

## Multilevel Cross-Classified and Multi-Membership Models

Don Hedeker

Division of Epidemiology & Biostatistics  
 Institute for Health Research and Policy  
 School of Public Health  
 University of Illinois at Chicago

email: hedeker@uic.edu  
 http://www.uic.edu/~hedeker/ml.html

1

## What are Cross-Classified Data?

- Subjects are classified by two or more types of clusters, but clusters are not hierarchical or nested within one another

*data collected on*      *who are clustered within*  
 students                      schools and neighborhoods  
 patients                        providers and hospitals

Here,

- students from the same neighborhoods go to different schools
- patients can be seen by the same provider at different hospitals

2

## Nested or Hierarchical Structure

	School 1	School 2	School 3	School 4
Neighborhood 1	x x x	x x		
Neighborhood 2			x x x x	x x x x x

students nested within schools within neighborhoods

## Crossed Structure

	School 1	School 2	School 3	School 4
Neighborhood 1	x x x x	x x	x x x	x x
Neighborhood 2	x x x		x x	x x x x

students nested within crossing of schools and neighborhoods

⇒ interest is on assessing effects of schools and neighborhoods on student outcomes

3

**Example:** Leckie, G. (2013). Cross-Classified Multilevel Models. LEMMA VLE Module 12. (<http://www.bristol.ac.uk/cmm/learning/course.html>)

Data from 3,435 children who attended 148 primary schools and 19 secondary schools in Scotland.

- VRQ: A verbal reasoning score from tests pupils took when they entered secondary school
- ATTAIN: Attainment score of pupils at age 16
- PID: Primary school identifying code
- SEXF: Pupil's gender (0 = boy and 1 = girl)
- SC: Pupil's social class scale (continuous score from low to high social class)
- SID: Secondary school identifying code
- FED: Father's education (0,1)
- CHOICE: Choice of secondary school that they attend (1=first choice, ... 4=fourth choice)
- MED: Mother's education (0,1)

4

Excel file: xwdata\_9var.xlsx

	A	B	C	D	E	F	G	H	I	J
1	VRQ	ATTAIN	PID	SEXF	SC	SID	FED	CHOICE	MED	
2	111	10	1	0	0	9	0	1	0	
3	74	2	1	1	0	9	0	1	0	
4	52	4	1	1	1	9	1	1	0	
5	98	4	1	0	0	9	0	1	0	
6	101	0	1	0	31	1	0	4	0	
7	52	5	1	1	0	9	0	1	0	
8	121	10	1	0	0	9	0	1	0	
9	90	5	1	1	0	9	1	1	1	
10	81	2	1	1	0	9	0	1	0	
11	96	4	1	1	0	9	0	1	0	
12	70	1	1	0	0	18	0	1	0	
13	76	2	1	1	0	1	0	4	0	
14	101	4	1	1	31	9	1	1	0	
15	112	9	1	0	0	9	0	1	0	
16	103	6	1	1	0	1	0	2	1	
17	96	3	1	1	31	9	0	1	0	
18	81	3	1	0	0	9	0	1	0	
19	100	6	1	0	0	9	0	1	1	
20	109	8	1	1	20	9	0	1	0	
21	107	9	1	1	0	9	1	1	0	
22	102	10	1	0	20	9	0	1	0	
23	83	6	1	1	0	1	0	1	0	
24	71	2	1	1	0	1	0	1	0	
25	105	4	1	1	0	9	0	1	0	
26	96	4	1	1	31	9	1	1	0	
27	75	2	1	1	0	9	0	1	0	
28	81	2	1	0	0	9	0	1	0	
29	91	4	1	0	0	9	1	1	0	
30	89	6	1	0	0	1	0	1	1	
31	63	4	1	1	0	1	0	2	0	

data are sorted by Primary School ID (PID), but appear unsorted in terms of Secondary School ID (SID)

5

## SAS code

```
PROC IMPORT OUT= WORK.xw DATAFILE="xwdata_9var.xlsx"
    DBMS=EXCEL; GETNAMES=YES;
```

```
RUN;
```

```
PROC MEANS DATA=xw;
```

```
RUN;
```

The MEANS Procedure

Variable	Label	N	Mean	Std Dev	Minimum	Maximum
VRQ	VRQ	3435	97.8043668	13.2929071	70.0000000	140.0000000
ATTAIN	ATTAIN	3435	5.6786026	3.0585043	1.0000000	10.0000000
PID	PID	3435	70.7377001	45.0257180	1.0000000	148.0000000
SEXF	SEXF	3435	0.4937409	0.5000336	0	1.0000000
SC	SC	3435	6.8448326	10.8876068	0	31.0000000
SID	SID	3435	10.2195051	5.5569402	1.0000000	19.0000000
FED	FED	3435	0.2754003	0.4467808	0	1.0000000
CHOICE	CHOICE	3435	1.1953421	0.6502375	1.0000000	4.0000000
MED	MED	3435	0.3420670	0.4744710	0	1.0000000

6

**PROC MIXED analyses** (using default REML estimation)

Null model

```
PROC MIXED DATA=xw COVTEST;
  CLASS pid sid ;
  MODEL attain = / S;
  RANDOM INT / SUB=pid;
  RANDOM INT / SUB=sid;
RUN;
```

Model including verbal reasoning score as a covariate

```
PROC MIXED DATA=xw COVTEST;
  CLASS pid sid;
  MODEL attain = vrq / S;
  RANDOM INT / SUB=pid;
  RANDOM INT / SUB=sid;
RUN;
```

SAS abbreviations: S=SOLUTION, SUB=SUBJECT, INT=INTERCEPT

**Alternative (simpler) syntax** (using default REML estimation)

Null model

```
PROC MIXED DATA=xw COVTEST;
  CLASS pid sid ;
  MODEL attain = / S;
  RANDOM pid sid;
RUN;
```

Model including verbal reasoning score as a covariate

```
PROC MIXED DATA=xw COVTEST;
  CLASS pid sid;
  MODEL attain = vrq / S;
  RANDOM pid sid;
RUN;
```

SAS abbreviation: S=SOLUTION

The Mixed Procedure

Model Information

Data Set	WORK.XW
Dependent Variable	ATTAIN
Covariance Structure	Variance Components
Subject Effects	PID, SID
Estimation Method	REML
Residual Variance Method	Profile
Fixed Effects SE Method	Model-Based
Degrees of Freedom Method	Containment

Class Level Information

Class	Levels	Values
PID	148	1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96 97 98 99 100 101 102

103	104	105	106	107	108	109								
110	111	112	113	114	115	116								
117	118	119	120	121	122	123								
124	125	126	127	128	129	130								
131	132	133	134	135	136	137								
138	139	140	141	142	143	144								
145	146	147	148											
SID	19	1	2	3	4	5	6	7	8	9	10	11	12	13
		14	15	16	17	18	19							

Dimensions

Covariance Parameters	3
Columns in X	1
Columns in Z Per Subject	167
Subjects	1
Max Obs Per Subject	3435

Number of Observations

Number of Observations Read	3435
Number of Observations Used	3435
Number of Observations Not Used	0

NULL MODEL WITH NO COVARIATES

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	PID	1.1300	0.2074	5.45	<.0001
Intercept	SID	0.3722	0.1743	2.14	0.0164
Residual		8.1107	0.2004	40.46	<.0001

Fit Statistics

-2 Res Log Likelihood	17150.8
AIC (smaller is better)	17156.8
AICC (smaller is better)	17156.8
BIC (smaller is better)	17150.8

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept	5.5017	0.1787	18	30.79	<.0001

MODEL WITH VERBAL REASONING AS COVARIATE

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Intercept	PID	0.2747	0.06171	4.45	<.0001
Intercept	SID	0.01436	0.02402	0.60	0.2749
Residual		4.2546	0.1050	40.54	<.0001

Fit Statistics

-2 Res Log Likelihood	14859.1
AIC (smaller is better)	14865.1
AICC (smaller is better)	14865.1
BIC (smaller is better)	14859.1

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept	-10.0257	0.2782	18	-36.04	<.0001
VRQ	0.1600	0.002766	3268	57.87	<.0001

## SPSS syntax after reading in Excel file (using default REML)

Null Model

MIXED

```
attain
/PRINT = SOLUTION TESTCOV
/RANDOM INTERCEPT | SUBJECT(pid)
/RANDOM INTERCEPT | SUBJECT(sid) .
```

Model with `vrq` as covariate

MIXED

```
attain WITH vrq
/FIXED = vrq
/PRINT = SOLUTION TESTCOV
/RANDOM INTERCEPT | SUBJECT(pid)
/RANDOM INTERCEPT | SUBJECT(sid) .
```

13

## Alternative (simpler) SPSS syntax

Null Model

MIXED

```
attain BY pid sid
/PRINT = SOLUTION TESTCOV
/RANDOM pid sid .
```

Model with `vrq` as covariate

MIXED

```
attain WITH vrq BY pid sid
/FIXED = vrq
/PRINT = SOLUTION TESTCOV
/RANDOM pid sid .
```

14

## SPSS output

Mixed Model Analysis

Model Dimension				
	Number of Levels	Covariance Structure	Number of Parameters	Subject Variables
Fixed Effects	Intercept 1		1	
	VRQ	1	1	
Random Effects	Intercept 1	Variance Components	1	PID
	Intercept 1	Variance Components	1	SID
Residual			1	
Total	4		5	

a Dependent Variable: ATTAIN.

Information Criteria

-2 Restricted Log Likelihood	14859.140
Akaike's Information Criterion (AIC)	14865.140
Hurvich and Tsai's Criterion (AICc)	14865.147
Bozdogan's Criterion (CAIC)	14886.563
Schwarz's Bayesian Criterion (BIC)	14883.563

The information criteria are displayed in smaller-is-better form.  
a Dependent Variable: ATTAIN.

15

Type III Tests of Fixed Effects

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	2179.567	11298.827	.000
VRQ	1	3356.599	13348.771	.000

a Dependent Variable: ATTAIN.

Estimates of Fixed Effects

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	-10.025716	.278189	2179.567	-36.039	.000	-10.571259	-9.480173
VRQ	1.160036	1.002766	3356.599	1.15614	.250	-.84614	1.165458

a Dependent Variable: ATTAIN.

Estimates of Covariance Parameters

Parameter	Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
					Lower Bound	Upper Bound
Residual	4.254604	1.104958	4.0536	.000	4.053785	4.465372
Intercept [subject = PID]	Variance .274656	1.061712	4.451	.000	1.76821	1.426624
Intercept [subject = SID]	Variance .014365	1.024020	1.598	.113	-.000542	1.380736

a Dependent Variable: ATTAIN.

16

## Alternative way to run cross-classified multilevel models

- SAS & SPSS perform cross-classified analyses seamlessly, but not all software can
- Some hierarchical multilevel software programs can be “tricked” into running cross-classified models if they allow
  - 3-level models
  - Equality constraints on variances of random effects
  - Zero covariances of random effects

17

## Alternative way to run cross-classified multilevel models

- Identify cluster level with fewest number of clusters; here, 148 primary schools and 19 secondary schools
- Create indicator variables for the secondary schools, **secs1-secs19** (0/1), which indicate the secondary school that a student belongs to (each student belongs to only one)
- Create a variable **cons** that equals 1 for all observations in the dataset
- At the third level, specify **cons** as the level-3 ID variable, and the 19 indicator variables **secs1-secs19** as random effects with EQUAL variance and zero covariances
- At the second level, specify the primary school ID nested within the level-3 ID (**pid(cons)** in SAS) and specify a random intercept

18

## Secondary School Indicator Variables

ID	secs1	secs2	secs3	secs4	secs5	secs6	secs7	...	secs19
sid = 1	1	0	0	0	0	0	0	...	0
sid = 2	0	1	0	0	0	0	0	...	0
sid = 3	0	0	1	0	0	0	0	...	0
sid = 4	0	0	0	1	0	0	0	...	0
sid = 5	0	0	0	0	1	0	0	...	0
sid = 6	0	0	0	0	0	1	0	...	0
sid = 7	0	0	0	0	0	0	1	...	0
...	...	...	...	...	...	...	...	...	...
...	...	...	...	...	...	...	...	...	...
sid = 19	0	0	0	0	0	0	0	...	1

⇒ 19 indicator variables for the 19 secondary schools

19

```
DATA xw2; SET xw;
cons=1;
ARRAY secschool(19) secs1-secs19;
DO i = 1 TO 19;
secschool(i)=0;
IF sid=i THEN secschool(i)=1;
END;

PROC MIXED DATA=xw2 COVTEST;
CLASS pid cons;
MODEL attain = / S;
RANDOM INT / SUB=pid(cons);
RANDOM secs1-secs19 / SUB=cons TYPE=TOEP(1);
RUN;
```

TOEP(1) is a structure in which all of the random effect variances (for the variables `secs1-secs19`) are equal and uncorrelated

20

## The Mixed Procedure

### Model Information

Data Set	WORK.ONE
Dependent Variable	ATTAIN
Covariance Structures	Variance Components, Banded Toeplitz
Subject Effects	PID(cons), cons
Estimation Method	REML
Residual Variance Method	Profile
Fixed Effects SE Method	Model-Based
Degrees of Freedom Method	Containment

### Class Level Information

Class	Levels	Values
PID	148	1 2 3 4 5 6 7 8 9 10 11 12 13
		14 15 16 17 18 19 20 21 22 23
		24 25 26 27 28 29 30 31 32 33
		34 35 36 37 38 39 40 41 42 43
		44 45 46 47 48 49 50 51 52 53
		54 55 56 57 58 59 60 61 62 63
		64 65 66 67 68 69 70 71 72 73
		74 75 76 77 78 79 80 81 82 83
		84 85 86 87 88 89 90 91 92 93

21

```
94 95 96 97 98 99 100 101 102
103 104 105 106 107 108 109
110 111 112 113 114 115 116
117 118 119 120 121 122 123
124 125 126 127 128 129 130
131 132 133 134 135 136 137
138 139 140 141 142 143 144
145 146 147 148

cons      1      1
```

### Dimensions

Covariance Parameters	3
Columns in X	1
Columns in Z Per Subject	167
Subjects	1
Max Obs Per Subject	3435

### Number of Observations

Number of Observations Read	3435
Number of Observations Used	3435
Number of Observations Not Used	0

22

### Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr >  z
Intercept	PID(cons)	1.1300	0.2074	5.45	<.0001
Variance	cons	0.3722	0.1743	2.14	0.0164
Residual		8.1107	0.2004	40.46	<.0001

### Fit Statistics

-2 Res Log Likelihood	17150.8
AIC (smaller is better)	17156.8
AICC (smaller is better)	17156.8
BIC (smaller is better)	17150.8

### Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept	5.5017	0.1787	147	30.79	<.0001

23

## Stata for cross-classified multilevel

- Stata uses this 3-level approach for cross-classified multilevel models in `xtmixed`
- It creates the school indicator variables, so you don't have to
- Uses ML estimation by default
- Stata is case-sensitive (the variable names were all upper case in this example after reading in the Excel file)

```
. import excel "C:\mixdemo\xwdata_9var.xlsx", sheet("Sheet1") firstrow
. xtmixed ATTAIN || _all: R.SID || PID:, reml
```

24



**Intraclass correlations** - model with RE interaction

Null model (no covariates), Residual var = 8.0873, Primary var = 0.9144, Secondary var = 0.3376, Interaction var = 0.2335

Students from same primary school, but different secondary schools

$$ICC = \frac{0.9144}{8.0873 + 0.9144 + 0.3376 + 0.2335} = 0.096$$

Students from same secondary school, but different primary schools

$$ICC = \frac{0.3376}{8.0873 + 0.9144 + 0.3376 + 0.2335} = 0.035$$

Students from same primary and secondary schools

$$ICC = \frac{0.9144 + 0.3376 + 0.2335}{8.0873 + 0.9144 + 0.3376 + 0.2335} = 0.155$$

**Crossed random effect models** - show me the equations!

Subject  $k$  nested within crossing of primary schools  $i$  and secondary schools  $j$

model with additive random effects

$$y_{ijk} = \mathbf{x}'_{ijk}\boldsymbol{\beta} + v_i + v_j + \epsilon_{ijk}$$

$$v_i \sim N(0, \sigma_P^2) \quad v_j \sim N(0, \sigma_S^2) \quad \epsilon_{ijk} \sim N(0, \sigma_\epsilon^2)$$

model with random effects interaction

$$y_{ijk} = \mathbf{x}'_{ijk}\boldsymbol{\beta} + v_i + v_j + v_{ij} + \epsilon_{ijk}$$

$$v_i \sim N(0, \sigma_P^2) \quad v_j \sim N(0, \sigma_S^2) \quad v_{ij} \sim N(0, \sigma_{PS}^2) \quad \epsilon_{ijk} \sim N(0, \sigma_\epsilon^2)$$

**Multi Membership Models**

- Subjects are nested within more than one cluster

*data collected on*      *who are clustered within*  
 students                more than one teacher  
 patients                more than one provider

Here,

- assume there are known weights that represent the degree of membership for a subject to the different clusters
- sum of weights equals one
- possibly do sensitivity analysis to examine how different choices for weights affect results

**Nested or Hierarchical Structure** weights

	Teacher 1	Teacher 2	Teacher 3	Teacher 4
Student 1	1	0	0	0
Student 2	0	1	0	0
Student 3	0	0	1	0
Student 4	0	0	0	1

students nested within teachers

**Multi Membership Structure** weights

	Teacher 1	Teacher 2	Teacher 3	Teacher 4
Student 1	.25	.25	.25	.25
Student 2	0	1	0	0
Student 3	.33	.33	0	.33
Student 4	0	0	.5	.5

students nested within multiple teachers

**Example:** Leckie, G. (2013). Multiple Membership Multilevel Models. LEMMA VLE Module 13. (<http://www.bristol.ac.uk/cmm/learning/course.html>)

Simulated data from 1,000 patients who were treated in all by 25 nurses: 400 treated by only one nurse, 300 treated by two nurses, 200 by three nurses, and 100 by four nurses.

- **patient:** Patient ID
- **satis:** Patient post-op satisfaction (mean=0, std=1)
- **assess:** Patient pre-op assessment (mean=0, std=1); higher scores are better
- **nurses:** Number of nurses seen by the patient (1 to 4)
- **n1st:** Nurse ID for patient's 1st nurse
- **n2nd:** Nurse ID for patient's 2nd nurse
- **n3rd:** Nurse ID for patient's 3rd nurse
- **n4th:** Nurse ID for patient's 4th nurse
- **p1:** Proportion of time with nurse 1
- **p2:** Proportion of time with nurse 2
- **:** **:**
- **p25:** Proportion of time with nurse 25
- **h1:** Job Happiness score for nurse 1
- **h2:** Job Happiness score for nurse 2
- **:** **:**
- **h25:** Job Happiness score for nurse 25

Excel file: nursedat2.xlsx - some subjects seen by only 1 nurse

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	patient	satis	assess	nurses	n1st	n2nd	n3rd	n4th	p1	p2	p3	p4	p5	p6
2	1	2.06536	0.779168	1	24	0	0	0	0	0	0	0	0	0
3	2	-0.12707	0.675926	1	10	0	0	0	0	0	0	0	0	0
4	3	-0.33507	-2.2283	1	15	0	0	0	0	0	0	0	0	0
5	4	-0.89718	0.627285	1	16	0	0	0	0	0	0	0	0	0
6	5	1.16036	-0.39504	1	5	0	0	0	0	0	0	0	0	1
7	6	-0.19741	0.218889	1	15	0	0	0	0	0	0	0	0	0
8	7	1.679402	0.93098	1	4	0	0	0	0	0	0	0	1	0
9	8	1.333309	1.040585	1	25	0	0	0	0	0	0	0	0	0
10	9	-1.16201	-0.63619	1	23	0	0	0	0	0	0	0	0	0
11	10	-0.76571	-0.83759	1	5	0	0	0	0	0	0	0	0	1
12	11	0.606306	-0.45204	1	1	0	0	0	1	0	0	0	0	0
13	12	-1.12415	-1.09006	1	12	0	0	0	0	0	0	0	0	0
14	13	1.334182	-1.77805	1	18	0	0	0	0	0	0	0	0	0
15	14	0.292212	0.05709	1	15	0	0	0	0	0	0	0	0	0
16	15	-0.63227	0.116375	1	10	0	0	0	0	0	0	0	0	0
17	16	0.238056	0.787561	1	22	0	0	0	0	0	0	0	0	0
18	17	-0.04273	-0.34001	1	9	0	0	0	0	0	0	0	0	0
19	18	-0.42192	-0.49124	1	25	0	0	0	0	0	0	0	0	0
20	19	-0.47706	0.5773	1	19	0	0	0	0	0	0	0	0	0
21	20	0.95667	0.53948	1	14	0	0	0	0	0	0	0	0	0
22	21	-2.4744	-0.92708	1	8	0	0	0	0	0	0	0	0	0
23	22	-1.06177	-0.42448	1	2	0	0	0	0	0	1	0	0	0
24	23	-1.1788	0.163655	1	21	0	0	0	0	0	0	0	0	0
25	24	0.049997	-0.19239	1	3	0	0	0	0	0	0	1	0	0

value of 1 for only one of the variables p1 to p25 (all others equal 0)



### SAS syntax for multi-membership multilevel models

```

PROC MIXED DATA=ndats COVTEST METHOD=ML;
  CLASS cons;
  MODEL satis = / SOLUTION;
  RANDOM p1-p25 / SUBJECT=cons TYPE=TOEPLITZ(1);

PROC MIXED DATA=ndats COVTEST METHOD=ML;
  CLASS cons;
  MODEL satis = assess / SOLUTION;
  RANDOM p1-p25 / SUBJECT=cons TYPE=TOEPLITZ(1);

PROC MIXED DATA=ndats COVTEST METHOD=ML;
  CLASS cons;
  MODEL satis = assess happiness / SOLUTION;
  RANDOM p1-p25 / SUBJECT=cons TYPE=TOEPLITZ(1);
RUN;

```

### NULL MODEL

The Mixed Procedure

Model Information

Data Set	WORK.NDATS
Dependent Variable	satis
Covariance Structure	Banded Toeplitz
Subject Effect	cons
Estimation Method	ML
Residual Variance Method	Profile
Fixed Effects SE Method	Model-Based
Degrees of Freedom Method	Containment

Dimensions

Covariance Parameters	2
Columns in X	1
Columns in Z Per Subject	25
Subjects	1
Max Obs Per Subject	1000

Number of Observations

Number of Observations Read	1000
Number of Observations Used	1000
Number of Observations Not Used	0

#### Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Variance	cons	0.2323	0.07503	3.10	0.0010
Residual		0.8145	0.03689	22.08	<.0001

#### Fit Statistics

-2 Log Likelihood	2686.0
AIC (smaller is better)	2692.0
AICC (smaller is better)	2692.0
BIC (smaller is better)	2686.0

#### Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept	-0.02653	0.1006	975	-0.26	0.7921

### WITH PATIENT COVARIATE ASSESS

#### Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Variance	cons	0.2550	0.07893	3.23	0.0006
Residual		0.5875	0.02661	22.08	<.0001

#### Fit Statistics

-2 Log Likelihood	2368.8
AIC (smaller is better)	2376.8
AICC (smaller is better)	2376.9
BIC (smaller is better)	2368.8

#### Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept	-0.03317	0.1039	974	-0.32	0.7497
assess	0.4904	0.02531	974	19.37	<.0001

### WITH NURSE COVARIATE JOB HAPPINESS

#### Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr > Z
Variance	cons	0.1689	0.05413	3.12	0.0009
Residual		0.5874	0.02660	22.08	<.0001

#### Fit Statistics

-2 Log Likelihood	2359.4
AIC (smaller is better)	2369.4
AICC (smaller is better)	2369.5
BIC (smaller is better)	2359.4

#### Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept	-0.03135	0.08579	974	-0.37	0.7148
assess	0.4912	0.02530	974	19.42	<.0001
happiness	0.2936	0.08710	974	3.37	0.0008

### SPSS syntax

```

GET FILE='C:\MixDemo\nursedat2.sav'.

COMPUTE cons=1.

COMPUTE happy = 0.
VECTOR ps = p1 TO p25 / hs = h1 TO h25.
LOOP i = 1 TO 25.
+ COMPUTE happy = happy + ps(i) * hs(i).
END LOOP.

MIXED
  satis WITH assess happy p1 TO p25
  /FIXED = assess happy
  /METHOD = ML
  /PRINT = SOLUTION TESTCOV
  /RANDOM p1 p2 p3 p4 p5 p6 p7 p8 p9 p10 p11 p12
  p13 p14 p15 p16 p17 p18 p19 p20 p21 p22
  p23 p24 p25 | SUBJECT(cons) COVTYPE(ID).

```



SPSS output - Dependent Variable: satis

Model Dimension				
	Number of Levels	Covariance Structure	Number of Parameters	Subject Variables
Fixed Effects	Intercept	1	1	
	assess	1	1	
	happy	1	1	
Random Effects	p1 + p2 + ... + p25	25	Identity	1
Residual				cons
Total				15

As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

Information Criteria	
-2 Log Likelihood	2359.406
Akaike's Information Criterion (AIC)	2369.406
Hurvich and Tsai's Criterion (AICC)	2369.467
Bozdogan's Criterion (CAIC)	2398.945
Schwarz's Bayesian Criterion (BIC)	2393.945

The information criteria are displayed in smaller-is-better form.

Type III Tests of Fixed Effects				
Source	Numerator df	Denominator df	F	Sig.
Intercept	1	23.106	1.134	.718
assess	1	981.019	1377.001	.000
happy	1	25.414	11.362	.002

Estimates of Fixed Effects						
Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval
						Lower Bound Upper Bound
Intercept	-.031354	.085791	23.106	-.365	.718	-.208781 .146073
assess	.491215	.025299	981.019	19.4171	.000	.441569 .540862
happy	.293575	.087095	25.414	3.371	.002	.114348 .472803

Estimates of Covariance Parameters						
Parameter	Estimate	Std. Error	Wald Z	Sig.	95% Confidence Interval	
						Lower Bound Upper Bound
Residual	.587433	.026604	22.081	.000	.537538 .641959	
p1 + p2 + ... + p25 [subject = cons] Variance	1.168940	1.054127	3.121	.002	.090160 .316558	

Stata syntax

```
. import excel "C:\mixdemo\nursedat2.xlsx", sheet("Sheet1") firstrow
. forvalues j = 1/25 {
    2. generate p'j'Xh'j' = p'j'*h'j'
    3. }
. egen happiness = rsum(p1Xh1-p25Xh25)
. xtmixed satis assess happiness || _all: p1-p25, nocons covariance(identity)
    mle variance
```

```
Performing EM optimization:
Performing gradient-based optimization:
Iteration 0: log likelihood = -1179.7032
Iteration 1: log likelihood = -1179.7032
Computing standard errors:
Mixed-effects ML regression      Number of obs   =   1000
Group variable: _all             Number of groups =    1
                                   Obs per group: min =   1000
                                                                 avg = 1000.0
                                                                 max = 1000
                                   Wald chi2(2)     =   386.22
Log likelihood = -1179.7032      Prob > chi2     =   0.0000
```

satis	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
assess	.4912155	.0252988	19.42	0.000	.4416306 .5408003
happiness	.2935754	.0870952	3.37	0.001	.1228719 .4642789
_cons	-.0313536	.0857909	-0.37	0.715	-.1995006 .1367934

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]
_all: Identity			
var(p1..p25)(1)	.1689407	.0541275	.0901602 .3165583
var(Residual)	.5874327	.0266036	.5375377 .6419591

LR test vs. linear regression: chibar2(01) = 121.39 Prob >= chibar2 = 0.0000  
 (1) p1 p2 p3 p4 p5 p6 p7 p8 p9 p10 p11 p12 p13 p14 p15 p16 p17 p18 p19 p20 p21 p22 p23 p24 p25

Multi-Membership Multilevel Model

Patient  $j$  nested within nurse(s)  $i$  ( $i = 1, \dots, N$ )

Model with only patient covariates

$$y_j = \mathbf{x}'_j \boldsymbol{\beta} + \sum_{i=1}^N p_{ij} v_i + \epsilon_{ij}$$

$$v_i \sim N(0, \sigma_v^2) \quad \epsilon_{ij} \sim N(0, \sigma_\epsilon^2) \quad \sum_{i=1}^N p_{ij} = 1 \forall j$$

Model with a nurse covariate  $x_i$

$$y_j = \mathbf{x}'_j \boldsymbol{\beta} + \left( \sum_{i=1}^N p_{ij} x_i \right) \beta_{x_i} + \sum_{i=1}^N p_{ij} v_i + \epsilon_{ij}$$

Model with  $N \times p$  nurse covariate matrix  $\mathbf{X}$  and  $N \times 1$  nurse weight vector  $\mathbf{p}_j$  for patient  $j$

$$y_j = \mathbf{x}'_j \boldsymbol{\beta} + \mathbf{p}'_j \mathbf{X} \boldsymbol{\beta}_X + \mathbf{p}'_j \mathbf{v} + \epsilon_{ij}$$

### Intraclass correlation - Leckie (2013)

- pairwise correlation of patients DV within a given cluster (conditional on covariates)
- ICCs vary depending on patient weights

Correlation for two patients cared for by the same nurse for the entire hospital stay (null model: nurse var = .2323, error var = .8145)

$$ICC = \frac{\sigma_v^2}{\sigma_v^2 + \sigma_\epsilon^2} = \frac{.2323}{.2323 + .8145} = 0.222$$

Correlation for two patients  $j$  and  $j'$  cared for by the same nurse, say nurse 2, for half their stays ( $p_{2j} = p_{2j'} = .5$ ), but different nurses for the rest of their stays, say  $p_{5j} = .5$  and  $p_{8j'} = .5$

$$ICC = \frac{p_{2j}p_{2j'}\sigma_v^2}{\sqrt{(p_{2j}^2 + p_{5j}^2)\sigma_v^2 + \sigma_\epsilon^2}\sqrt{(p_{2j'}^2 + p_{8j'}^2)\sigma_v^2 + \sigma_\epsilon^2}} = \frac{.25 \times .2323}{.5 \times .2323 + .8145} = 0.062$$

55

### Summary

- Cross-classified models are useful when subjects are classified in two or more cluster types, but cluster types are not nested within each other; more than 1 level of (crossed) clustering
  - Students within primary and secondary schools
- Multi-membership models apply when subjects are clustered within potentially multiple clusters (at the same level)
  - Patients seen by multiple nurses
- Can be computationally demanding because of specification of many random effects; SAS HPMIXED is potentially useful for this

56