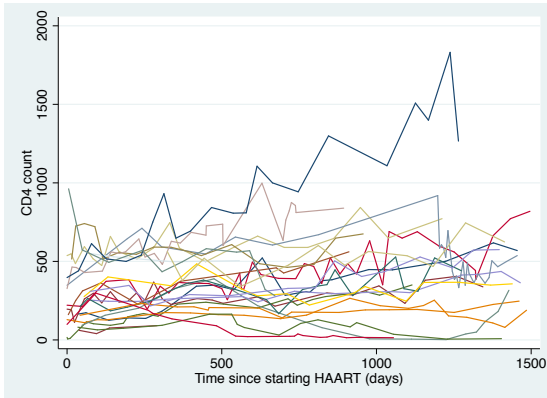


Longitudinal Data Fall 2015



Chapter 7

Mixed, Random Effects, Random Coefficients, Multilevel, ...Models

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Many names, some more general

- Mixed Models (most general)
- Random effects models
- Random Coefficient Models
- Hierarchical Linear Models (HLM' s)
- Multilevel models (MLM' s)
- Nested modeling

What's being “Mixed”?

- A mixed model has two types of effects, fixed and random.
- A fixed effect means that all levels of the variable are contained in the data and the effect is universal to all in the target population – parameters.
- A random effect means that the levels (effects) of the variable comprise random samples of the levels (effects) in the target population – random variables.
- Consider a treatment effect. Fixed, Random, Both?

Motivation for using MLM's (mixed models)

- It allows different subjects to have different responses to a treatment, risk variable, etc., thus has intuitive appeal.
- Rarely interesting, but can also provide post-estimation estimates of the random effects.
- You get the entire data-generating distribution.
 - Use the virtues of having a likelihood.
 - Can simulate data from the resulting parameter estimates
 - In contrast with other approaches that only target a specific aspect of the data-generating distribution.

Estimation of coefficients using mixed models

- As we've showed in class and homework, random effects models imply certain variance-covariance structures.
- For instance, a simple random effects model results in equal correlation (exchangeable or compound symmetry) among all observations measured on the same subject.
- We know that if the variance-covariance matrix (V) is known, then the most efficient estimate of the coefficients is weighted-least squares:

$$\hat{\beta} = (X^T W X)^{-1} X^T W Y$$

where $W = V^{-1}$.

Estimation of coefficients using mixed models, cont.

- The Mixed Linear Model procedure works by:
 1. Converting the random effects model into its implied variance-covariance matrix, V ,
 2. starting with the independent model (OLS) it gets residuals and then estimates V based on this model,
 3. creates weight matrix as $W = \hat{V}^{-1}$,
 4. does weighted least squares and gets residuals,
 5. repeats until convergence.

- The SE's the procedure return come from:

$$\text{var}(\hat{\beta}_{\hat{V}}) = (X^T W X)^{-1} = (X^T \hat{V}^{-1} X)^{-1}$$

Model Based inference

When deriving the inference on coefficients, $SE(\hat{\beta})$ the estimating procedure assumes that the variance-covariance model of the outcome implied by the model IS CORRECT (i.e., it's always naïve, not “robust”).

The Simplest Example.

- The Model:

$$Y_{ij} = \mu + \alpha_i + e_{ij}$$

- $E(\alpha_i)=0, E(e_{ij})=0, E[\alpha_i e_{ij}]=0.$

- $\text{Var}(\alpha_i) = \sigma^2_{\alpha}.$

- $\text{Var}(e_{ij}) = \sigma^2_e .$

- What are the fixed and random effects in this model?

Likelihood

- Given α_i :

$$f(Y_{ij} | \alpha_i) = \phi\left(\frac{Y_{ij} - \alpha_i - \mu}{\sigma_e^2}\right), f(\vec{Y}_i | \alpha_i) = \prod_{j=1}^{n_i} \phi\left(\frac{Y_{ij} - \alpha_i - \mu}{\sigma_e^2}\right)$$

- Likelihood of observed data (for one unit) is:

$$f(\vec{Y}_i) = \int_{\alpha} f(\vec{Y}_i | \alpha) f(\alpha) d\alpha = \int_{\alpha} \prod_{j=1}^{n_i} \phi\left(\frac{Y_{ij} - \alpha - \mu}{\sigma_e^2}\right) \phi\left(\frac{\alpha}{\sigma_{\alpha}^2}\right) d\alpha$$

Random Intercepts and *Random Associations*

- The Model: $Y_{ij} = (\beta_0 + \beta_{0i}) + (\beta_1 + \beta_{1i})x_{ij} + e_{ij}$
- $E(\beta_{0i})=0, E(\beta_{1i})=0, E(e_{ij})=0.$
- $Var(\beta_{0i})= \sigma^2_0, Var(\beta_{1i})= \sigma^2_1, Var(e_{ij})= \sigma^2$
- $cov(\beta_{0i}, \beta_{1i})= \sigma_{12}, cov(\beta_{0i}, e_{ij})=0, cov(\beta_{1i}, e_{ij})=0.$
- What are the fixed and random effects in this model?

Reminder of our GEE analysis:
Association of Baseline Covariate (Age)
on CD4 count.

- Binary age (X_{ij}) = 0 (<40) or 1 (>40)

- Fit simple linear model:

$$E[Y_{ij} \mid X_{ij} = x_i] = \beta_0 + \beta_1 x_i$$

- Compare results of Models A-D

	Naive	Robust
Unweighted OLS	A	B
Weighted LS	C	D

Summary of Results of Association of Baseline Covariate (Age) on CD4 count

	β_0 (SE)	
	Naive	Robust
Unweighted OLS	225.9 (9.9)	225.9 (12.6)
Weighted LS	225.9 (13.3)	225.9 (12.6)
	β_1 (SE)	
	Naive	Robust
Unweighted OLS	24.24 (14.2)	24.24 (19.3)
Weighted LS	24.24 (19.2)	24.24 (19.3)

Random Effects Model of CD4 vs. Baseline Age

- Fit simple random effects model:
with same assumptions as above

$$Y_{ij} = \beta_0 + \beta_{0i} + \beta_1 X_{ij} + e_{ij}$$

```
. xtreg cd4 binage, i(id) re
```

```
Random-effects GLS regression
Group variable (i): id
```

```
Number of obs      =      594
Number of groups   =      297
```

```
R-sq:  within =      .
       between = 0.0054
       overall = 0.0049
```

```
Obs per group: min =      2
                avg  =     2.0
                max  =      2
```

```
Random effects u_i ~ Gaussian
corr(u_i, X)      = 0 (assumed)
```

```
Wald chi2(1)      =      1.59
Prob > chi2       =     0.2075
```

```
-----
              cd4 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
est of  $\beta_1$  binage      24.2404    19.22938     1.26   0.207    -13.44848     61.92928
est of  $\beta_0$  _cons     225.902    13.38962    16.87   0.000     199.6588    252.1451
-----+-----

sigma_u | 157.74218 estimate of  $\sigma^2_0$ 
sigma_e | 71.379705 estimate of  $\sigma^2$ 
rho     | .83003801 (fraction of variance due to u_i)
-----
```

Association of Time-Varying Covariate (Viral Load) on CD4 count.

- Binary VL: $X_{ij} = 0$ (<2000) or 1 (>2000) – all subjects included have one low and one high VL.
- Fit simple linear model:

$$E[Y_{ij} \mid X_{ij} = x_i] = \beta_0 + \beta_1 x_{ij}$$

- Compare results of Models A-D

	Naive	Robust
Unweighted OLS	A	B
Weighted LS	C	D

Summary of Results of Association of Time Varying Covariate (VL) on CD4 count (note, different data that last lecture)

	β_0 (SE)	
	Naive	Robust
Unweighted OLS	355.1(21.7)	355.1(23.6))
Weighted LS	355.1(21.7)	355.1(22.9)
	β_1 (SE)	
	Naive	Robust
Unweighted OLS	-79.3(30.7)	-79.3(17.1)
Weighted LS	-79.3(17.0)	-79.3(17.1)
t-test (difference)	-79.3(17.1)	

Random Effects Model of CD4 vs. $\log_{10}(\text{viral load})$

- Fit simple random effects model:
with same assumptions as above

$$Y_{ij} = \beta_0 + \beta_{0i} + \beta_1 X_{ij} + e_{ij}$$

```
. xtreg cd4 medvl, i(id) re
```

```
Random-effects GLS regression
Group variable (i): id
```

```
Number of obs      =      174
Number of groups   =       87
```

```
R-sq:  within = 0.0000
       between = 0.0000
       overall = 0.0370
```

```
Obs per group: min =       2
               avg  =      2.0
               max  =       2
```

```
Random effects u_i ~ Gaussian
corr(u_i, X)      = 0 (assumed)
```

```
Wald chi2(1)      =      21.44
Prob > chi2       =      0.0000
```

cd4	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
medvl	-79.34483	17.13523	-4.63	0.000	-112.9293	-45.76039
_cons	355.0805	21.80987	16.28	0.000	312.3339	397.827
-----+-----						
sigma_u	169.148	estimate of σ^2_0				
sigma_e	113.0146	estimate of σ^2				
rho	.69136617	(fraction of variance due to u_i)				

Multiple and varying observations per person

CD4 (Y) vs. continuous (log) Viral Load (X)

$$E[Y_{ij} \mid X_{i1} = x_{i1}, X_{ij} = x_{ij}] = \beta_0 + \beta_1 x_{i1} + \beta_2 (x_{ij} - x_{i1})$$

- β_2 represents the expected change in Y given a change in X_{ij} relative to the baseline value (X_{i1}) - longitudinal effect.
- β_1 represents the expected difference in average Y across two sub-populations that differ by their baseline values, X_{i1} - cross-sectional effect.

Summary of Results of Association of Time-Varying Covariate (VL) on CD4 count – multiple observations per person

	$\beta_0(\text{SE})$	
	Naive	Robust
Unweighted OLS	618.9(11.6)	618.9(35.2)
Weighted LS	509.1(31.2)	509.1(32.9)
	$\beta_1(\text{SE})$	
	Naive	Robust
Unweighted OLS	-83.7(3.0)	-83.7(8.3)
Weighted LS	-52.7(7.4)	-52.7(7.7)
	$\beta_2(\text{SE})$	
	Naive	Robust
Unweighted OLS	-99.2(2.4)	-99.2(6.8)
Weighted LS	-54.7(2.2)	-54.7(3.2)

General Method for Choosing Random Effects/Correlation Model

- Choose fixed effects model – more elaborate the better.
- For every combination of random effects and correlation you would consider, fit the model using the same fixed effects model, record Aikake Information Criterion (AIC) – which is a fit statistic penalized by the number of parameters.
- Choose the model with the smallest AIC.

$AIC = -2 * \loglik + 2 * p$, p is the number of parameters

$$Y_{ij} = \beta_0 + \beta_{0i} + \beta_1 X_{i1} + \beta_2 (X_{ij} - X_{i1}) + e_{ij}$$

$$\sigma_{\beta_{0i}}^2 \equiv \text{var}(\beta_{0i}), \quad \sigma_e^2 \equiv \text{var}(e_{ij})$$

```
. mixed cd4 logvlbase logvlchange || id:, stddev
```

```

                                Wald chi2(2)      =      832.00
Log likelihood = -43826.581      Prob > chi2      =      0.0000

```

cd4		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----							
$\hat{\beta}_1$	logvlbase	-52.05566	8.121493	-6.41	0.000	-67.97349	-36.13782
$\hat{\beta}_2$	logvlchange	-53.47144	1.855169	-28.82	0.000	-57.10751	-49.83538
$\hat{\beta}_0$	_cons	506.5567	34.39893	14.73	0.000	439.1361	573.9774
-----+-----							

Random-effects Parameters		Estimate	Std. Err.	[95% Conf. Interval]	
-----+-----					
id: Identity	$\hat{\sigma}_{\beta_{0i}}$ sd(_cons)	186.629	6.760737	173.8376	200.3615
-----+-----					
	$\hat{\sigma}_e$ sd(Residual)	108.3884	.9402027	106.5612	110.2469
-----+-----					

```
LR test vs. linear regression: chibar2(01) = 7437.72 Prob >= chibar2 = 0.0000
```

Intraclass Correlation Coefficient and Measure of Fit (AIC)

```
. estat icc
```

Residual intraclass correlation

Level	ICC	Std. Err.	[95% Conf. Interval]	
id	.7477793	.0140775	.719203	.7743597

$$\frac{\hat{\sigma}_{\beta_{0i}}^2}{\hat{\sigma}_{\beta_{0i}}^2 + \hat{\sigma}_e^2} = \frac{\text{Estimated Between Subject Variance}}{\text{Total Variance} = \text{var}(Y_{ij})}$$

```
. estat ic
```

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
-----+-----						
.	7053	.	-43826.58	5	87663.16	87697.47

Note: N=Obs used in calculating BIC; see [R] BIC note

Re-do with *Robust* Standard Errors

```
. mixed cd4 logvlbase logvlchange || id:, stddev cluster(id)
```

(Std. Err. adjusted for 406 clusters in id)

		Robust				
cd4	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
logvlbase	-52.05566	7.76666	-6.70	0.000	-67.27803	-36.83328
logvlchange	-53.47144	3.163293	-16.90	0.000	-59.67138	-47.2715
_cons	506.5567	33.09145	15.31	0.000	441.6987	571.4148

		Robust			
Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]		
id: Identity					
sd(_cons)	186.629	9.162828	169.5072	205.4802	
sd(Residual)	108.3884	3.435494	101.8598	115.3354	

Random Coefficient Model

$$Y_{ij} = (\beta_0 + \beta_{0i}) + \beta_1 X_{i1} + (\beta_2 + \beta_{2i}) * (X_{ij} - X_{i1}) + e_{ij}$$

$$\sigma_{\beta_{0i}}^2 \equiv \text{var}(\beta_{0i}), \sigma_{\beta_{2i}}^2 \equiv \text{var}(\beta_{2i}), \sigma_e^2 \equiv \text{var}(e_{ij}), \sigma_{10} \equiv \text{cov}(\beta_{0i}, \beta_{2i})$$

```
. mixed cd4 logvlbase logvlchange || id: logvlchange,
      stddev cov(unstruct)
```

	cd4	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
$\hat{\beta}_1$							
	logvlbase	-66.69168	6.935967	-9.62	0.000	-80.28593	-53.09743
$\hat{\beta}_2$	logvlchange	-54.16069	2.975448	-18.20	0.000	-59.99246	-48.32892
$\hat{\beta}_0$	_cons	553.9275	28.89506	19.17	0.000	497.2942	610.5607

	Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
id: Unstructured					
$\hat{\sigma}_{\beta_{2i}}$	sd(logvlc~e)	41.14181	2.911627	35.81322	47.26323
$\hat{\sigma}_{\beta_{0i}}$	sd(_cons)	164.0304	6.245377	152.2353	176.7394
$\text{corr}(\beta_{0i}, \beta_{2i})$	corr(logvlc~e, _cons)	-.5886842	.0676882	-.7057546	-.4403184
$\hat{\sigma}_e$	sd(Residual)	104.7828	.9310012	102.9739	106.6235

```
LR test vs. linear regression:      chi2(3) = 7729.27   Prob > chi2 = 0.0000
```

Fit Statistics

```
. estat ic
```

Akaike's information criterion and Bayesian information criterion

Model		Obs	ll (null)	ll (model)	df	AIC	BIC
-----+-----							
.		7053	.	-43680.8	7	87375.61	87423.63

Re-do with Robust Estimated of Variance

```
. mixed cd4 logvlbase logvlchange || id: logvlchange, stddev cov(unstruct) cluster(id)
```

(Std. Err. adjusted for 406 clusters in id)

		Robust				
cd4		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----						
logvlbase		-66.69168	7.022014	-9.50	0.000	-80.45458 -52.92879
logvlchange		-54.16069	3.008829	-18.00	0.000	-60.05789 -48.26349
_cons		553.9275	30.89291	17.93	0.000	493.3785 614.4765

			Robust		
Random-effects Parameters			Estimate	Std. Err.	[95% Conf. Interval]
-----+-----					
id: Unstructured					
	sd(logvlc~e)		41.14181	3.762318	34.39086 49.21797
	sd(_cons)		164.0304	8.518709	148.1557 181.6061
	corr(logvlc~e,_cons)		-.5886842	.0836119	-.7289279 -.4010203
-----+-----					
	sd(Residual)		104.7828	3.357696	98.40426 111.5748

Model	Parameter	Estimate	SE(Naïve)	SE(Robust)
Simple Random Effects $Y_{ij} = \beta_0 + \beta_{0i} + \beta_1 X_{i1} + \beta_2 (X_{ij} - X_{i1}) + e_{ij}$	β_0	506.5	34.4	33.1
	β_1	-52.1	8.1	7.8
	β_2	-53.5	1.8	3.2
	SD(β_{0i})	186.6	6.8	9.2
	SD(e_{ij})	108.4	0.94	3.4
	ICC	0.75	0.014	N/A
Fit Statistic	AIC	87663		
Random Coefficients $Y_{ij} = (\beta_0 + \beta_{0i}) + \beta_1 X_{i1} + (\beta_2 + \beta_{2i})(X_{ij} - X_{i1}) + e_{ij}$	β_0	553.9	28.9	30.9
	β_1	-66.7	6.9	7.0
	β_2	-54.2	3.0	3.0
	SD(β_{0i})	164.0	6.2	8.5
	SD(β_{2i})	41.1	2.9	3.8
	SD(e_{ij})	104.8	0.93	3.4
	Cor(β_{0i}, β_{2i})	-0.59	0.068	0.084
Fit Statistic	AIC	87375	Smaller than above	***

Using Estimated Random Coefficients Distributions

$$Y_{ij} = (\beta_0 + \beta_{0i}) + \beta_1 X_{i1} + (\beta_2 + \beta_{2i})(X_{ij} - X_{i1}) + e_{ij}$$

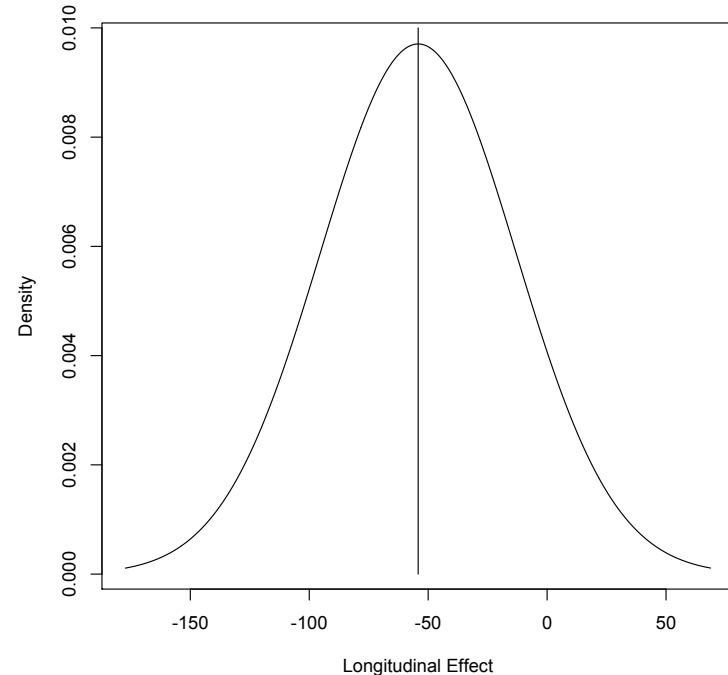
- This estimated distribution of β_{2i} can be used to estimate the quartiles of the longitudinal effect of changes in log10 viral load across the population.
- Specifically, the estimated distribution of the longitudinal effect is \sim Normal with mean -54.2 and standard deviation 41.1.

Using Estimated Longitudinal Effect Distribution to exam how it might vary in population

Estimated IQR then
is

$$(\hat{\beta}_2 - Z_{0.75} * \hat{\sigma}_{\beta_{2i}}, \hat{\beta}_2 + Z_{0.75} * \hat{\sigma}_{\beta_{2i}})$$

or,



```
. display "("-54.2-invnormal(0.75)*41.1 " , " -54.2+invnormal(0.75)*41.1 " )"
```

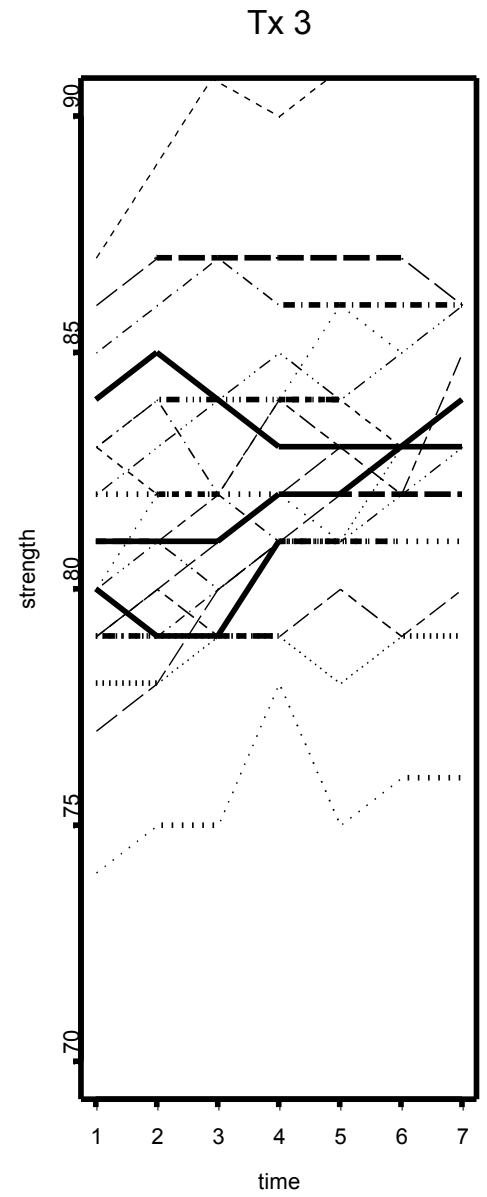
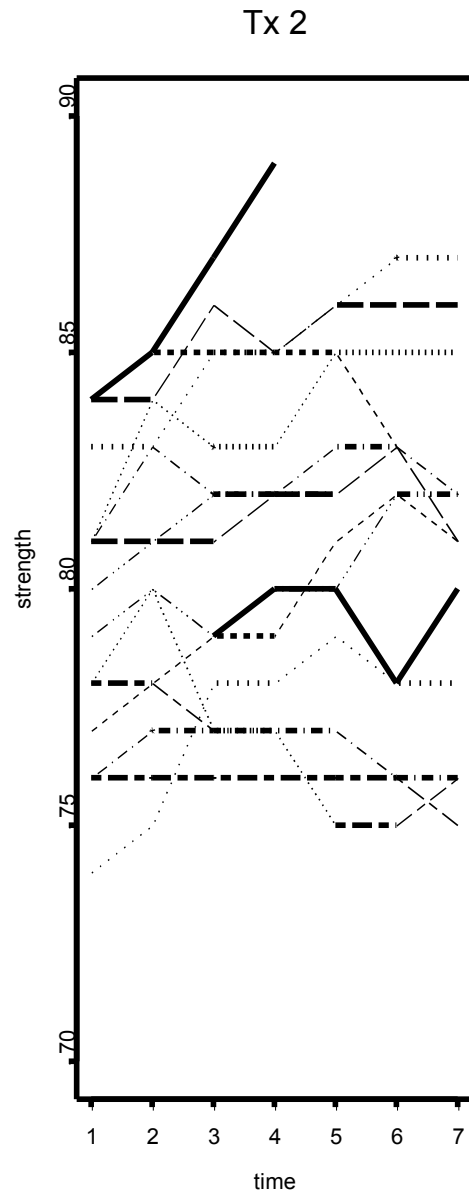
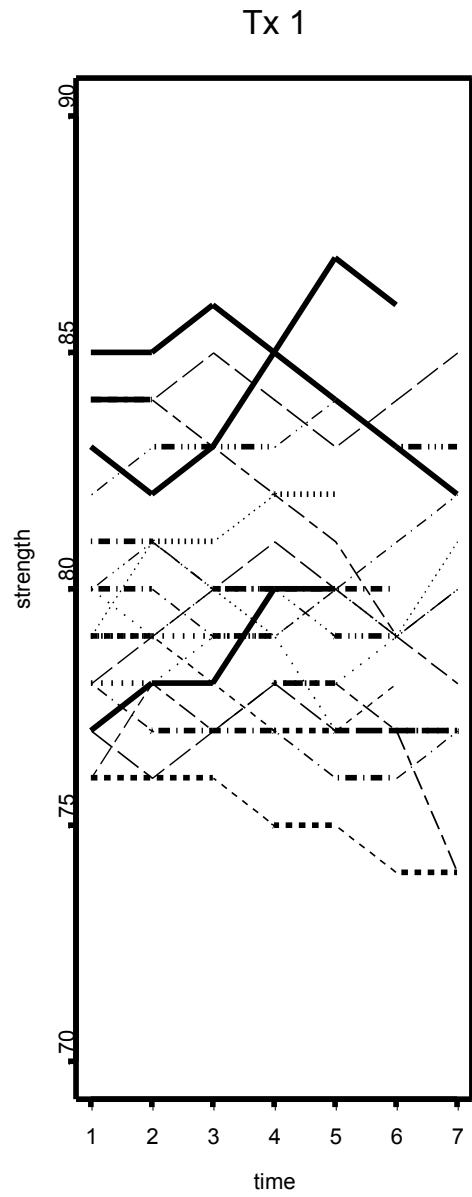
```
(-81.921529 , -26.478471 )
```

Strength Data

- Subjects randomized to one of 3 treatments
 1. No training (tx=1)
 2. Weight training with light weights and high repetition (tx=2)
 3. Weight training with heavy weights and low repetition (tx=3)
- Subjects were followed for 7 weeks and a measure of muscle strength was recorded each week.
- The questions of interest are
 1. Does weight training have any impact on strength?
 2. Is there a difference between tx 2 and 3?
 3. Which training program works quickest to increase strength?

Strength Data

	id	tx	y	time
1.	1	1	85	1
2.	1	1	85	2
3.	1	1	86	3
4.	1	1	85	4
5.	1	1	87	5
6.	1	1	86	6
7.	1	1	.	7
8.	2	1	80	1
9.	2	1	79	2
10.	2	1	.	3
11.	2	1	78	4
12.	2	1	78	5
13.	2	1	79	6
14.	2	1	.	7



Mixed Model I for Strength Data

- First, the Model (X_{ij} , time of ij th measurement, Tx_i is the treatment assignment for i th person).

$$Y_{ij} = (\beta_0 + \beta_{0i}) + \beta_1 X_{ij} + \beta_2 I(Tx_i = 1) + \beta_3 I(Tx_i = 2) + \beta_4 I(Tx_i = 1) * X_{ij} + \beta_5 I(Tx_i = 2) * X_{ij} + e_{ij}$$

- $E(\beta_{0i})=0, \quad E(e_{ij})=0.$
- $\text{Var}(\beta_{0i})= \sigma^2_0, \quad \text{Var}(e_{ij})= \sigma^2$
- $\text{cov}(\beta_{0i}, e_{ij})=0.$
- What are the fixed and random effects in this model?

STATA for Strength Data - XTREG

```
. gen tx1 = tx==1
. gen tx2 = tx==2
. gen tx1time = tx1*time
. gen tx2time = tx2*time

. xtmixed y tx1 tx2 time tx1time tx2time || id:, stddev
```

Computing standard errors:

```
Mixed-effects ML regression      Number of obs      =      370
Group variable: id              Number of groups    =      57

                                Obs per group: min =      5
                                avg =      6.5
                                max =      7

                                Wald chi2(5)      =      69.34
                                Prob > chi2       =      0.0000

Log likelihood = -663.52557
```

y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
tx1	-.9568027	.9747114	-0.98	0.326	-2.867202	.9535965
tx2	-1.148717	1.035119	-1.11	0.267	-3.177514	.8800792
time	.3038536	.0482746	6.29	0.000	.2092371	.3984701
tx1time	-.3731916	.0680399	-5.48	0.000	-.5065475	-.2398358
tx2time	-.0611408	.0714343	-0.86	0.392	-.2011495	.0788679
_cons	81.0185	.6810689	118.96	0.000	79.68363	82.35337

Variance Components

```
-----
Random-effects Parameters |   Estimate   Std. Err.   [95% Conf. Interval]
-----+-----
id: Identity              |
      sd(_cons)           |   2.977532    .284653    2.468774    3.591134
-----+-----
      sd(Residual)        |   1.074968    .042967    .9939687    1.162569
-----
LR test vs. linear regression: chibar2(01) =   571.45 Prob >= chibar2 = 0.0000
```

. estat icc

Residual intraclass correlation

```
-----
Level |      ICC   Std. Err.   [95% Conf. Interval]
-----+-----
id    |   .8846894   .0212074    .8361909    .9201994
-----
```

. estat ic

Akaike's information criterion and Bayesian information criterion

```
-----
Model |   Obs   ll(null)   ll(model)   df       AIC       BIC
-----+-----
.     |   370      .   -663.5256     8   1343.051   1374.359
-----
```

STATA for Strength Data, cont.

- Test of no treatment effect, $H_0: \beta_4 = \beta_5 = 0$

```
. test tx1time tx2time
```

```
( 1)  [y]tx1time = 0
```

```
( 2)  [y]tx2time = 0
```

```
          chi2( 2) =    34.17  
Prob > chi2 =    0.0000
```

Re-do with robust SE's

```
. xtmixed y tx1 tx2 time tx1time tx2time || id:, stddev cluster(id)
```

```

                                Wald chi2(5)      =      33.81
Log pseudolikelihood = -663.52557                Prob > chi2      =      0.0000

```

(Std. Err. adjusted for 57 clusters in id)

		Robust					
y		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----							
tx1		-.9568027	.9449005	-1.01	0.311	-2.808774	.8951683
tx2		-1.148717	1.056909	-1.09	0.277	-3.22022	.9227856
time		.3038536	.0699036	4.35	0.000	.1668452	.4408621
tx1time		-.3731916	.103697	-3.60	0.000	-.576434	-.1699493
tx2time		-.0611408	.1321063	-0.46	0.643	-.3200644	.1977829
_cons		81.0185	.7301918	110.96	0.000	79.58735	82.44965

Re-do with robust SE's

Random-effects Parameters		Estimate	Robust Std. Err.	[95% Conf. Interval]	
id: Identity					
	sd(_cons)	2.977532	.2615252	2.506646	3.536876
	sd(Residual)	1.074968	.0642565	.9561254	1.208583

```
. test tx1time tx2time
```

```
( 1)  [y]tx1time = 0
```

```
( 2)  [y]tx2time = 0
```

```
      chi2( 2) =    13.72
Prob > chi2 =    0.0010
```

Equivalent STATA for Strength Data, XTGEE with exchangeable

```
.xtgee y tx1 tx2 time tx1time tx2time, i(id) cor(exc)
```

```
GEE population-averaged model      Number of obs      =      370
Group variable:                     id      Number of groups   =      57
Link:                               identity  Obs per group: min =      5
Family:                             Gaussian      avg =      6.5
Correlation:                        exchangeable      max =      7
                                      Wald chi2(5)      =      64.83
Scale parameter:                    9.918406      Prob > chi2      =      0.0000
```

```
-----
            y |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
      tx1 |   - .956994   .9684046    -0.99   0.323    -2.855032   .9410442
      tx2 |  -1.148591   1.028411    -1.12   0.264    -3.164239   .8670575
      time |   .3037201   .0501318     6.06   0.000     .2054634   .4019767
  tx1time |  - .3730803   .0706584    -5.28   0.000    - .5115681  - .2345924
  tx2time |  - .0611578   .0741834    -0.82   0.410    - .2065545   .0842389
      _cons |   81.0188    .6766896   119.73   0.000     79.69251   82.34509
-----
```

Equivalent STATA for Strength Data, XTGEE with exchangeable

```
. xtcorr
```

	c1	c2	c3	c4	c5	c6	c7
r1	1.0000						
r2	0.8743	1.0000					
r3	0.8743	0.8743	1.0000				
r4	0.8743	0.8743	0.8743	1.0000			
r5	0.8743	0.8743	0.8743	0.8743	1.0000		
r6	0.8743	0.8743	0.8743	0.8743	0.8743	1.0000	
r7	0.8743	0.8743	0.8743	0.8743	0.8743	0.8743	1.0000

Equivalent STATA for Strength Data, XTGEE with exchangeable, robust

```
. xtgee y tx1 tx2 time tx1time tx2time, i(id) cor(exc) robust
```

```
GEE population-averaged model          Number of obs      =          370
Group variable:                        id      Number of groups   =           57
Link:                                identity  Obs per group: min =           5
Family:                               Gaussian          avg =          6.5
Correlation:                          exchangeable          max =           7
                                         Wald chi2(5)         =          33.82
Scale parameter:                      9.918406    Prob > chi2           =          0.0000
```

(standard errors adjusted for clustering on id)

		Semi-robust				
y		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
-----+-----						
tx1		-.956994	.9449735	-1.01	0.311	-2.809108 .89512
tx2		-1.148591	1.057032	-1.09	0.277	-3.220334 .9231534
time		.3037201	.0698707	4.35	0.000	.1667761 .440664
tx1time		-.3730803	.1036701	-3.60	0.000	-.57627 -.1698906
tx2time		-.0611578	.1320877	-0.46	0.643	-.3200449 .1977294
_cons		81.0188	.7302755	110.94	0.000	79.58749 82.45011

Mixed Model II for Strength Data (Random Coefficients Model)

■ The Model:

$$Y_{ij} = (\beta_0 + \beta_{0i}) + (\beta_1 + \beta_{1i})X_{ij} + \beta_2 I(Tx_i = 1) + \beta_3 I(Tx_i = 2) + \beta_4 I(Tx_i = 1) * X_{ij} + \beta_5 I(Tx_i = 2) * X_{ij} + e_{ij}$$

$$■ E(\beta_{0i})=0, E(\beta_{1i})=0, E(e_{ij})=0.$$

$$■ \text{Var}(\beta_{0i})= \sigma^2_0, \text{Var}(\beta_{1i})= \sigma^2_1, \text{Var}(e_{ij})= \sigma^2$$

$$■ \text{cov}(\beta_{0i}, \beta_{1i})= \sigma_{12}, \text{cov}(\beta_{0i}, e_{ij})=0, \text{cov}(\beta_{1i}, e_{ij})=0.$$

Model II

```
. xtmixed y tx1 tx2 time tx1time tx2time || id: time, stddev cov(un)
```

Mixed-effects ML regression
Group variable: id

Number of obs = 370
Number of groups = 57

Obs per group: min = 5
avg = 6.5
max = 7

Log likelihood = -621.59666

Wald chi2(5) = 26.99
Prob > chi2 = 0.0001

y		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----							
tx1		-.8791863	.9353663	-0.94	0.347	-2.712471	.954098
tx2		-1.033765	.9932793	-1.04	0.298	-2.980556	.9130267
time		.3360225	.0821817	4.09	0.000	.1749494	.4970957
tx1time		-.4004078	.1169682	-3.42	0.001	-.6296614	-.1711543
tx2time		-.101627	.123829	-0.82	0.412	-.3443273	.1410734
_cons		80.93097	.6536334	123.82	0.000	79.64987	82.21207

Model II, cont

Random-effects Parameters		Estimate	Std. Err.	[95% Conf. Interval]	
id: Unstructured					
	sd(time)	.3337638	.0395831	.2645392	.4211031
	sd(_cons)	2.907665	.2887834	2.393342	3.532515
	corr(time,_cons)	-.1421759	.1489017	-.4144803	.1534946
	sd(Residual)	.8151804	.0360695	.7474643	.8890313

LR test vs. linear regression: chi2(3) = 655.31 Prob > chi2 = 0.0000

. estat icc

Conditional intraclass correlation

Level	ICC	Std. Err.	[95% Conf. Interval]	
id	.9271284	.0148245	.8921923	.9513603

Note: ICC is conditional on zero values of random-effects covariates.

. estat ic

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
-----+-----						
.	370	.	-621.5967	10	1263.193	1302.328

Model II, cont

```
. test tx1time tx2time
```

```
( 1)  [y]tx1time = 0
```

```
( 2)  [y]tx2time = 0
```

```
      chi2( 2) =    12.49
```

```
Prob > chi2 =    0.0019
```

Model II, robust SE

```
. xtmixed y tx1 tx2 time tx1time tx2time || id: time, stddev cov(un)
  cluster(id)
```

(Std. Err. adjusted for 57 clusters in id)

		Robust				
y	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
tx1	-.8791863	.9320558	-0.94	0.346	-2.705982	.9476095
tx2	-1.033765	1.054272	-0.98	0.327	-3.1001	1.03257
time	.3360225	.0760073	4.42	0.000	.1870509	.4849942
tx1time	-.4004078	.1064014	-3.76	0.000	-.6089508	-.1918649
tx2time	-.101627	.1363948	-0.75	0.456	-.3689559	.165702
_cons	80.93097	.7207356	112.29	0.000	79.51836	82.34359

Random-effects Parameters	Estimate	Robust Std. Err.	[95% Conf. Interval]	
id: Unstructured				
sd(time)	.3337638	.0417162	.2612461	.4264112
sd(_cons)	2.907665	.2469605	2.461774	3.434319
corr(time,_cons)	-.1421759	.1668982	-.4438449	.1884383
sd(Residual)	.8151804	.044396	.732649	.9070089

Comparison of Results for Strength Data

Variable	Coef.	SE Simple Random Effects Model	SE GEE exch., not robust	SE GEE exch., robust	Coef. Random Coeff. Model	SE Random Coeff. Model
tx1	-0.96	0.975	0.968	0.945	-0.878	0.935
tx2	-1.15	1.035	1.028	1.057	-1.034	0.993
time	0.30	0.048	0.050	0.070	0.336	0.082
tx1time	-0.37	0.068	0.071	0.104	-0.400	0.117
tx2time	-0.06	0.071	0.074	0.132	-0.102	0.124
_cons	81.02	0.681	0.677	0.730	80.931	0.654
AIC	1343				1263	

General Method for Choosing Random Effects/Correlation Model

- Choose fixed effects model – more elaborate the better.
- For every combination of random effects and correlation you would consider, fit the model using the same fixed effects model, record Aikake Information Criterion (AIC) – which is a fit statistic penalized by the number of parameters.
- Choose the model with the smallest AIC.

$AIC = -2 * \loglik + 2 * p$, p is the number of parameters