	3117.191	40.97597	76.07	0.000	3036.88	3197.503
/sigma_u	338.7674	6.296444			326.6487	351.3358
/sigma_e	370.6654	3.867707			363.1618	378.324
rho	.4551282	.0119411			.4318152	.4785967

Likelihood-ratio test of sigma_u=0: chibar2(01)= 1108.77 Prob>=chibar2 = 0.000

Smoking and birth weight example from text: xtmixed

```
. xtmixed birwt smoke male mage hsgrad somecoll collgrad married black
> kessner2 kessner3 novisit pretri2 pretri3, || momid:, mle
Mixed-effects ML regression      Number of obs      =      8604
Group variable: momid            Number of groups   =      3978
                                Obs per group: min =         2
                                avg =         2.2
                                max =         3

                                Wald chi2(13)         =      693.74
                                Prob > chi2           =      0.0000

Log likelihood = -65145.752
```

birwt	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
smoke	-218.3286	18.15946	-12.02	0.000	-253.9205	-182.7368
male	120.9375	9.558003	12.65	0.000	102.2042	139.6708
mage	8.100566	1.344573	6.02	0.000	5.465251	10.73588
hsgrad	56.84716	25.03543	2.27	0.023	7.778611	105.9157
somecoll	80.68605	27.30906	2.95	0.003	27.16127	134.2108
collgrad	90.83268	27.99498	3.24	0.001	35.96354	145.7018
married	49.92022	25.50309	1.96	0.050	-.0649248	99.90537
black	-211.4138	28.27764	-7.48	0.000	-266.8369	-155.9906
kessner2	-92.91882	19.92617	-4.66	0.000	-131.9734	-53.86424
kessner3	-150.8758	40.83027	-3.70	0.000	-230.9017	-70.84992
novisit	-30.0303	65.69165	-0.46	0.648	-158.7836	98.72298
pretri2	92.85784	23.19067	4.00	0.000	47.40497	138.3107
pretri3	178.7294	51.63677	3.46	0.001	77.5232	279.9356
_cons	3117.191	40.88824	76.24	0.000	3037.051	3197.33

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
momid: Identity				
sd(_cons)	338.7686	6.296449	326.6499	351.337
sd(Residual)	370.6648	3.867695	363.1613	378.3234

LR test vs. linear regression: chibar2(01) = 1108.77 Prob >= chibar2 = 0.0000

Smoking and birth weight example from text: results compared

Table 3.1: Maximum likelihood estimates for smoking data (in grams)

	Full model		Null model		Level-2 cov.	
	Est	(SE)	Est	(SE)	Est	(SE)
Fixed part						
β_1 [_cons]	3,117	(41)	3,468	(7)	3,216	(26)
β_2 [smoke]	-218	(18)				
β_3 [male]	121	(10)				
β_4 [mage]	8	(1)				
β_5 [hsgrad]	57	(25)			131	(25)
β_6 [somecoll]	81	(27)			181	(27)
β_7 [collgrad]	91	(28)			233	(26)
β_8 [married]	50	(26)			115	(25)
β_9 [black]	-211	(28)			-201	(29)
β_{10} [kessner2]	-93	(20)				
β_{11} [kessner3]	-151	(41)				
β_{12} [novisit]	-30	(66)				
β_{13} [pretri2]	93	(23)				
β_{14} [pretri3]	179	(52)				
Random part						
$\sqrt{\psi}$	339		368		348	
$\sqrt{\theta}$	371		378		378	
Derived estimates						
R^2	0.09		0.00		0.05	
ρ	0.46		0.49		0.46	

Measures of fit for random intercept models

- ▶ Consider a null model without covariates, compared to a model with covariates
- ▶ The R^2 with OLS is the *proportional reduction in variance* from using the covariates model versus the null model:

$$R^2 = \frac{\hat{\sigma}_0^2 - \hat{\sigma}_1^2}{\hat{\sigma}_0^2}$$

- ▶ Snijders and Bosker (1999) propose a similar measures for the linear random-intercept model:

$$R^2 = \frac{\hat{\psi}_0 + \hat{\theta}_0 - (\hat{\psi}_0 + \hat{\theta}_0)}{\hat{\psi}_0 + \hat{\theta}_0}$$

- ▶ From the smoking and birthweight example (see earlier table):

$$\hat{\psi}_1 + \hat{\theta}_1 = 338.7686^2 + 370.6648^2 = 252156.56$$

It follows that

$$R^2 = \frac{278260.43 - 252156.56}{278260.43} = 0.09$$