

Multilevel Workshop

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Table of contents

1	Introduction	6
1.1	Background	6
1.2	Simulated Multilevel Data	6
2	Estimation of p Values	8
2.1	Grouped and Individual Data	8
2.2	Analyses	9
2.2.1	OLS	9
2.2.2	MLM	9
2.2.3	Compare OLS and MLM	9
3	Estimation of β Coefficients	10
3.1	Introduction	10
3.2	Graphs	10
3.2.1	A “Naive” Graph	10
3.2.2	An “Aware” Graph	11
3.3	Regressions	12
3.3.1	A “Naive” OLS Analysis	12
3.3.2	An “Aware” MLM Analysis	12
3.3.3	Compare The Models	12
3.4	A Thought Experiment	13
4	Two Level Cross Sectional; And Three Level Longitudinal Models	14
4.1	Cross Sectional Model	14
4.1.1	Get Data	14
4.1.2	The Equation	14
4.1.3	Descriptive Statistics	14
4.1.4	Spaghetti Plot	15
4.1.5	Unconditional Model	15
4.1.6	Conditional Model	17
4.2	Longitudinal Model	18
4.2.1	Get Data	18
4.2.2	The Equation	18
4.2.3	Descriptive Statistics	18
4.2.4	Alternate Plot	19

4.2.5	Unconditional Model	19
4.2.6	Conditional Model	20
4.2.7	Nice Table of Results	21
4.3	QUESTIONS???	22
5	Cross-Classified Models	23
5.1	Introduction	23
5.2	Get Data	23
5.3	Cross Classified Model	23
5.3.1	Standard (Less Computationally Efficient) Syntax	23
5.3.2	Cross Classified With Computationally Efficient Syntax	24
5.4	Three Level Model	25
5.5	Nice Table of Results of Three Level and Cross Classified Model	27
5.6	Verification of Syntax Equivalence for Cross Classified Model	27
5.7	QUESTIONS???	28
References		29
License and Citation		30
License	30
Citation	30
BibTeX Citation	30

List of Figures

4.1	Spaghetti Plot of Outcome by Warmth by Country	15
4.2	Alternate Plot of Outcome by Time by Individual; First 10 Observations	19

List of Tables

1.1	Variables in Simulated Multilevel Data	7
1.2	Sample Data From Simulated Multilevel Data	7

1 Introduction

“Listening to the world. Well, I did that, and I still do it. I still do it.” (Mary Oliver in Oliver and Tippett 2015)

This site contains materials for a workshop on multilevel modeling.

1.1 Background

Multilevel models are useful when you have data that are nested or clustered inside social units such as schools, neighborhoods, states, or countries.

Multilevel models are also useful when you have longitudinal data where repeated measures are collected for study participants.

The Importance of Multilevel Models

Multilevel models may improve one’s statistical inferences in two important substantive ways.

- Multilevel models adjust standard errors for clustering, and thus calculate appropriate p values. Failure to use a model that accounts for the clustering in the data may lead to improperly calculated standard errors and p values, possibly leading to false attributions of statistical significance (false positives) (see Chapter 2).
- Multilevel models adjust regression coefficients (β ’s) for the presence of clustering. Failure to use a model that accounts for the clustering in the data may lead to improperly calculated regression coefficients (β ’s) which may have the wrong magnitude, the wrong statistical significance, and even the wrong sign (see Chapter 3).

1.2 Simulated Multilevel Data

The data used in these workshop materials are *simulated* data on parents, children and families. The data are simulated to come from 30 hypothetical countries around the world. These are the same data used and discussed in my book *Multilevel Thinking: Discovering Variation, Universals, and Particulars in Cross-Cultural Research*.

There are two versions of the data: a *cross-sectional* data set from a single point in time; a *longitudinal* version of the data spanning several time points.

i The Data Can Be Downloaded Here:

- [Cross Sectional Data](#)
- [Longitudinal Data](#)

Table 1.1: Variables in Simulated Multilevel Data

pos	variable	label
1	country	country id
2	HDI	Human Development Index
3	family	family id
4	id	unique country family id
5	identity	hypothetical identity group variable
6	intervention	received intervention
7	physical_punishment	physical punishment in past week
8	warmth	parental warmth in past week
9	outcome	beneficial outcome

Table 1.2: Sample Data From Simulated Multilevel Data

country	HDI	family	id	identity	intervention	physical_punishment	warmth	outcome
15	77	59	15.59	0	0	3	6	57.13
2	83	49	2.49	0	1	3	4	57.51
16	57	50	16.50	1	0	1	5	51
24	82	38	24.38	0	0	1	6	59.41
28	53	32	28.32	0	0	5	2	45.1

2 Estimation of p Values

2.1 Grouped and Individual Data

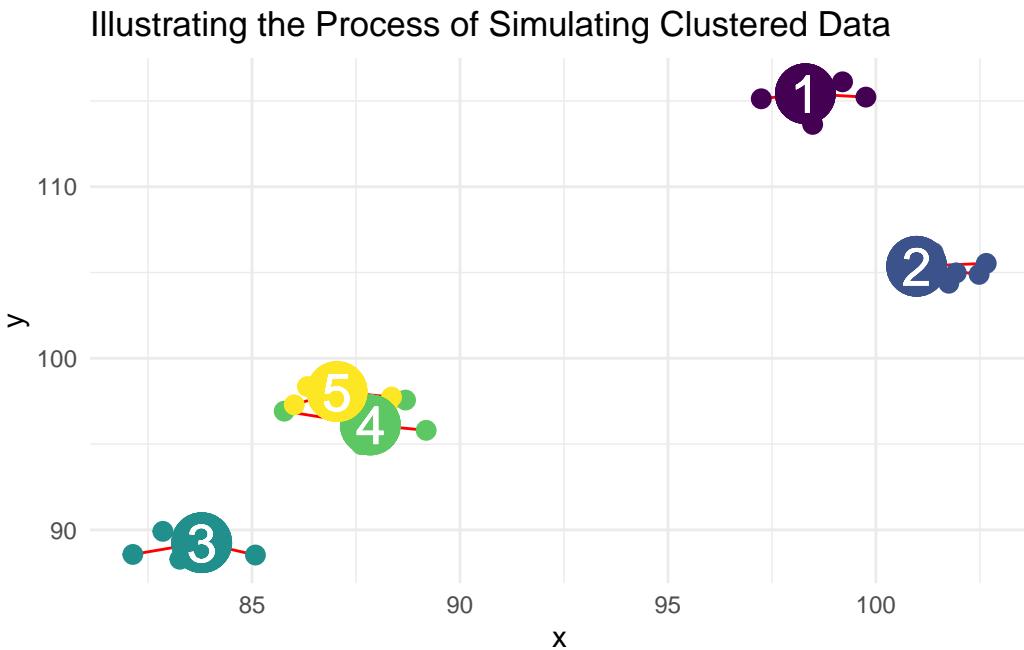
Bland and Altman (1994) suggested the following procedure for simulating some data:

"The data were generated from random numbers, and there is no relation between X and Y at all. Firstly, values of X and Y were generated for each 'subject,' then a further random number was added to make the individual observation." (Bland and Altman 1994)

So... we follow their procedure.

Simulating The Data

The graph below illustrates the process of simulating the data.



2.2 Analyses

2.2.1 OLS

An OLS analysis indicates that there is a statistically significant association of x and y .

```
OLS1
-----
x_individual      1.046 **
Intercept         4.488
Number of observations   25
-----
** p<.01, * p<.05
```

2.2.2 MLM

In contrast, an MLM analysis (correctly) finds that there is no statistically significant association of x and y .

```
MLM1
-----
x_individual      0.039
Intercept         97.005 **
var(_cons)        74.523
var(e)            0.594
Number of observations   25
-----
** p<.01, * p<.05
```

2.2.3 Compare OLS and MLM

	OLS1	MLM1
x_individual	1.046 **	0.039
Intercept	4.488	97.005 **
var(_cons)		74.523
var(e)		0.594
Number of observations	25	25

** p<.01, * p<.05

3 Estimation of β Coefficients

3.1 Introduction

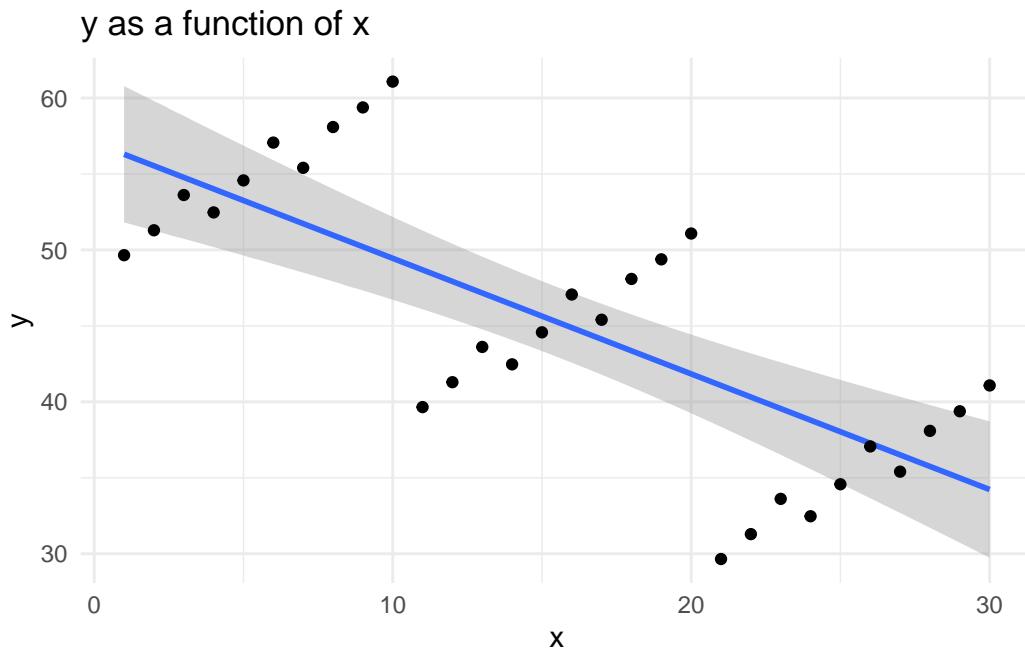
Associations between two variables can be *very different* (or even *reversed*) depending upon whether or not the analysis is “aware” of the grouped, nested, or clustered nature of the data (Nieuwenhuis 2015; Diez Roux 2003; Gelman et al. 2007). In multilevel analysis, the groups are often schools, neighborhoods, communities, or countries.

A model that is “aware” of the clustered nature of the data may provide very different—likely better—substantive conclusions than a model that is not aware of the clustered nature of the data. This phenomena is closely related to the “ecological fallacy”: the idea that group level and individual level relationships are not necessarily the same (Firebaugh 2001).

3.2 Graphs

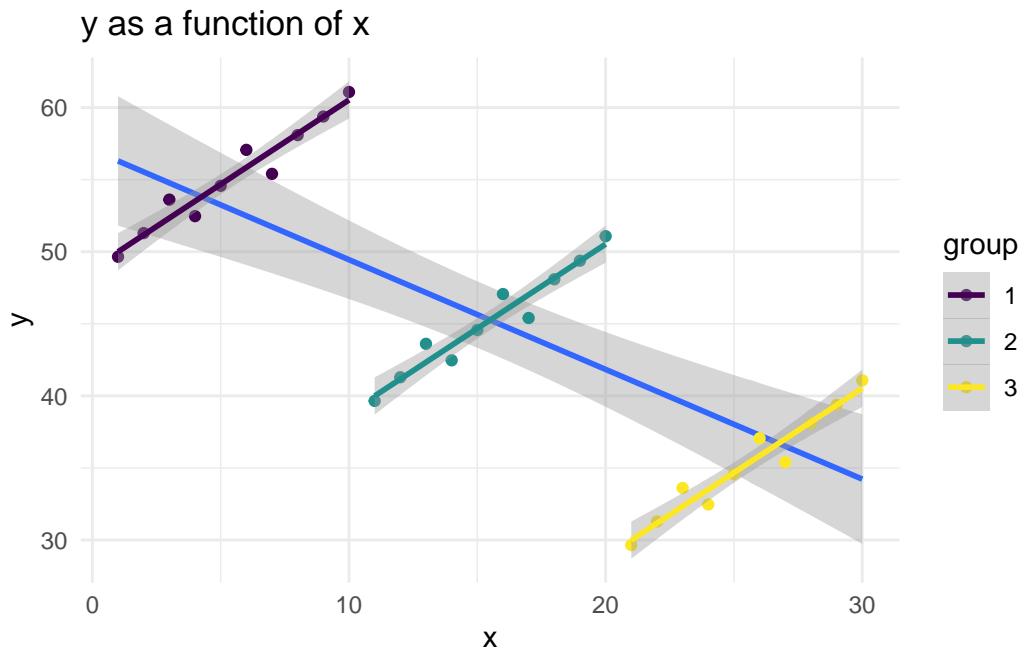
3.2.1 A “Naive” Graph

This “naive” graph is unaware of the grouped nature of the data.



3.2.2 An “Aware” Graph

This “aware” graph is aware of the grouped nature of the data.



3.3 Regressions

3.3.1 A “Naive” OLS Analysis

The OLS model with only x as a covariate is not aware of the grouped structure of the data, and the coefficient for x reflects this.

OLS2	
<hr/>	
x	-0.761 **
Intercept	57.057 **
Number of observations	30
<hr/>	
** p<.01, * p<.05	

3.3.2 An “Aware” MLM Analysis

The multilevel model is aware of the grouped structure of the data, and the coefficient for x reflects this.

MLM2	
<hr/>	
x	1.166 **
Intercept	27.192 **
var(_cons)	312.623
var(e)	0.806
Number of observations	30
<hr/>	
** p<.01, * p<.05	

3.3.3 Compare The Models

	OLS2	MLM2
<hr/>		
x	-0.761 **	1.166 **
Intercept	57.057 **	27.192 **
var(_cons)		312.623
var(e)		0.806
Number of observations	30	30
<hr/>		
** p<.01, * p<.05		

3.4 A Thought Experiment

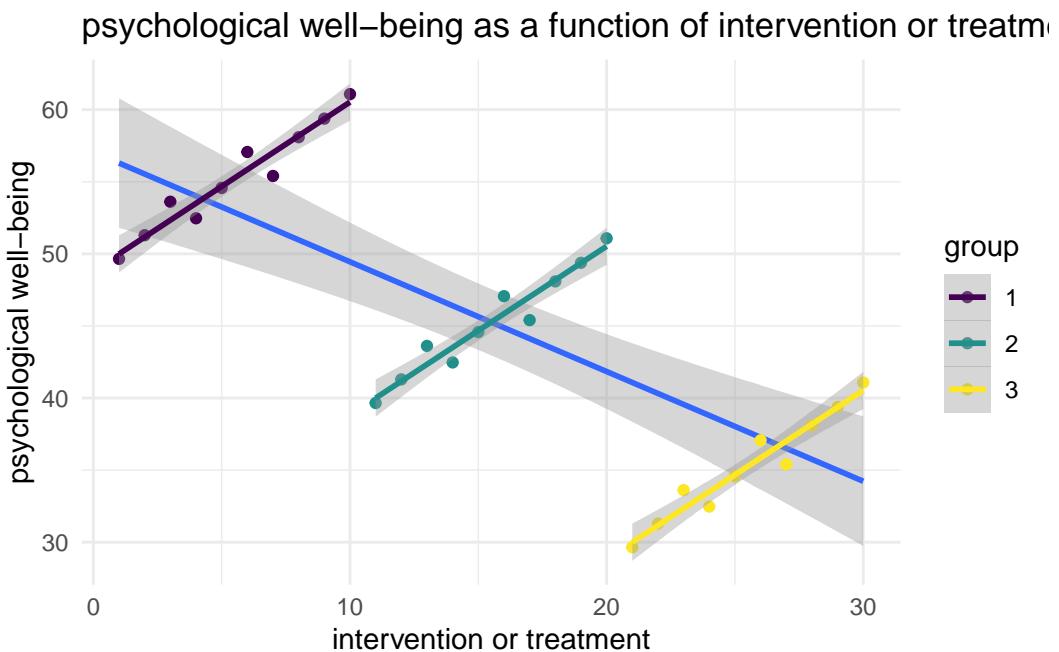
When might a situation like this arise in practice? This is surprisingly difficult to think through.

Imagine that x is a protective factor, or an intervention or treatment. Imagine that y is a desirable outcome, like improved mental health or psychological well being.

Now imagine that people provide more of the protective factor or more of the intervention in communities where there are lower levels of the desirable outcome. If we think about it, this is a very plausible situation.

A Naive Analysis Would Misconstrue The Results

A naive analysis that was unaware of the grouped nature of the data would therefore misconstrue the results, suggesting that the intervention was harmful, when it was in fact helpful.



These data are constructed to provide this kind of extreme example, but it's easy to see how multilevel analysis may provide better answers than we would get if we ignored the grouped nature of the data.

4 Two Level Cross Sectional; And Three Level Longitudinal Models

4.1 Cross Sectional Model

4.1.1 Get Data

```
use "simulated_multilevel_data.dta", clear
```

4.1.2 The Equation

$$\text{outcome}_{ij} = \beta_0 + \beta_1 \text{parental warmth} + \beta_2 \text{physical punishment} + \\ \beta_3 \text{identity} + \beta_4 \text{intervention} + \beta_5 \text{HDI} + \\ u_{0j} + u_{1j} \times \text{parental warmth} + e_{ij} \quad (4.1)$$

4.1.3 Descriptive Statistics

```
summarize // descriptive statistics
```

Variable	Obs	Mean	Std. dev.	Min	Max
country	3,000	15.5	8.656884	1	30
HDI	3,000	64.76667	17.24562	33	87
family	3,000	50.5	28.87088	1	100
id	0				
identity	3,000	.4976667	.5000779	0	1
<hr/>					
intervention	3,000	.4843333	.4998378	0	1
physical_p~t	3,000	2.478667	1.360942	0	5
warmth	3,000	3.521667	1.888399	0	7
outcome	3,000	52.43327	6.530996	29.60798	74.83553

4.1.4 Spaghetti Plot

```
spagplot outcome warmth, id(country) scheme(stcolor)  
graph export spagplot1.png, width(1000) replace
```

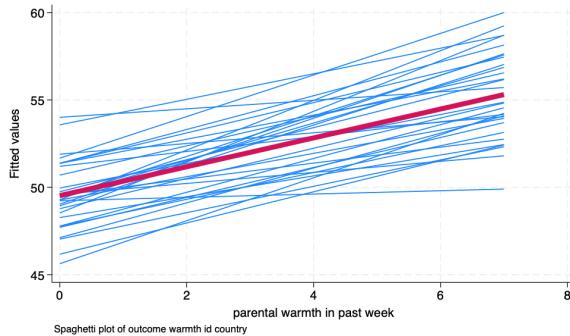


Figure 4.1: Spaghetti Plot of Outcome by Warmth by Country

💡 Random Slopes and Random Intercepts

This spaghetti plot is illustrating the idea of *random intercepts* and *random slopes*. The multilevel model is estimating *group specific regression lines*, in this case *country specific regression lines*. Each *country specific regression line* has its own intercept and its own slope. The results presented in the multilevel model are the result of *averaging* these estimates into one *overall estimate*.

4.1.5 Unconditional Model

4.1.5.1 Model

```
mixed outcome || country: // unconditional model
```

Performing EM optimization ...

Performing gradient-based optimization:
Iteration 0: Log likelihood = -9802.8371
Iteration 1: Log likelihood = -9802.8371

Computing standard errors ...

Mixed-effects ML regression
Group variable: country

Number of obs = 3,000
Number of groups = 30
Obs per group:
min = 100
avg = 100.0
max = 100
Wald chi2(0) = .
Prob > chi2 = .

Log likelihood = -9802.8371

outcome	Coefficient	Std. err.	z	P> z	[95% conf. interval]
_cons	52.43327	.3451217	151.93	0.000	51.75685 53.1097

Random-effects parameters		Estimate	Std. err.	[95% conf. interval]
country: Identity				
var(_cons)		3.178658	.9226736	1.799552 5.614658
var(Residual)		39.46106	1.024013	37.50421 41.52

LR test vs. linear model: chibar2(01) = 166.31 Prob >= chibar2 = 0.0000

4.1.5.2 ICC

```
estat icc
```

Intraclass correlation

Level		ICC	Std. err.	[95% conf. interval]
country		.0745469	.0201254	.0434963 .1248696

4.1.6 Conditional Model

```

mixed outcome warmth physical_punishment identity i.intervention HDI || country: warmth // m
est store crosssectional // store estimates

Performing EM optimization ...

Performing gradient-based optimization:
Iteration 0: Log likelihood = -9626.6279
Iteration 1: Log likelihood = -9626.607
Iteration 2: Log likelihood = -9626.607

Computing standard errors ...

Mixed-effects ML regression
Number of obs      = 3,000
Group variable: country
Number of groups =      30
Obs per group:
min =        100
avg =     100.0
max =        100
Wald chi2(5)      = 334.14
Log likelihood = -9626.607
Prob > chi2       = 0.0000

-----
          outcome | Coefficient Std. err.      z   P>|z| [95% conf. interval]
-----+
           warmth |   .8345368   .0637213   13.10   0.000    .7096453   .9594282
physical_punishm~t | -.9916657   .0797906  -12.43   0.000   -1.148052  -.8352791
         identity |  -.3004767   .2170295   -1.38   0.166   -.7258466   .1248933
  1.intervention |   .6396427   .2174519    2.94   0.003    .2134448   1.065841
            HDI |  -.003228   .0199257   -0.16   0.871   -.0422817   .0358256
         _cons |  51.99991   1.371257   37.92   0.000    49.3123   54.68753
-----+
-----+
          Random-effects parameters | Estimate Std. err. [95% conf. interval]
-----+
country: Independent |
           var(warmth) |   .0227504   .0257784    .0024689   .2096436
           var(_cons) |   2.963975   .9737647    1.556777  5.643163
-----+

```

```

-----+
      var(Residual) |   34.97499   .9097109    33.23668    36.80422
-----+
LR test vs. linear model: chi2(2) = 205.74                         Prob > chi2 = 0.0000
Note: LR test is conservative and provided only for reference.

```

4.2 Longitudinal Model

4.2.1 Get Data

```
use "simulated_multilevel_longitudinal_data.dta", clear
```

4.2.2 The Equation

$$\text{outcome}_{ij} = \beta_0 + \beta_1 \text{parental warmth} + \beta_2 \text{physical punishment} + \beta_3 \text{time} + \\ \beta_4 \text{identity}_2 + \beta_5 \text{intervention} + \beta_5 HDI + \\ u_{0j} + u_{1j} \times \text{parental warmth} + \\ v_{0i} + v_{1i} \times t + e_{ij} \quad (4.2)$$

4.2.3 Descriptive Statistics

```
summarize // descriptive statistics
```

Variable	Obs	Mean	Std. dev.	Min	Max
country	9,000	15.5	8.655922	1	30
HDI	9,000	64.76667	17.2437	33	87
family	9,000	50.5	28.86767	1	100
id	0				
identity	9,000	.4976667	.5000223	0	1
<hr/>					
intervention	9,000	.4843333	.4997823	0	1
t	9,000	2	.8165419	1	3
physical_p~t	9,000	2.485333	1.373639	0	5

warmth	9,000	3.514222	1.8839	0	7
outcome	9,000	53.37768	6.572285	29.60798	79.02199

4.2.4 Alternate Plot

```
encode id, generate(idNUMERIC) // numeric version of id

* spagplot outcome t if idNUMERIC <= 10, id(idNUMERIC) scheme(stcolor)

twoway (lfit outcome t) (scatter outcome t) if idNUMERIC <= 10, by(idNUMERIC) scheme(stcolor)

graph export spagplot2.png, width(1000) replace
```

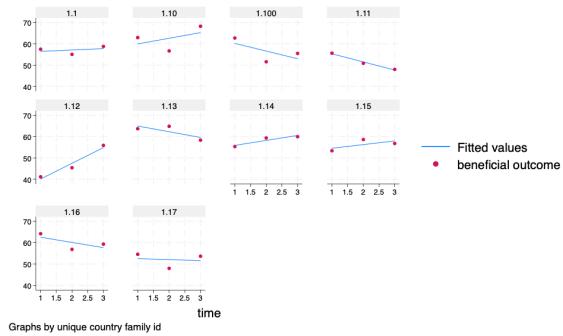


Figure 4.2: Alternate Plot of Outcome by Time by Individual; First 10 Observations

4.2.5 Unconditional Model

4.2.5.1 Model

```
mixed outcome || country: || id: // unconditional model
```

4.2.5.2 ICC

```
estat icc
```

Intraclass correlation

Level	ICC	Std. err.	[95% conf. interval]
<hr/>			
country	.0748336	.0190847	.0450028 .1219141
id country	.3462837	.0171461	.3134867 .3806097

4.2.6 Conditional Model

```
mixed outcome t warmth physical_punishment i.identity i.intervention HDI || country: warmth  
est store longitudinal // store estimates
```

Performing EM optimization ...

Performing gradient-based optimization:

Iteration 0: Log likelihood = -28523.49
Iteration 1: Log likelihood = -28499.953
Iteration 2: Log likelihood = -28499.735
Iteration 3: Log likelihood = -28499.604
Iteration 4: Log likelihood = -28499.603

Computing standard errors ...

Mixed-effects ML regression Number of obs = 9,000

Grouping information

Group variable	No. of groups	Observations per group		
		Minimum	Average	Maximum
country	30	300	300.0	300
id	3,000	3	3.0	3

Log likelihood = -28499.603 Wald chi2(6) = 1096.15
Prob > chi2 = 0.0000

outcome	Coefficient	Std. err.	z	P> z	[95% conf. interval]
<hr/>					
t	.943864	.0658716	14.33	0.000	.814758 1.07297
warmth	.9134959	.0423732	21.56	0.000	.8304461 .9965458
physical_punishm~t	-1.007897	.0497622	-20.25	0.000	-1.105429 -.9103647
1.identity	-.1276926	.1515835	-0.84	0.400	-.4247908 .1694056
1.intervention	.8589966	.1519094	5.65	0.000	.5612596 1.156734
HDI	-.0005657	.0196437	-0.03	0.977	-.0390666 .0379352
_cons	50.46724	1.338318	37.71	0.000	47.84418 53.09029
<hr/>					
<hr/>					
Random-effects parameters	Estimate	Std. err.		[95% conf. interval]	
<hr/>					
country: Independent					
var(warmth)	.0107585	.0127845		.0010477	.1104712
var(_cons)	3.167087	.9146767		1.798155	5.578185
<hr/>					
id: Independent					
var(t)	5.69e-10	1.29e-07		1.1e-202	3.0e+183
var(_cons)	8.387268	.4724189		7.510624	9.366236
<hr/>					
var(Residual)	26.02734	.4753703		25.11211	26.97592
<hr/>					
LR test vs. linear model: chi2(4) = 1247.03				Prob > chi2 = 0.0000	

Note: LR test is conservative and provided only for reference.

4.2.7 Nice Table of Results

```
etable, estimates(crosssectional longitudinal) ///
showstars showstarsnote /// show stars and note
column(estimate) // column is modelname
```

	crosssectional longitudinal	
parental warmth in past week	0.835 **	0.913 **
	(0.064)	(0.042)
physical punishment in past week	-0.992 **	-1.008 **

	(0.080)	(0.050)
hypothetical identity group variable	-0.300 (0.217)	
recieved intervention		
1	0.640 ** (0.217)	0.859 ** (0.152)
Human Development Index	-0.003 (0.020)	-0.001 (0.020)
time		0.944 ** (0.066)
hypothetical identity group variable		
1		-0.128 (0.152)
Intercept	52.000 ** (1.371)	50.467 ** (1.338)
var(warmth)	0.023 (0.026)	0.011 (0.013)
var(_cons)	2.964 (0.974)	3.167 (0.915)
var(e)	34.975 (0.910)	26.027 (0.475)
var(_cons)		8.387 (0.472)
var(t)		0.000 (0.000)
Number of observations	3000	9000

** p<.01, * p<.05

4.3 QUESTIONS???

5 Cross-Classified Models

5.1 Introduction

A two level multilevel model imagines that *Level 1* units are nested in *Level 2* units. A three level multilevel model imagines that *Level 1* units are nested in *Level 2* units, which are in turn nested in *Level 3* units.

A cross-classified model imagines that the nesting is not hierarchical, but rather that there are two sets of clusters or nestings which overlap, but are not hierarchical.

5.2 Get Data

```
use "simulated_multilevel_longitudinal_data.dta", clear
```

5.3 Cross Classified Model

We can treat these random effects as being *cross classified*.

This might be useful if we had data where individuals lived in different countries at different times.

However, because `id` is in fact nested inside `country`, in this case, estimating the random effects as cross classified will be more time consuming, but will give us equivalent results to a three level model.

5.3.1 Standard (Less Computationally Efficient) Syntax

The below syntax will take a very long time to run with the full sample, and thus we have commented it out.

```
* mixed outcome t warmth physical_punishment || _all: R.country || _all: R.id
* est store crossed1
```

The documentation notes that we can use a *much* more computationally efficient version of the above command, which is what we do in these notes. The user can verify that both versions of the command will produce equivalent results.

In fact, at the end of handout we verify the similarity of both sets of syntax using a random sample.

5.3.2 Cross Classified With Computationally Efficient Syntax

```
mixed outcome t warmth physical_punishment || _all: R.country || id:
est store crossed2 // store crossed effects result
```

Performing EM optimization ...

Performing gradient-based optimization:
 Iteration 0: Log likelihood = -28516.314
 Iteration 1: Log likelihood = -28516.277
 Iteration 2: Log likelihood = -28516.277

Computing standard errors ...

Mixed-effects ML regression Number of obs = 9,000

Grouping information

Group variable		No. of groups	Observations per group		
			Minimum	Average	Maximum
_all		1	9,000	9,000.0	9,000
id		3,000	3	3.0	3

Log likelihood = -28516.277 Wald chi2(3) = 1168.69
 Prob > chi2 = 0.0000

outcome	Coefficient	Std. err.	z	P> z	[95% conf. interval]
<hr/>					
t	.9434605	.065866	14.32	0.000	.8143654 1.072556
warmth	.9053924	.0380439	23.80	0.000	.8308277 .9799572
physical_punishment	-1.014385	.0499354	-20.31	0.000	-1.112257 -.916514
_cons	50.8301	.4123007	123.28	0.000	50.022 51.63819

Random-effects parameters		Estimate	Std. err.	[95% conf. interval]
<hr/>				
_all: Identity				
var(R.country)		3.429974	.930313	2.015668 5.836634
<hr/>				
id: Identity				
var(_cons)		8.608872	.4757699	7.725107 9.59374
<hr/>				
var(Residual)		26.02862	.4752444	25.11363 26.97695
<hr/>				
LR test vs. linear model: chi2(2) = 1260.84				Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

5.4 Three Level Model

```
mixed outcome t warmth physical_punishment || country: || id: // 3 level w/ random intercept
est store threelevel // store random intercept model
```

Performing EM optimization ...

Performing gradient-based optimization:
Iteration 0: Log likelihood = -28516.314
Iteration 1: Log likelihood = -28516.277
Iteration 2: Log likelihood = -28516.277

Computing standard errors ...

Mixed-effects ML regression

Number of obs = 9,000

Grouping information

Group variable		No. of groups	Observations per group		
			Minimum	Average	Maximum
country		30	300	300.0	300
id		3,000	3	3.0	3

Log likelihood = -28516.277

Wald chi2(3) = 1168.69
Prob > chi2 = 0.0000

outcome	Coefficient	Std. err.	z	P> z	[95% conf. interval]
t	.9434605	.065866	14.32	0.000	.8143654 1.072556
warmth	.9053924	.0380439	23.80	0.000	.8308277 .9799572
physical_punishm~t	-1.014385	.0499354	-20.31	0.000	-1.112257 -.916514
_cons	50.8301	.4123007	123.28	0.000	50.022 51.63819

Random-effects parameters		Estimate	Std. err.	[95% conf. interval]
country: Identity				
var(_cons)		3.429974	.930313	2.015668 5.836634
id: Identity				
var(_cons)		8.608872	.4757699	7.725107 9.59374
var(Residual)		26.02862	.4752444	25.11363 26.97695

LR test vs. linear model: chi2(2) = 1260.84

Prob > chi2 = 0.0000

Note: LR test is conservative and provided only for reference.

5.5 Nice Table of Results of Three Level and Cross Classified Model

```
etable, estimates(threelevel crossed2), ///
showstars showstarsnote /// show stars and note
column(estimate) // column is modelname

invalid 'showstars'
r(198);

r(198);
```

5.6 Verification of Syntax Equivalence for Cross Classified Model

```
keep if family <= 5 // random sample of families

quietly mixed outcome t warmth physical_punishment || _all: R.country || _all: R.id

est store crossed1A // less efficient syntax

quietly mixed outcome t warmth physical_punishment || _all: R.country || id:

est store crossed2A // more efficient syntax

etable, estimates(crossed1A crossed2A) ///
showstars showstarsnote /// show stars and note
column(estimate) // column is modelname

(8,550 observations deleted)
```

crossed1A crossed2A

time	0.745 **	0.745 **
	(0.281)	(0.281)
parental warmth in past week	0.871 **	0.871 **
	(0.160)	(0.160)
physical punishment in past week	-1.262 **	-1.262 **
	(0.206)	(0.206)
Intercept	51.755 **	51.755 **
	(1.009)	(1.009)
var(R_country)	2.245	2.245
	(1.319)	(1.319)
var(R_id)	5.425	
	(1.843)	
var(e)	23.638	23.638
	(1.933)	(1.933)
var(_cons)		5.425
		(1.843)
Number of observations	450	450

** p<.01, * p<.05

5.7 QUESTIONS???

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