

Multilevel Workshop

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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	recieved 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 The Importance of Accounting for Clustered Data

2.1 Grouped and Individual Data

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

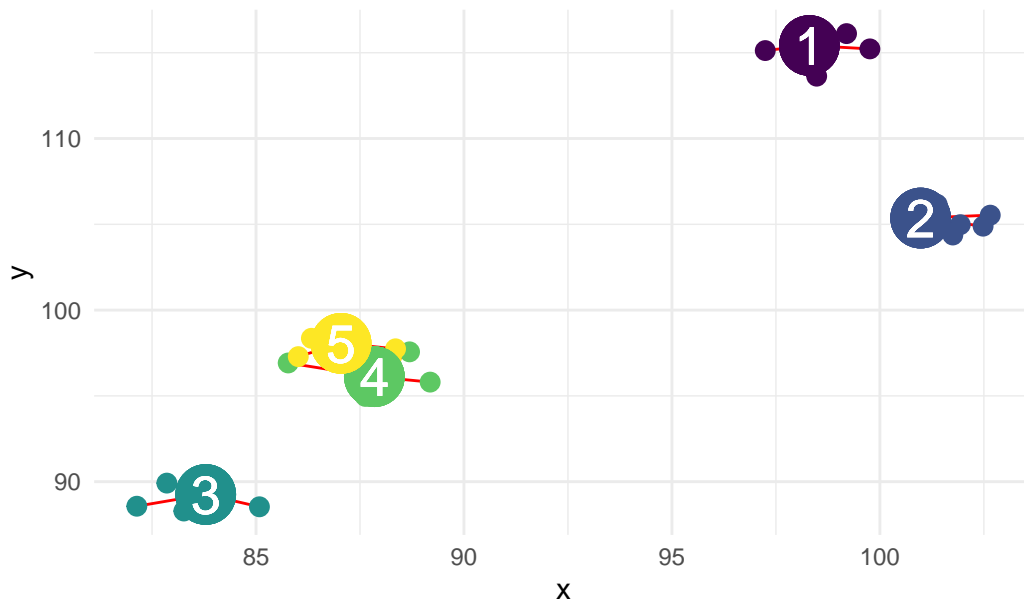
“The data were generated from random numbers, and there is no relation between X and Y at all. Firstly, values of X and Y were generated for each ‘subject,’ then a further random number was added to make the individual observation.” (Bland and Altman 1994)

So... we follow their procedure.

i Simulating The Data

The graph below illustrates the process of simulating the data.

Illustrating the Process of Simulating Clustered 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

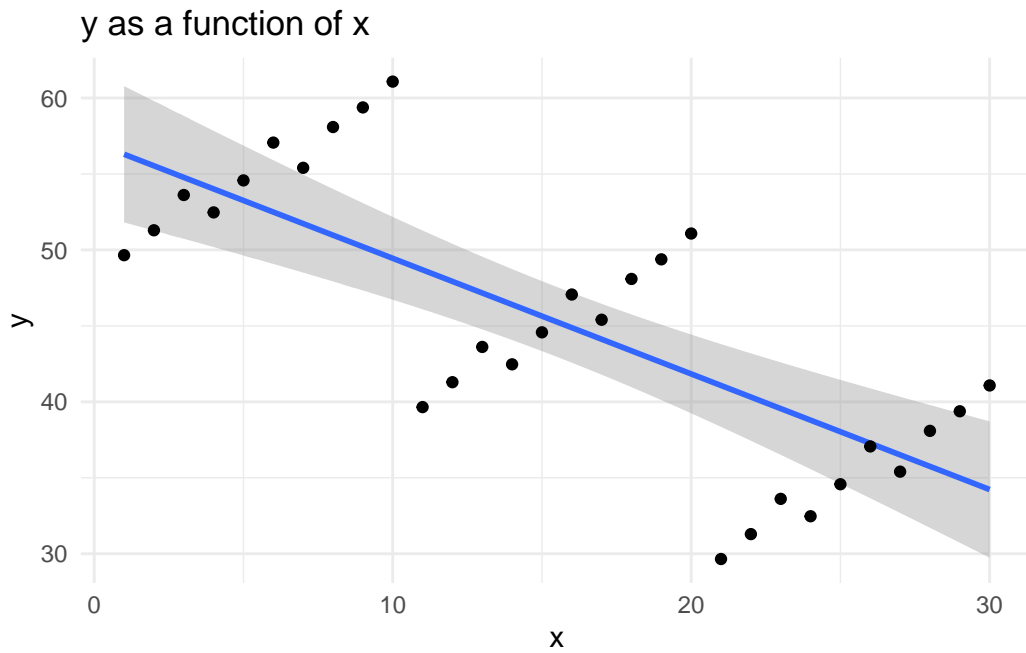
Associations between two variables can be *very different* (or even *reversed*) depending upon whether or not the analysis is “aware” of the grouped, nested, or clustered nature of the data (Nieuwenhuis 2015; Diez Roux 2003; Gelman et al. 2007). In multilevel analysis, the groups are often schools, neighborhoods,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

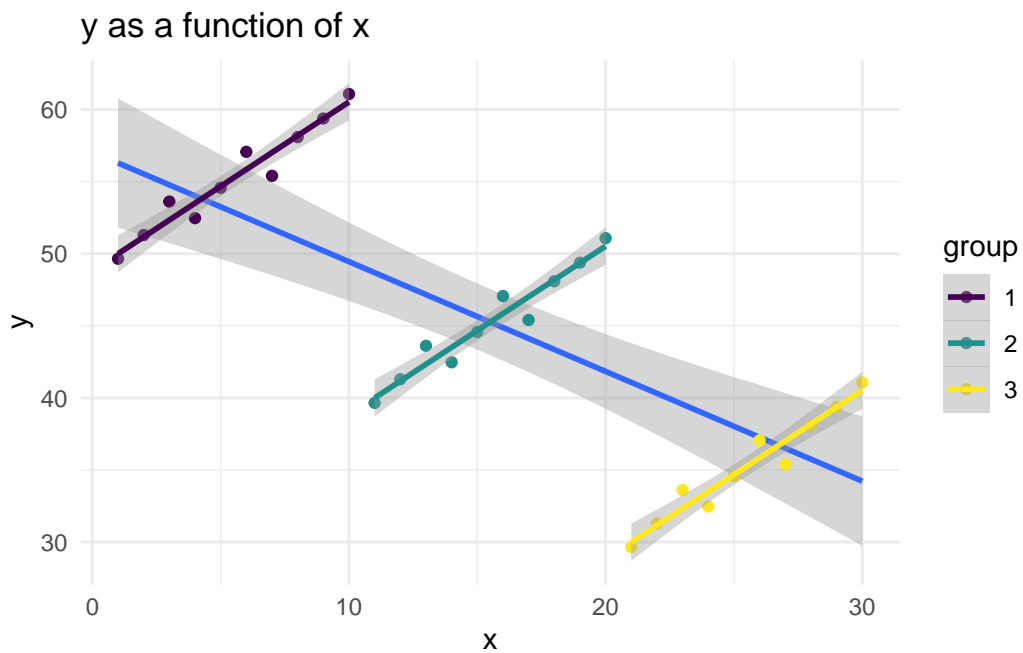
3.2.1 A “Naive” Graph

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

3.3.3 Compare The Models

```

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

3.4 A Thought Experiment

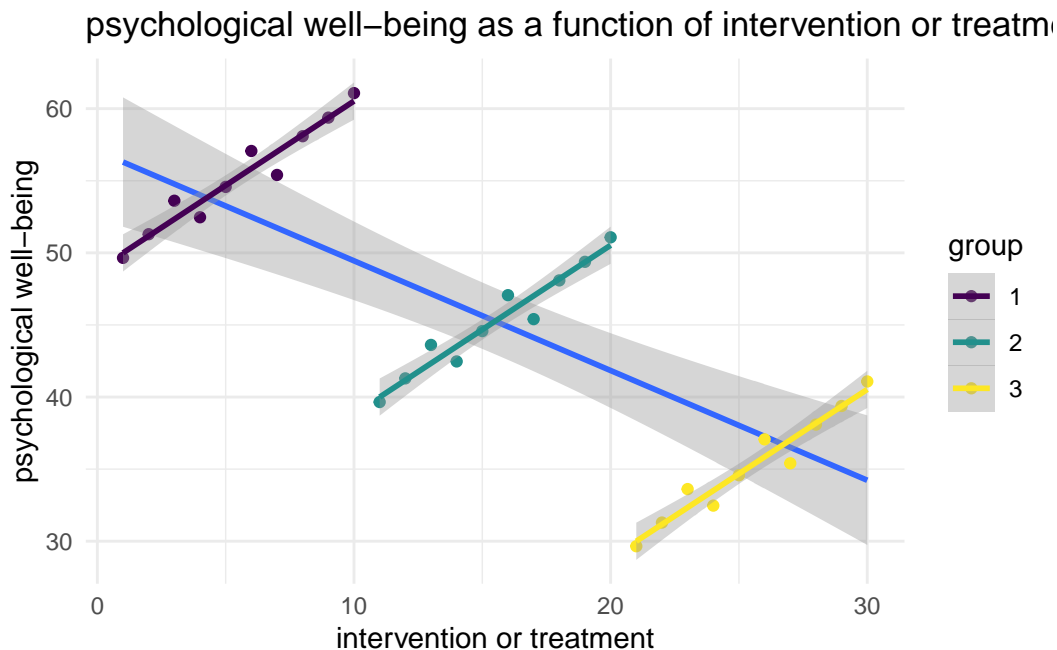
When might a situation like this arise in practice? This is surprisingly difficult to think through.

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 is 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

$$\text{outcome}_{ij} = \beta_0 + \beta_1 \text{parental warmth} + \beta_2 \text{physical punishment} + \beta_3 \text{identity}_2 + \beta_4 \text{intervention} + \beta_5 \text{HDI} + u_{0j} + u_{1j} \times \text{identity}_2$$

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
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
```

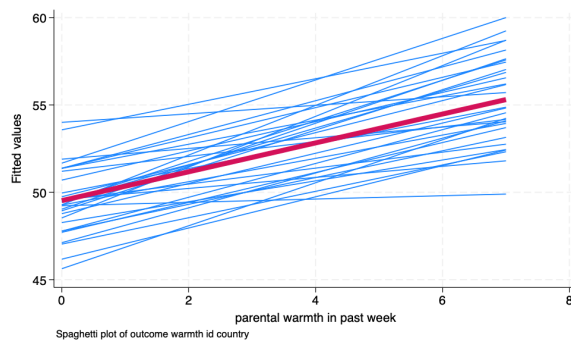


Figure 4.1: Spaghetti Plot of Outcome by Warmth by Country

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

Group variable: country

Number of obs = 3,000

Number of groups = 30

Obs per group:

min = 100

avg = 100.0

max = 100

Wald chi2(5) = 334.14

Prob > chi2 = 0.0000

Log likelihood = -9626.607

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

$$\text{outcome}_{ij} = \beta_0 + \beta_1 \text{parental warmth} + \beta_2 \text{physical punishment} + \beta_3 \text{time} +$$

$$\beta_4 \text{identity}_2 + \beta_5 \text{intervention} + \beta_5 \text{HDI} +$$

$$u_{0j} + u_{1j} \times \text{parental warmth} +$$

$$v_{0i} + v_{1i} \times t + e_{ij}$$

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
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
```

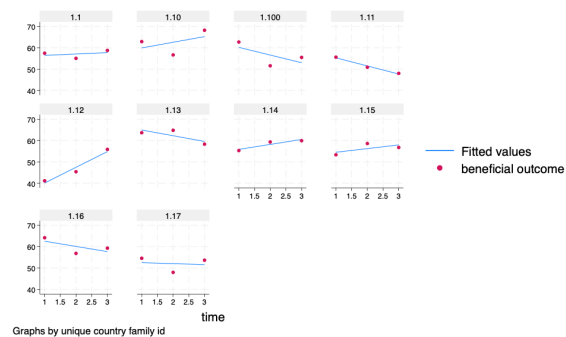


Figure 4.2: Alternate Plot of Outcome by Time by Individual; First 10 Observations

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]	
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]
---------	-------------	-----------	---	------	----------------------

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

Random-effects parameters		Estimate	Std. err.	[95% conf. interval]	
country: Independent					
	var(warmth)	.0107585	.0127845	.0010477	.1104712
	var(_cons)	3.167087	.9146767	1.798155	5.578185
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
	var(Residual)	26.02734	.4753703	25.11211	26.97592
LR test vs. linear model: chi2(4) = 1247.03			Prob > chi2 = 0.0000		

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

4.3 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 **	0.859 **
	(0.217)	(0.152)
Human Development Index	-0.003	-0.001
	(0.020)	(0.020)
time		0.944 **
		(0.066)
hypothetical identity group variable		
1		-0.128
		(0.152)
Intercept	52.000 **	50.467 **
	(1.371)	(1.338)
var(warmth)	0.023	0.011
	(0.026)	(0.013)
var(_cons)	2.964	3.167
	(0.974)	(0.915)
var(e)	34.975	26.027
	(0.910)	(0.475)
var(_cons)		8.387
		(0.472)
var(t)		0.000
		(0.000)
Number of observations	3000	9000

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

4.4 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]	
	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]	
_all: Identity					
	var(R.country)	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: $\chi^2(2) = 1260.84$ Prob > $\chi^2 = 0.0000$

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
                   (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???

References

- Bland, J M, and D G Altman. 1994. "Statistics Notes: Correlation, Regression, and Repeated Data." *BMJ* 308 (April): 896. <https://doi.org/10.1136/bmj.308.6933.896>.
- Diez Roux, Ana. 2003. "Potentialities and Limitations of Multilevel Analysis in Public Health and Epidemiology." In *Methodology and Epistemology of Multilevel Analysis: Approaches from Different Social Sciences*, edited by Daniel Courgeau, 93–119. Kluwer Academic Publishers.
- Firebaugh, Glen. 2001. "Ecological Fallacy, Statistics Of." In *International Encyclopedia of the Social & Behavioral Sciences*, edited by Neil J. Smelser and Paul B. Baltes, 4023–26. Oxford: Pergamon. <https://doi.org/10.1016/B0-08-043076-7/00765-8>.
- Gelman, Andrew, Boris Shor, Joseph Bafumi, and David Park. 2007. "Rich State, Poor State, Red State, Blue State: What's the Matter with Connecticut?" *Quarterly Journal of Political Science* 2 (November): 345–67. <https://doi.org/10.2139/ssrn.1010426>.
- Nieuwenhuis, Rense. 2015. "Association, Aggregation, and Paradoxes: On the Positive Correlation Between Fertility and Women's Employment." *Demographic Research* 32 (March). <https://www.demographic-research.org/volumes/vol32/23/>.
- Oliver, Mary, and Krista Tippett. 2015. "Mary Oliver: 'I Got Saved by the Beauty of the World.'" The On Being Project. <https://onbeing.org/programs/mary-oliver-i-got-saved-by-the-beauty-of-the-world/>.

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