

SOCY7708: Hierarchical Linear Modeling
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Class notes: Cross-Nested Models

In this unit, we will look at cross-nested (or cross-classified or cross-effects) models. These are models where lower-level units simultaneously belong to two higher-level units—these could be two units of the same type (for example, two neighborhoods where a person lived at different periods of time or two schools that they attended) or two units of different type (e.g., neighborhoods and schools).

For our first example, we will use data from a study of neighborhood and school contribution to educational attainment in Scotland (as used in the *Hierarchical Linear Models* textbook by Raudenbush and Bryk, 2002). We will use attain.dta file from the website; it contains data on individuals nested in neighborhoods ($N=542$) and schools ($N=17$) in such a way that people from the same neighborhood can be attending different schools, so three-level model is not possible. Here, we have to have two IDs, one for each higher-level unit – SCHID and NEIGHID.

The variables available on level 1 are:

- ATTAIN, a measure of educational attainment
- P7VRQ, denoting primary 7 verbal reasoning quotient
- P7READ, denoting primary 7 reading test scores
- DADOCC, indicating the father's occupation scaled on the Hope-Goldthorpe scale in conjunction with the Registrar General's social-class index
- DADUNEMP, an indicator for father's unemployment status (1 if unemployed, 0 otherwise)
- DADED, an indicator for father's educational level (1 if schooling past the age of 15, 0 otherwise)
- MOMED, an indicator for mother's educational level (1 if schooling past the age of 15, 0 otherwise)
- MALE, an indicator for student gender (1 if male, 0 if female)

A variable at neighborhood level is:

- DEPRIVE, an index of social deprivation for the local community where the respondent lived

We do not have any variables on school level but we could aggregate level 1 variables to create such aggregated measures.

First, how many different neighborhoods do people in specific schools come from, and how many different schools do people in a given neighborhood attend? Let's count:

```
. use attain.dta, clear  
. sort neighid schid  
. bysort neighid schid: gen num=_n
```

```

. gen count=(num==1)

. bysort neighid: egen schoolsinneigh=total(count)

. egen neightag=tag(neighid)

. tab schoolsinneigh if neightag==1

schoolsine |
    igh |      Freq.      Percent      Cum.
-----+-----
    1 |      309      58.97      58.97
    2 |      176      33.59      92.56
    3 |       33       6.30      98.85
    4 |        6       1.15     100.00
-----+-----
    Total |      524      100.00

. bysort schid neighid: gen n=_n

. gen countn=(n==1)

. bysort schid: egen neightperschool=total(countn)

. egen schtag=tag(schid)

. tab neightperschool if schtag==1

neightpersch |
    ool |      Freq.      Percent      Cum.
-----+-----
    11 |       1       5.88       5.88
    29 |       1       5.88      11.76
    31 |       1       5.88      17.65
    37 |       1       5.88      23.53
    40 |       1       5.88      29.41
    41 |       1       5.88      35.29
    42 |       2      11.76      47.06
    43 |       1       5.88      52.94
    46 |       1       5.88      58.82
    47 |       1       5.88      64.71
    52 |       2      11.76      76.47
    53 |       1       5.88      82.35
    61 |       1       5.88      88.24
    65 |       1       5.88      94.12
    92 |       1       5.88     100.00
-----+-----
    Total |      17      100.00

```

To estimate a cross-nested model in Stata, we use a work-around solution creating a “fake” three level model, wherein individuals are nested in neighborhoods which are then nested in an entire set but with random effects for dummy variables for schools which have their variances constrained to the same number and covariances constrained to zero. That effectively gives us two variances, one for each level. Therefore, for schools, we use specification `_all: R.schid`.

```

. mixed attain || _all: R.schid || neighid:

Mixed-effects ML regression                               Number of obs      =      2,310
-----+
|      No. of          Observations per Group

```

Group	Variable	Groups	Minimum	Average	Maximum
_all		1	2,310	2,310.0	2,310
neighid		524	1	4.4	16

Wald chi2(0) = .
 Log likelihood = -3178.3557
 Prob > chi2 = .

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_cons	.0753532	.0722216	1.04	0.297	-.0661987 .216905

Random-effects Parameters | Estimate Std. Err. [95% Conf. Interval]

	Estimate	Std. Err.	[95% Conf. Interval]
_all: Identity			
var(R.schid)	.075445	.0316491	.0331553 .1716755
neighid: Identity			
var(_cons)	.1412201	.0218651	.104257 .191288
var(Residual)	.7990182	.0263652	.7489788 .8524007

LR test vs. linear model: chi2(2) = 207.44
 Prob > chi2 = 0.0000

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

We could use these variance components to calculate the percentage of variance due to each level of nesting; alternatively, to get a rough sense, I will estimate two two-level models and get their ICC:

```
. mixed attain || neighid:
```

Mixed-effects ML regression
 Group variable: neighid
 Number of obs = 2,310
 Number of groups = 524

Obs per group:
 min = 1
 avg = 4.4
 max = 16

Wald chi2(0) = .
 Log likelihood = -3207.9847
 Prob > chi2 = .

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_cons	.0820248	.0284356	2.88	0.004	.0262921 .1377575

Random-effects Parameters | Estimate Std. Err. [95% Conf. Interval]

	Estimate	Std. Err.	[95% Conf. Interval]
neighid: Identity			
var(_cons)	.2015382	.0257242	.1569317 .2588237
var(Residual)	.8043706	.0265743	.7539364 .8581785

LR test vs. linear model: chibar2(01) = 148.18
 Prob >= chibar2 = 0.0000

```
. estat icc
```

Intraclass correlation

```

-----+
          Level |      ICC     Std. Err.    [95% Conf. Interval]
-----+
          neighid |  .2003543  .0223053   .1601713  .2476457
-----+
. mixed attain || schid:

Mixed-effects ML regression                         Number of obs = 2,310
Group variable: schid                           Number of groups = 17

Obs per group:
                min = 22
                avg = 135.9
                max = 286

Wald chi2(0) = .
Prob > chi2 = .

Log likelihood = -3221.0818
-----+
          attain |     Coef.   Std. Err.      z   P>|z|    [95% Conf. Interval]
-----+
          _cons |  .0822691  .0756785   1.09  0.277  -.0660581  .2305963
-----+
Random-effects Parameters |   Estimate   Std. Err.    [95% Conf. Interval]
-----+
schid: Identity |
          var(_cons) |  .0887424  .0348585   .0410937  .1916405
-----+
          var(Residual) |  .9344115  .0276055   .8818425  .9901144
-----+
LR test vs. linear model: chibar2(01) = 121.98      Prob >= chibar2 = 0.0000

. estat icc

Intraclass correlation
-----+
          Level |      ICC     Std. Err.    [95% Conf. Interval]
-----+
          schid |  .0867342  .0312367   .0420038  .1706151
-----+

```

Let's compare the model where school effects are estimated as constrained random effects of dummy indicators with the one where neighborhood effects are estimated that way. Typically, we select which variable we would like to specify as clusters within `_all` depending on which one has fewer clusters because that will estimate faster. But also, if we want to have random slopes by cluster, we cannot specify that clustering variable within `_all` (we will see that below).

```

. mixed attain || _all: R.schid || neighid:

Mixed-effects ML regression                         Number of obs = 2,310
-----+
          Group Variable |   No. of Groups   Observations per Group
                                Minimum     Average     Maximum
-----+
          _all |           1        2,310    2,310.0    2,310
          neighid |        524            1         4.4       16
-----+
Wald chi2(0) = .

```

```

Log likelihood = -3178.3557                               Prob > chi2      =
-----
          attain |     Coef.    Std. Err.      z     P>|z|      [95% Conf. Interval]
-----+
          _cons |  .0753532  .0722216   1.04    0.297    -.0661987  .216905
-----+

```



```

Random-effects Parameters |   Estimate   Std. Err.      [95% Conf. Interval]
-----+
_all: Identity          |
    var(R.schid) |  .075445   .0316491   .0331553  .1716755
-----+
neighid: Identity       |
    var(_cons) |  .1412201  .0218651   .104257   .191288
-----+
    var(Residual) |  .7990182  .0263652   .7489788  .8524007
-----+

```



```

LR test vs. linear model: chi2(2) = 207.44                  Prob > chi2 = 0.0000

```

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

```
. mixed attain || _all: R.neighid || schid:
```

```

Mixed-effects ML regression                               Number of obs      =      2,310
-----
          |   No. of      Observations per Group
Group Variable |   Groups   Minimum   Average   Maximum
-----+
          _all |        1    2,310    2,310.0    2,310
          schid |       17     22     135.9     286
-----+

```

```

Wald chi2(0)      =      .
Log likelihood = -3178.3557                           Prob > chi2      =
-----
          attain |     Coef.    Std. Err.      z     P>|z|      [95% Conf. Interval]
-----+
          _cons |  .0753532  .0722216   1.04    0.297    -.0661987  .216905
-----+

```



```

Random-effects Parameters |   Estimate   Std. Err.      [95% Conf. Interval]
-----+
_all: Identity          |
    var(R.neighid) |  .1412201  .0218651   .104257   .191288
-----+
schid: Identity         |
    var(_cons) |  .075445   .0316491   .0331553  .1716755
-----+
    var(Residual) |  .7990182  .0263652   .7489788  .8524007
-----+

```



```

LR test vs. linear model: chi2(2) = 207.44                  Prob > chi2 = 0.0000

```

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

Let's add level 1 predictors to our model:

```
. mixed attain p7vrq p7read dadocc dadunemp daded momed male || _all: R.schid ||
neighid:
```

```

Mixed-effects ML regression                               Number of obs      =      2,310
-----
          |   No. of      Observations per Group
-----+

```

Group	Variable	Groups	Minimum	Average	Maximum			
	_all	1	2,310	2,310.0	2,310			
	neighid	524	1	4.4	16			
<hr/>								
Log likelihood = -2402.2937								
Wald chi2(7) = 2415.24								
Prob > chi2 = 0.0000								
attain	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]			
p7vrq	.028283	.0022758	12.40	0.000	.0237696 .0326904			
p7read	.0269051	.0017587	15.30	0.000	.0234581 .0303521			
dadocc	.0091773	.0013584	6.76	0.000	.0065148 .0118398			
dadunemp	-.1464694	.0469	-3.12	0.002	-.2383916 -.0545471			
daded	.1487033	.0410774	3.62	0.000	.068193 .2292136			
momed	.0649316	.0376491	1.72	0.085	-.0088593 .1387225			
male	-.0540241	.0285779	-1.89	0.059	-.1100358 .0019875			
_cons	.0805349	.0272663	2.95	0.003	.027094 .1339758			
<hr/>								
Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]					
all: Identity								
var(R.schid)	.0030572	.0024765	.0006249 .0149566					
neighid: Identity								
var(_cons)	.0122113	.0072414	.0038194 .0390422					
var(Residual)	.4551568	.0148446	.4269722 .4852018					
<hr/>								
LR test vs. linear model: chi2(2) = 7.40								
Prob > chi2 = 0.0248								

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

We can compare the variance components to the previous model; we see that much of school and neighborhood level variance has been explained. Let's explore random slopes for level 1 predictors:

```
. mixed attain p7vrq p7read dadocc dadunemp daded momed male || _all: R.schid ||
neighid: p7vrq p7read dadocc dadunemp daded momed male
```

Mixed-effects ML regression	Number of obs				
<hr/>					
Log likelihood = -2400.0715					
<hr/>					
Group Variable	No. of Groups	Observations per Group	Minimum	Average	Maximum
_all	1	2,310	2,310.0	2,310	
neighid	524	1	4.4	16	
<hr/>					
Wald chi2(7) = 2344.98					
Prob > chi2 = 0.0000					
attain	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
p7vrq	.0282256	.0022713	12.43	0.000	.023774 .0326772
p7read	.0268055	.0017535	15.29	0.000	.0233688 .0302422
dadocc	.0089163	.0013768	6.48	0.000	.0062177 .0116149
dadunemp	-.1460657	.0476964	-3.06	0.002	-.239549 -.0525824
daded	.1524186	.0421274	3.62	0.000	.0698505 .2349868
momed	.0620998	.0393571	1.58	0.115	-.0150386 .1392382

male	-.05107	.0289833	-1.76	0.078	-.1078761	.0057362
_cons	.0773173	.0264105	2.93	0.003	.0255536	.129081
<hr/>						
Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]			
<hr/>						
_all: Identity						
var(R.schid)	.0026377
<hr/>						
neighid: Independent						
var(p7vrq)	1.26e-22
var(p7read)	2.00e-22
var(dadocc)	8.74e-06
var(dadunemp)	.0176157
var(daded)	.0168711
var(momed)	.0378511
var(male)	.0115381
var(_cons)	.0086013
<hr/>						
var(Residual)	.4379232
<hr/>						

LR test vs. linear model: chi2(9) = 11.84 Prob > chi2 = 0.2224

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

. mixed attain p7vrq p7read dadocc dadunemp daded momed male || _all: R.schid ||
neighid: dadocc dadunemp daded momed male

Mixed-effects ML regression	Number of obs	=	2,310
<hr/>			
Group Variable	No. of Groups	Observations per Group	
		Minimum	Average
_all	1	2,310	2,310.0
neighid	524	1	4.4
<hr/>			

Log likelihood = -2400.0715 Wald chi2(7) = 2344.97
Prob > chi2 = 0.0000

attain	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
<hr/>					
p7vrq	.0282256	.0022713	12.43	0.000	.023774 .0326771
p7read	.0268055	.0017535	15.29	0.000	.0233688 .0302422
dadocc	.0089163	.0013769	6.48	0.000	.0062177 .0116149
dadunemp	-.1460655	.0476964	-3.06	0.002	-.2395488 -.0525823
daded	.1524182	.0421275	3.62	0.000	.0698499 .2349866
momed	.0621001	.0393571	1.58	0.115	-.0150384 .1392385
male	-.0510699	.0289832	-1.76	0.078	-.1078759 .0057362
_cons	.077317	.0264105	2.93	0.003	.0255533 .1290807
<hr/>					

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
<hr/>				
_all: Identity				
var(R.schid)	.0026377	.0023525	.0004592	.0151495
<hr/>				
neighid: Independent				
var(dadocc)	8.74e-06	.000039	1.41e-09	.054177
var(dadunemp)	.0176157	.0348477	.0003648	.8506678
var(daded)	.0168731	.0286061	.0006083	.4680537
var(momed)	.0378509	.02812	.0088248	.1623482
var(male)	.0115365	.0158341	.000783	.169969

```

var(_cons) |   .008602    .007611    .0015186    .0487237
-----+-----+-----+-----+
var(Residual) |   .4379224   .0169907   .405856   .4725225
-----+-----+
LR test vs. linear model: chi2(7) = 11.84                         Prob > chi2 = 0.1059

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

. mixed attain p7vrq p7read dadocc dadunemp daded momed male || _all: R.schid ||
neighid: dadunemp daded momed male

Mixed-effects ML regression                                         Number of obs      =      2,310
-----+
|          No. of          Observations per Group
Group Variable | Groups     Minimum     Average     Maximum
-----+-----+-----+-----+
_all |           1       2,310     2,310.0     2,310
neighid |        524          1         4.4         16
-----+-----+-----+-----+-----+-----+-----+-----+
Wald chi2(7)      =      2352.90
Log likelihood = -2400.0975                                     Prob > chi2 = 0.0000
-----+
attain |      Coef.    Std. Err.      z     P>|z|    [95% Conf. Interval]
-----+-----+-----+-----+-----+-----+-----+
p7vrq |   .028238   .0022708    12.44    0.000    .0237873   .0326887
p7read |   .0267925  .0017535    15.28    0.000    .0233557   .0302294
dadocc |   .0089268  .0013663     6.53    0.000    .006249   .0116047
dadunemp |  -.1456732  .0477354    -3.05    0.002   -.2392329  -.0521135
daded |   .1526091  .0421365     3.62    0.000    .0700231   .2351951
momed |   .0619572  .0393694     1.57    0.116   -.0152055   .1391198
male |  -.0513633  .0289873    -1.77    0.076   -.1081773   .0054507
_cons |   .0777818  .0264007     2.95    0.003    .0260375   .1295261
-----+-----+-----+-----+-----+-----+-----+-----+
Random-effects Parameters |      Estimate     Std. Err.    [95% Conf. Interval]
-----+-----+-----+-----+
_all: Identity |
var(R.schid) |   .0026311   .0023503   .0004569   .0151525
-----+-----+
neighid: Independent |
var(dadunemp) |   .0181434   .0348393   .0004209   .7820113
var(daded) |   .0173458   .0284977   .000693   .4341538
var(momed) |   .0383208   .0280697   .0091187   .1610401
var(male) |   .0116597   .015826   .0008153   .1667422
var(_cons) |   .0087237   .0075905   .0015851   .0480106
-----+-----+
var(Residual) |   .4386847   .0166627   .4072124   .4725893
-----+-----+
LR test vs. linear model: chi2(6) = 11.79                         Prob > chi2 = 0.0668

```

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

We could do significance testing to see which slopes should be allowed to vary. We could also examine random slopes by school instead of neighborhoods – for that, we would reestimate it with `_all: R.neigh`. But for the sake of time, let's look at adding predictors on neighborhood and school level. Let's aggregate:

```

. for var p7vrq - male: bysort neighid: egen X_nei=mean(X)
-> bysort neighid: egen p7vrq_nei=mean(p7vrq)

```

```

-> bysort neighid: egen p7read_nei=mean(p7read)
-> bysort neighid: egen dadocc_nei=mean(dadocc)
-> bysort neighid: egen dadunemp_nei=mean(dadunemp)
-> bysort neighid: egen daded_nei=mean(daded)
-> bysort neighid: egen momed_nei=mean(momed)
-> bysort neighid: egen male_nei=mean(male)

. for var p7vrq - male: bysort schid: egen X_sch=mean(X)

-> bysort schid: egen p7vrq_sch=mean(p7vrq)
-> bysort schid: egen p7read_sch=mean(p7read)
-> bysort schid: egen dadocc_sch=mean(dadocc)
-> bysort schid: egen dadunemp_sch=mean(dadunemp)
-> bysort schid: egen daded_sch=mean(daded)
-> bysort schid: egen momed_sch=mean(momed)
-> bysort schid: egen male_sch=mean(male)

. mixed attain p7vrq p7read dadocc dadunemp daded momed male deprive p7vrq_nei
> p7read_nei dadocc_nei dadunemp_nei daded_nei momed_nei male_nei || _all: R
> .schid || neighid: dadunemp daded momed male

```

Mixed-effects ML regression Number of obs = 2,310

Group Variable	No. of Groups	Observations per Group		
		Minimum	Average	Maximum
_all	1	2,310	2,310.0	2,310
neighid	524	1	4.4	16

Wald chi2(15) = 2504.39
 Log likelihood = -2373.3516 Prob > chi2 = 0.0000

attain	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
p7vrq	.0260616	.0025478	10.23	0.000	.021068 .0310552
p7read	.0262333	.0020008	13.11	0.000	.0223118 .0301549
dadocc	.0060222	.0015824	3.81	0.000	.0029208 .0091236
dadunemp	-.1094969	.0535435	-2.05	0.041	-.2144402 -.0045537
daded	.1078427	.0468705	2.30	0.021	.0159782 .1997073
momed	.0585125	.0440004	1.33	0.184	-.0277268 .1447517
male	-.057422	.0320584	-1.79	0.073	-.1202553 .0054114
deprive	-.1068588	.0289249	-3.69	0.000	-.1635506 -.0501669
p7vrq_nei	.0076765	.0054024	1.42	0.155	-.002912 .0182651
p7read_nei	-.0022259	.0040418	-0.55	0.582	-.0101477 .0056959
dadocc_nei	.006009	.0031406	1.91	0.056	-.0001465 .0121644
dadunemp_nei	-.0782511	.109447	-0.71	0.475	-.2927633 .1362611
daded_nei	.1801198	.0970098	1.86	0.063	-.0100158 .3702555
momed_nei	-.0423525	.0895377	-0.47	0.636	-.2178431 .1331381
male_nei	.0428611	.0705518	0.61	0.544	-.0954179 .18114
_cons	.0505329	.0439281	1.15	0.250	-.0355646 .1366304

Random-effects Parameters		Estimate	Std. Err.	[95% Conf. Interval]	
<hr/>					
<u>_all:</u> Identity					
<hr/>					
	var(R.schid)	.0037432	.0025493	.0009852	.0142217
<hr/>					
neighid: Independent					
<hr/>					
	var(dadunemp)	.0073473	.0328626	1.15e-06	47.13606
	var(daded)	.0115766	.0271607	.0001165	1.149878
	var(momed)	.0352373	.0264951	.008072	.1538242
	var(male)	.0103147	.0142086	.0006933	.1534618
	var(_cons)	8.08e-12	1.81e-11	9.89e-14	6.60e-10
<hr/>					
	var(Residual)	.4387169	.0159951	.4084609	.4712139
<hr/>					
LR test vs. linear model: chi2(6) = 10.55				Prob > chi2 = 0.1034	

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

```
. mixed attain p7vrq p7read dadocc dadunemp daded momed male deprive p7vrq_sch
p7read_sch dadocc_sch dadunemp_sch daded_sch momed_sch male_sch || _all: R.schid ||
neighid: dadunemp daded momed male
```

Mixed-effects ML regression			Number of obs	=	2,310
<hr/>					
Group	Variable	No. of Groups	Observations per Group		
			Minimum	Average	Maximum
<hr/>					
	_all	1	2,310	2,310.0	2,310
	neighid	524	1	4.4	16
<hr/>					

Wald chi2(15)	=	2554.09
Log likelihood = -2378.1708	Prob > chi2	= 0.0000

	attain	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
<hr/>						
	p7vrq	.0273469	.002274	12.03	0.000	.0228899 .0318038
	p7read	.0262508	.0017552	14.96	0.000	.0228108 .0296909
	dadocc	.0077382	.0013713	5.64	0.000	.0050504 .0104259
	dadunemp	-.1256167	.0477079	-2.63	0.008	-.2191225 -.0321109
	daded	.1495834	.0420635	3.56	0.000	.0671404 .2320264
	momed	.0545836	.0391762	1.39	0.164	-.0222003 .1313675
	male	-.0544371	.0288055	-1.89	0.059	-.1108948 .0020207
	deprive	-.1631975	.0262269	-6.22	0.000	-.2146014 -.1117937
	p7vrq_sch	.0263455	.0171515	1.54	0.125	-.0072708 .0599618
	p7read_sch	-.0199684	.0135388	-1.47	0.140	-.0465039 .0065672
	dadocc_sch	.0248499	.0191866	1.30	0.195	-.0127552 .062455
	dadunemp_sch	1.113901	.5183483	2.15	0.032	.0979574 2.129846
	daded_sch	-.6698207	.447016	-1.50	0.134	-1.545956 .2063146
	momed_sch	.4964818	.6049023	0.82	0.412	-.6891049 1.682069
	male_sch	.3916443	.416703	0.94	0.347	-.4250787 1.208367
	_cons	-.210726	.2503211	-0.84	0.400	-.7013464 .2798944
<hr/>						

Random-effects Parameters		Estimate	Std. Err.	[95% Conf. Interval]	
<hr/>					
<u>_all:</u> Identity					
<hr/>					
	var(R.schid)	.0006947	.0015285	9.31e-06	.0518265
<hr/>					
neighid: Independent					
<hr/>					
	var(dadunemp)	.0178082	.03453	.0003982	.7963269

```

      var(daded) |   .0185407   .0282593   .0009348   .367715
      var(momed) |   .0377594   .0272576   .0091741   .1554129
      var(male)  |   .0100372   .0143958   .0006037   .1668946
      var(_cons) |  1.00e-14   2.19e-14   1.37e-16   7.33e-13
-----
+-----+
      var(Residual) |   .4395822   .0159506   .4094055   .4719832
-----
LR test vs. linear model: chi2(6) = 5.69                         Prob > chi2 = 0.4594

```

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

We should probably mean-center some predictors, and also examine which of them should stay (most are not significant). We could also examine some cross-level interactions, but in general, there is not that much slope variance, and very little school-level and neighborhood-level unexplained variance left.

Cross-nested models for longitudinal data

Cross-nested models can also be used with longitudinal data like NYS dataset we used earlier. Here, we can treat observations as nested both within individuals and within time points. That is, in our earlier analysis, we assumed that the trajectory of age (from 14 to 18) is linear and student-specific (a random slope). In this cross-nested model, we will assume that the effect due to specific age is systematic to that age and common to all students. The rationale behind that could be assuming that the students were measured contemporaneously, and there may have been some year-specific factors happening that affected all the students, making everyone's deviance attitude score either higher or lower in that given year. So we will estimate a two-way crossed-nested model, with the student effects u_i being crossed with the age effects v_j :

```

. use nys.dta, clear

. reshape long attit expo, i(id) j(age)
(note: j = 14 15 16 17 18)

Data                                wide    ->    long
-----
Number of obs.                      241    ->    1205
Number of variables                 14     ->     7
j variable (5 values)              ->    age
xij variables:
    attit14 attit15 ... attit18    ->    attit
    expo14 expo15 ... expo18     ->    expo
-----

. mixed attit || _all: R.age || id:

Performing EM optimization:

Performing gradient-based optimization:

Iteration 0:  log likelihood =  34.695287
Iteration 1:  log likelihood =  34.695287

Computing standard errors:

Mixed-effects ML regression          Number of obs      =      1,066
-----
```

Group Variable	No. of Groups	Minimum	Average	Maximum
_all	1	1,066	1,066.0	1,066
id	241	1	4.4	5

Wald chi2(0) = .
Log likelihood = 34.695287 Prob > chi2 = .

attit	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_cons	.4923777	.0267443	18.41	0.000	.4399598 .5447955

Random-effects Parameters | Estimate Std. Err. [95% Conf. Interval]

	Estimate	Std. Err.	[95% Conf. Interval]
_all: Identity			
var(R.age)	.002475	.0016883	.00065 .0094237
id: Identity			
var(_cons)	.0443494	.0048906	.035729 .0550496
var(Residual)	.0357432	.0017678	.0324411 .0393815

LR test vs. linear model: chi2(2) = 415.72 Prob > chi2 = 0.0000

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

For this kind of model to make sense, we should have more time points than we do here – 5 time points is better for fixed effects of time rather than for a random variable – we do it here for demonstration purposes only. So this kind of analysis makes sense if you have a LONG time-series rather than a short one.

We can now add the trajectory, first linear non-varying, then linear randomly varying, then quadratic randomly varying:

```
. gen age16=age-16
. mixed attit age16 || _all: R.age16 || id:

Mixed-effects ML regression Number of obs = 1,066
-----
```

Group Variable	No. of Groups	Minimum	Average	Maximum
_all	1	1,066	1,066.0	1,066
id	241	1	4.4	5

Wald chi2(1) = 20.21
Log likelihood = 38.657761 Prob > chi2 = 0.0000

attit	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
age16	.0322932	.0071842	4.50	0.000	.0182124 .046374
_cons	.492564	.0169588	29.04	0.000	.4593255 .5258026

Random-effects Parameters		Estimate	Std. Err.	[95% Conf. Interval]	
<u>_all: Identity</u>					
	<u>var(R.age16)</u>	.0003369	.0003345	.0000481	.0023583
<u>id: Identity</u>					
	<u>var(_cons)</u>	.0443475	.0048856	.0357351	.0550355
	<u>var(Residual)</u>	.0357263	.0017662	.0324271	.0393611

LR test vs. linear model: chi2(2) = 401.35 Prob > chi2 = 0.0000

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

. mixed attit age16 || _all: R.age16 || id: age16

Mixed-effects ML regression		Number of obs			=	1,066
		No. of Groups	Observations per Group			
Group Variable			Minimum	Average	Maximum	
<u>_all</u>		1	1,066	1,066.0	1,066	
<u>id</u>		241	1	4.4	5	

Wald chi2(1) = 15.60
Log likelihood = 60.274204 Prob > chi2 = 0.0001

		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
<u>attit</u>		.032264	.0081687	3.95	0.000	.0162537 .0482743
<u>_cons</u>		.4929646	.0172185	28.63	0.000	.4592169 .5267122

Random-effects Parameters		Estimate	Std. Err.	[95% Conf. Interval]	
<u>_all: Identity</u>					
	<u>var(R.age16)</u>	.0003816	.000345	.0000649	.0022449
<u>id: Independent</u>					
	<u>var(age16)</u>	.0031574	.0006363	.0021271	.0046868
	<u>var(_cons)</u>	.0455911	.0048767	.0369683	.0562251
	<u>var(Residual)</u>	.0282275	.0016269	.0252124	.0316033

LR test vs. linear model: chi2(3) = 444.59 Prob > chi2 = 0.0000

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

. mixed attit c.age16##c.age16 || _all: R.age16 || id: c.age16##c.age16

Mixed-effects ML regression		Number of obs			=	1,066
		No. of Groups	Observations per Group			
Group Variable			Minimum	Average	Maximum	
<u>_all</u>		1	1,066	1,066.0	1,066	
<u>id</u>		241	1	4.4	5	

Wald chi2(2) = 38.20
Log likelihood = 65.811166 Prob > chi2 = 0.0000

```

-----+
 attit |      Coef.    Std. Err.      z     P>|z|    [95% Conf. Interval]
-----+
 age16 |   .0319722   .0057991    5.51    0.000    .0206062   .0433381
 |
 c.age16#|
 c.age16 |  -.010505   .0038782   -2.71    0.007   -.0181062  -.0029038
 |
 _cons |   .5137537   .0167022   30.76    0.000    .481018   .5464895
-----+
-----+
 Random-effects Parameters | Estimate    Std. Err.    [95% Conf. Interval]
-----+
 _all: Identity          |
 var(R.age16) |   .0000505   .000123    4.25e-07   .0059915
-----+
 id: Independent          |
 var(age16) |   .0034223   .0006344   .0023797   .0049217
 var(age16#age16) |   .0005715   .0002493   .0002431   .0013437
 var(_cons) |   .0466065   .0051029   .0376053   .0577622
-----+
 var(Residual) |   .0251662   .0018311   .0218214   .0290237
-----+
 LR test vs. linear model: chi2(4) = 450.29                      Prob > chi2 = 0.0000

```

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

Here we note that the variance for the random effects of time points is very close to 0 – it doesn't seem that individual time points have much of an effect beyond what's specified by random trajectory. Let's compare some specifications of time here:

```

. est store quadratic_re

. mixed attit c.age16##c.age16 || id: c.age16##c.age16

Mixed-effects ML regression                               Number of obs      =      1,066
Group variable: id                                    Number of groups   =        241
                                                              
Obs per group:
               min =           1
               avg =        4.4
               max =           5
                                                              
Wald chi2(2) = 46.07
Prob > chi2 = 0.0000
Log likelihood = 65.681561
-----+
 attit |      Coef.    Std. Err.      z     P>|z|    [95% Conf. Interval]
-----+
 age16 |   .0319353   .0053468    5.97    0.000    .0214557   .0424148
 |
 c.age16#|
 c.age16 |  -.0105168   .0033811   -3.11    0.002   -.0171436  -.00389
 |
 _cons |   .5137654   .0159545   32.20    0.000    .4824951   .5450357
-----+
-----+
 Random-effects Parameters | Estimate    Std. Err.    [95% Conf. Interval]
-----+
 id: Independent          |
 var(age16) |   .0034152   .000635    .0023721   .0049169
 var(age16#age16) |   .0005646   .0002491   .0002378   .0013407

```

```

var(_cons) |   .0465887   .0051017   .0375897   .057742
-----+
var(Residual) |   .0252557   .0018322   .0219083   .0291146
-----+
LR test vs. linear model: chi2(3) = 450.03                         Prob > chi2 = 0.0000

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

. est store quadratic

. est stats quadratic quadratic_re

Akaike's information criterion and Bayesian information criterion

-----
Model |      N    ll(null)    ll(model)      df      AIC      BIC
-----+
quadratic | 1,066          .  65.68156     7  -117.3631  -82.56144
quadratic_re | 1,066          .  65.81117     8  -115.6223  -75.84898
-----+
Note: BIC uses N = number of observations. See [R] BIC note.

. lrtest quadratic quadratic_re

Likelihood-ratio test                                         LR chi2(1) =      0.26
(Assumption: quadratic nested in quadratic_re)             Prob > chi2 = 0.6107

Note: The reported degrees of freedom assumes the null hypothesis is not on
the boundary of the parameter space. If this is not true, then the
reported test is conservative.

. mixed attit c.age16##c.age16 || _all: R.age16 || id:

Mixed-effects ML regression                                     Number of obs = 1,066
-----
|      No. of Observations per Group
Group Variable | Groups   Minimum   Average   Maximum
-----+
_all |       1   1,066   1,066.0   1,066
_id |    241      1       4.4       5
-----+
Wald chi2(2) =      67.13
Log likelihood =  41.042581                         Prob > chi2 = 0.0000
-----
attit |      Coef.   Std. Err.      z   P>|z|   [95% Conf. Interval]
-----+
age16 |   .0322139   .0042397    7.60   0.000   .0239042   .0405236
|
c.age16#|
c.age16 |  -.0103426   .0034938   -2.96   0.003  -.0171903  -.0034948
|
_cons |   .5130924   .0163665   31.35   0.000   .4810147   .5451701
-----+
Random-effects Parameters |      Estimate   Std. Err.   [95% Conf. Interval]
-----+
_all: Identity |
var(R.age16) |  4.80e-07   .0001233   8.4e-226   2.7e+212
-----+
id: Identity |
var(_cons) |   .044296   .0048806   .0356925   .0549734
-----+

```

```

      var(Residual) |   .0357288   .0017669     .0324282   .0393653
-----+
LR test vs. linear model: chi2(2) = 400.75          Prob > chi2 = 0.0000

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

. est store noslopevar

. est stats quadratic quadratic_re noslopevar

Akaike's information criterion and Bayesian information criterion

-----+
Model |      N    ll(null)    ll(model)      df      AIC      BIC
-----+
quadratic |  1,066       .    65.68156      7  -117.3631  -82.56144
quadratic_re |  1,066       .    65.81117      8  -115.6223  -75.84898
noslopevar |  1,066       .    41.04258      6  -70.08516  -40.25515
-----+

```

Note: BIC uses N = number of observations. See [R] BIC note.

The model with just the randomly varying quadratic trajectory seems to be better than either the model with the randomly varying quadratic trajectory PLUS individual time point effects, or the model with just the individual time point effects and non-varying quadratic trajectory. So we would probably set aside the idea of cross-nested model here and stick with the randomly varying quadratic trajectory model. But otherwise, we could continue adding predictors etc.