

Example 2: Unconditional Polynomial Models for Change in Number Match 3 Response Time (complete data, syntax, and output available for SAS, SPSS, and STATA electronically)

These data (in "Example23" data files) come from a short-term longitudinal study of 6 observations over 2 weeks for 101 adults age 65–80. The goal is to see how performance on this processing speed task ("number match 3"), as measured by response time in milliseconds, declines over the 6 practice sessions.

SAS Code for Data Manipulation:

```
* SAS code to import data, center time for polynomial models;
DATA work.example23; SET filepath.example23;
    clsess = session - 1; LABEL clsess = "clsess: Session Centered at 1";
RUN;
```

SPSS Code for Data Manipulation:

```
* SPSS code to import data, center time for polynomial models.
GET FILE = "example/Example23.sav".
DATASET NAME example23 WINDOW=FRONT.
COMPUTE clsess = session - 1.
VARIABLE LABELS clsess "clsess: Session Centered at 1".
```

STATA Code for Data Manipulation:

```
* STATA code to center time for polynomial models (and make quadratic version)
gen clsess = session - 1
gen clsess2 = clsess * clsess
label variable clsess "clsess: Session Centered at 1"
label variable clsess2 "clsess2: Quadratic Session Centered at 1"
```

Model 1a. Most Conservative Baseline: Empty Means, Random Intercept

$$\text{Level 1: } y_{ti} = \beta_{0i} + e_{ti}$$

$$\text{Level 2: Intercept: } \beta_{0i} = \gamma_{00} + U_{0i}$$

```
TITLE1 "SAS Model 1a: Empty Means, Random Intercept Only";
PROC MIXED DATA=work.example23 NOCLPRINT NOITPRINT
    COVTEST NAMELEN=100 METHOD=REML;
    CLASS ID session;
    MODEL nm3rt = / SOLUTION DDFM=Satterthwaite;
    RANDOM INTERCEPT / G V VCORR TYPE=UN SUBJECT=ID;
    REPEATED session / R TYPE=VC SUBJECT=ID; RUN;
```

METHOD = ML or REML (default)
CLASS = categorical predictors, nesting
MODEL dv = fixed effects / print solution
RANDOM = person variances in **G**
REPEATED = residuals in **R** matrix

```
TITLE "SPSS Model 1a: Empty Means, Random Intercept".
MIXED nm3rt BY ID session
    /METHOD = REML
    /PRINT = SOLUTION TESTCOV G R
    /FIXED =
    /RANDOM = INTERCEPT | SUBJECT(ID) COVTYPE(UN)
    /REPEATED = session | SUBJECT(ID) COVTYPE(ID).
```

MIXED dv BY categorical predictors
WITH continuous predictors
/METHOD = REML or ML
/PRINT = regression solution
/FIXED = predictors for means model
/RANDOM = person variances in **G**

```
* STATA Model 1a: Empty Means, Random Intercept
xtmixed nm3rt , || id: , ///
    variance reml covariance(unstructured) residuals(independent,t(session)),
    estat ic, n(101)
    estat recovariance, level(id)
```

DV = nm3rt, random part after ||
Level 2 ID is PersonID, random intercept by default
Print variances instead of SD, use reml
covariance(unstructured) refers to G matrix
residuals(independent) → refers to R matrix by session
estat ic → Print IC given N = 101 persons

STATA output:

```
Mixed-effects REML regression      Number of obs      =      606
Group variable: id                 Number of groups   =      101

                                   Obs per group: min =      6
                                   avg     =      6.0
                                   max     =      6
                                   Wald chi2(0) =      .
                                   Prob > chi2  =      .

Log restricted-likelihood = -4268.4304
```

NOTE: LL is given rather than -2LL

nm3rt	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
_cons	1770.701	45.42063	38.98	0.000	1681.679 1859.724

This is the fixed intercept (just grand mean so far).

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]
id: Identity			
var(_cons)	200883	29471.23	150683.2 267806.8
var(Residual)	44899.96	2825.63	39689.76 50794.13

Calculate the ICC for the Number Match 3 outcome:

$$ICC = \frac{200883}{200883 + 44900} = .82$$

This LR test tells us that the random intercept variance is significantly greater than 0, and thus so is the ICC.

LR test vs. linear regression: chibar2(01) = 691.74 Prob >= chibar2 = 0.0000

```
. estat ic, n(101)
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	101	.	-4268.43	3	8542.861	8550.706

REML-based AIC and BIC are calculated differently in STATA (they count fixed effects), so they won't match the values in other programs.

Note: N=101 used in calculating BIC

```
. estat recovariance, level(id)
Random-effects covariance matrix for level id
```

	_cons
_cons	200883

This is the level-2 **G** matrix, just a random intercept variance so far.

Extra SAS output not provided by STATA:

Estimated R Matrix for ID 101

Row	Col1	Col2	Col3	Col4	Col5	Col6
1	44900					
2		44900				
3			44900			
4				44900		
5					44900	
6						44900

This level-1 **R** matrix (with equal variance over time, no covariance of any kind, known as VC or independence) will be used repeatedly as we add fixed and random effects.

Estimated G Matrix

Row	Effect	Participant ID	Col1
1	Intercept	101	200883

This is the level-2 **G** matrix, just a random intercept variance so far.

Estimated V Matrix for ID 101

Row	Col1	Col2	Col3	Col4	Col5	Col6
1	245783	200883	200883	200883	200883	200883
2	200883	245783	200883	200883	200883	200883
3	200883	200883	245783	200883	200883	200883
4	200883	200883	200883	245783	200883	200883
5	200883	200883	200883	200883	245783	200883
6	200883	200883	200883	200883	200883	245783

The **V** matrix is the total variance-covariance matrix after combining the level-2 **G** and level-1 **R** matrices.

Model 1b. Most Liberal Baseline – Saturated Means, Unstructured Variances (Model Answer Key)

```
TITLE1 "SAS Model 1b: Saturated Means, Unstructured Variances";
PROC MIXED DATA=work.example23 NOCLPRINT NOITPRINT COVTEST NAMELEN=100 METHOD=REML;
  CLASS ID session;
  MODEL nm3rt = session / SOLUTION DDFM=Satterthwaite;
  REPEATED session / R RCORR TYPE=UN SUBJECT=ID;
  LSMEANS session /; RUN;
```

Placing *session* on the CLASS/BY statements and in the FIXED/MODEL statements treats it as a categorical predictor. So this is an ANOVA means model. No RANDOM statements mean no random effects.

```
TITLE "SPSS Model 1b: Saturated Means, Unstructured Variances".
MIXED nm3rt BY ID session
  /METHOD = REML
  /PRINT = SOLUTION TESTCOV R
  /FIXED = session
  /REPEATED = session | SUBJECT(ID) COVTYPE(UN)
  /EMMEANS = TABLES(session).
```

i. indicates categorical predictor of *session* (ref=last to match others) noconstant = no random intercept (just **R** matrix)

```
* STATA Model 1b: Saturated Means, Unstructured Variances
xtmixed nm3rt ib(last).session, || id: , noconstant ///
  variance reml residuals(unstructured, t(session)),
  estat ic, n(101),
  contrast session, // omnibus test of mean differences
  margins i.session, // observed means per session
  marginsplot name(observed_means, replace) // plot observed means
```

STATA output:

```
Mixed-effects REML regression          Number of obs   =      606
Group variable: id                    Number of groups =      101
                                       Obs per group:  min =       6
                                       avg   =      6.0
                                       max   =       6

                                       Wald chi2(5)     =      83.60
Log restricted-likelihood = -4114.8942  Prob > chi2     =     0.0000
```

This is the multivariate Wald test for all the fixed effects simultaneously (5 mean differences from the fixed intercept here).

nm3rt	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
session						
1	289.7574	32.69997	8.86	0.000	225.6666	353.8481
2	143.0364	26.20308	5.46	0.000	91.67927	194.3935
3	77.89864	22.8842	3.40	0.001	33.04642	122.7509
4	45.66045	20.78533	2.20	0.028	4.921952	86.39894
5	35.03972	18.11681	1.93	0.053	-.468579	70.54802
_cons	1672.136	44.13439	37.89	0.000	1585.634	1758.638

Mean diffs relative to session 6

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
-----+-----				
id:	(empty)			
-----+-----				
Residual: Unstructured				
var(e1)	301983.1	42696.65	228893.4	398411.6
var(e2)	259148.8	36635.7	196433.4	341887.4
var(e3)	233366.9	32990.48	176891.6	307872.9
var(e4)	217542.8	30753.82	164896.4	286997.6
var(e5)	212096.8	29984.63	160767.3	279814.7
var(e6)	196732.3	27812.21	149121.6	259543.9
cov(e1,e2)	235657.1	36563.79	163993.4	307320.8

These are the total variances at each occasion...

cov(e1,e3)		217992.5	34336.3	150694.6	285290.4
cov(e1,e4)		202605.4	32657.69	138597.5	266613.2
cov(e1,e5)		192152.4	31762.13	129899.7	254405
cov(e1,e6)		195358.7	31224.07	134160.6	256556.7
cov(e2,e3)		230215.6	33672.52	164218.7	296212.5
cov(e2,e4)		213230.6	31899.27	150709.2	275752
cov(e2,e5)		202091	30938.65	141452.3	262729.6
cov(e2,e6)		193267.2	29707.66	135041.2	251493.1
cov(e3,e4)		205208	30462.92	145501.8	264914.2
cov(e3,e5)		196917.7	29697.89	138710.9	255124.5
cov(e3,e6)		188603.5	28532.39	132681	244525.9
cov(e4,e5)		193674.7	28910.48	137011.2	250338.2
cov(e4,e6)		185320	27762.64	130906.2	239733.8
cov(e5,e6)		187839.5	27739.82	133470.5	242208.6

And these are the total covariances across occasions...

LR test vs. linear regression: chi2(20) = 925.64 Prob > chi2 = 0.0000

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.

This is the LRT of whether the unstructured R model fits better than the e-only R model...

```
. estat ic, n(101),
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	101	.	-4114.894	27	8283.788	8354.397

Note: N=101 used in calculating BIC

```
. contrast session, // omnibus test of mean differences
```

Contrasts of marginal linear predictions

Margins : asbalanced

	df	chi2	P>chi2
nm3rt			
session	5	83.60	0.0000

This is the omnibus test of mean differences across 6 sessions.

```
. margins i.session, // observed means per session
```

Adjusted predictions Number of obs = 606

Expression : Linear prediction, fixed portion, predict()
THESE ARE THE SATURATED MEANS THE FIXED EFFECTS WILL BE TRYING TO REPRODUCE.

session	Margin	Delta-method			[95% Conf. Interval]	
		Std. Err.	z	P> z		
1	1961.893	54.68027	35.88	0.000	1854.722	2069.065
2	1815.172	50.65402	35.83	0.000	1715.892	1914.452
3	1750.035	48.06832	36.41	0.000	1655.822	1844.247
4	1717.796	46.41001	37.01	0.000	1626.835	1808.758
5	1707.176	45.82541	37.25	0.000	1617.36	1796.992
6	1672.136	44.13439	37.89	0.000	1585.634	1758.638

Extra SAS output not provided by STATA:

Estimated R Matrix for ID 101

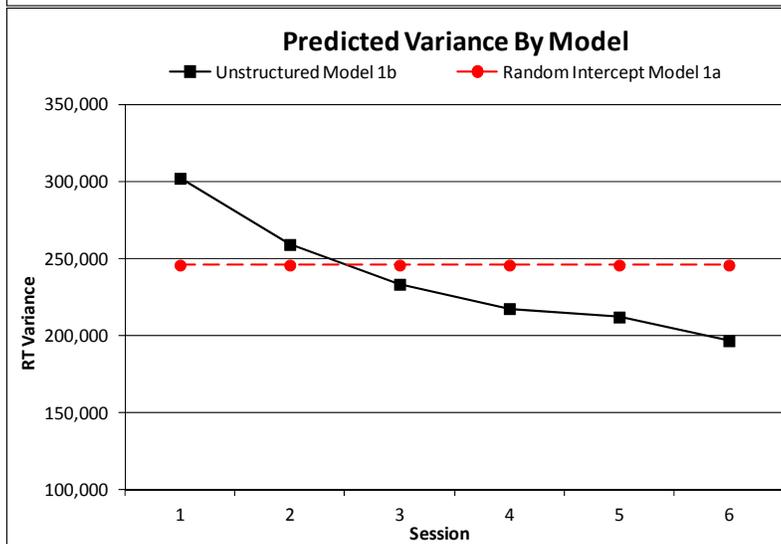
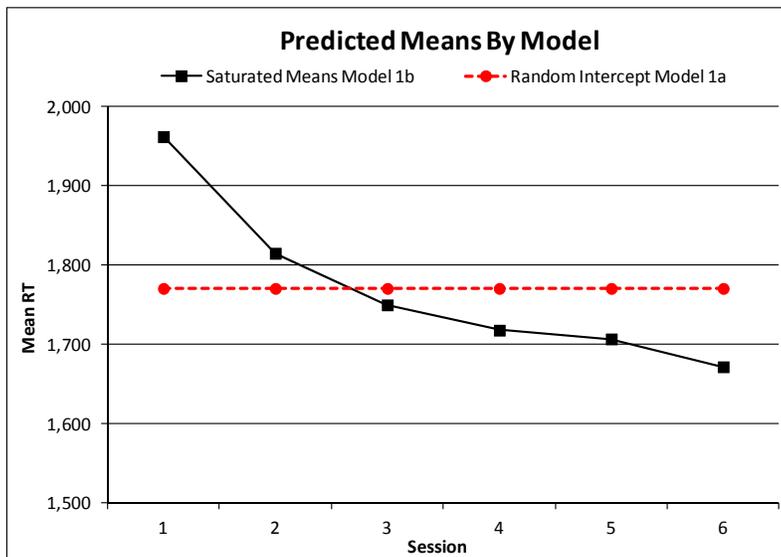
Row	Co11	Co12	Co13	Co14	Co15	Co16
1	301985	235659	217994	202607	192154	195360
2	235659	259150	230217	213232	202092	193268
3	217994	230217	233368	205209	196919	188604
4	202607	213232	205209	217544	193676	185321
5	192154	202092	196919	193676	212098	187840
6	195360	193268	188604	185321	187840	196733

This Unstructured **R** matrix estimates all variances and covariances separately. THIS IS THE DATA we are trying to duplicate with our model for the variances.

Estimated R Correlation Matrix for ID 101

Row	Co11	Co12	Co13	Co14	Co15	Co16
1	1.0000	0.8424	0.8212	0.7905	0.7593	0.8015
2	0.8424	1.0000	0.9361	0.8981	0.8620	0.8559
3	0.8212	0.9361	1.0000	0.9108	0.8851	0.8802
4	0.7905	0.8981	0.9108	1.0000	0.9016	0.8958
5	0.7593	0.8620	0.8851	0.9016	1.0000	0.9196
6	0.8015	0.8559	0.8802	0.8958	0.9196	1.0000

So here is what are we trying to model—means and variances, where model 1b is the data:



Model 2a. Fixed Linear Time, Random Intercept

$$\text{Level 1: } y_{ti} = \beta_{0i} + \beta_{1i}(\text{Session}_{ti} - 1) + e_{ti}$$

$$\text{Level 2: Intercept: } \beta_{0i} = \gamma_{00} + U_{0i}$$

$$\text{Linear Session: } \beta_{1i} = \gamma_{10}$$

```
TITLE1 "SAS Model 2a: Fixed Linear Time, Random Intercept";
PROC MIXED DATA=work.example23 NOCLPRINT NOITPRINT COVTEST NAMELEN=100 METHOD=REML;
  CLASS ID session;
  MODEL nm3rt = c1sess / SOLUTION DDFM=Satterthwaite;
  RANDOM INTERCEPT / G V VCORR TYPE=UN SUBJECT=ID;
  REPEATED session / R TYPE=VC SUBJECT=ID; RUN;
```

The predictor of *c1sess* will be treated as continuous given that it is not on the CLASS statement (SAS) and it is on WITH (SPSS).

```
TITLE "SPSS Model 2a: Fixed Linear Time, Random Intercept".
MIXED nm3rt BY ID session WITH c1sess
  /METHOD = REML
  /PRINT = SOLUTION TESTCOV G R
  /FIXED = c1sess
  /RANDOM = INTERCEPT | SUBJECT(ID) COVTYPE(UN)
  /REPEATED = session | SUBJECT(ID) COVTYPE(ID).
```

```
* STATA Model 2a: Fixed Linear Time, Random Intercept
xtmixed nm3rt c.c1sess, || id: , ///
  variance reml covariance(un) residuals(independent,t(session)),
  estat ic, n(101),
  estimates store FixLin
```

DV = nm3rt, c. means continuous fixed slope for *c1sess*
 Level 2 ID is id, random intercept by default
 estimates → save results as "FixLin" for next LRT

STATA output:

```
Mixed-effects REML regression
Group variable: id
Number of obs = 606
Number of groups = 101
Obs per group: min = 6
                avg = 6.0
                max = 6
Wald chi2(1) = 131.82
Prob > chi2 = 0.0000
Log restricted-likelihood = -4207.344
```

nm3rt	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
c1sess	-51.57185	4.491815	-11.48	0.000	-60.37565	-42.76806
_cons	1899.631	46.7882	40.60	0.000	1807.928	1991.334

The fixed linear effect of *c1sess* is significant according to the Wald test (*p*-value for fixed effect).

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
id: Identity				
var(_cons)	202422.7	29469.85	152172.6	269266.3
var(Residual)	35661.79	2246.481	31519.73	40348.16

Relative to the empty means, random intercept model 1a, the fixed linear effect of session explained ~21% of the residual variance (which made the random intercept variance increase due to its residual variance correction factor).

```
LR test vs. linear regression: chibar2(01) = 787.61 Prob >= chibar2 = 0.0000
. estat ic, n(101),
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	101	.	-4207.344	4	8422.688	8433.149

Note: N=101 used in calculating BIC

Model 2b. Random Linear Time

```
TITLE1 "SAS Model 2b: Random Linear Time";
PROC MIXED DATA=work.example23 NOCLPRINT
NOITPRINT COVTEST NAMELEN=100 METHOD=REML;
  CLASS ID session;
  MODEL nm3rt = c1sess / SOLUTION DDFM=Satterthwaite;
  RANDOM INTERCEPT c1sess / G V VCORR TYPE=UN SUBJECT=ID;
  REPEATED session / R TYPE=VC SUBJECT=ID; RUN;
```

$$\text{Level 1: } y_{ti} = \beta_{0i} + \beta_{1i} (\text{Session}_{ti} - 1) + e_{ti}$$

$$\text{Level 2: Intercept: } \beta_{0i} = \gamma_{00} + U_{0i}$$

$$\text{Linear Session: } \beta_{1i} = \gamma_{10} + U_{1i}$$

```
TITLE "SPSS Model 2b: Random Linear Time".
MIXED nm3rt BY ID session WITH c1sess
/METHOD = REML
/PRINT = SOLUTION TESTCOV G R
/FIXED = c1sess
/RANDOM = INTERCEPT c1sess | SUBJECT(ID) COVTYPE(UN)
/REPEATED = session | SUBJECT(ID) COVTYPE(ID).
```

Now there are 2 random effects: intercept and linear slope, given by c1sess on the RANDOM statements.

*** STATA Model 2b: Random Linear Time**

```
xtmixed nm3rt c.c1sess, || id: c1sess, ///
variance reml covariance(un) residuals(independent,t(session)),
estat ic, n(101),
estat recovariance, level(id),
estimates store RandLin,
lrtest RandLin FixLin
```

DV = nm3rt, c. means continuous fixed slope for c1sess
Level 2 ID is id, random intercept and c1sess now estimates → save results as "RandLin" for LRT

STATA output:

```
Mixed-effects REML regression          Number of obs      =      606
Group variable: id                    Number of groups   =      101
                                      Obs per group: min =         6
                                      avg      =         6.0
                                      max      =         6

                                      Wald chi2(1)       =      70.17
Log restricted-likelihood = -4186.0512  Prob > chi2        =      0.0000
```

nm3rt	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
c1sess	-51.57185	6.156722	-8.38	0.000	-63.63881	-39.5049
_cons	1899.631	51.4998	36.89	0.000	1798.693	2000.569

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
id: Unstructured				
var(c1sess)	2233.833	552.9239	1375.178	3628.626
var(_cons)	253258	37897.26	188881.9	339575.3
cov(c1sess,_cons)	-12700.79	3621.977	-19799.74	-5601.848
var(Residual)	27905.42	1963.419	24310.74	32031.62

```
LR test vs. linear regression:      chi2(3) = 830.20  Prob > chi2 = 0.0000
Note: LR test is conservative and provided only for reference.
```

```
.      estat ic, n(101),
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	101	.	-4186.051	6	8384.102	8399.793

Note: N=101 used in calculating BIC

```

.      estat recovariance, level(id),

Random-effects covariance matrix for level id
      |      c1sess      _cons
-----+-----
c1sess | 2233.833
_cons  | -12700.79    253258

.      estimates store RandLin,
.      lrtest RandLin FixLin
    
```

Is the random linear time model (2b) better than the fixed linear time, random intercept model (2a)?

Yep, $-2\Delta LL = 43$, which is bigger than the critical value of 5.99ish on $df \approx 2$ ish

```

Likelihood-ratio test          LR chi2(2) =    42.59
(Assumption: FixLin nested in RandLin)  Prob > chi2 =    0.0000
    
```

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. Note: LR tests based on REML are valid only when the fixed-effects specification is identical for both models.

Extra SAS output not provided by STATA:

Estimated R Matrix for ID 101

Row	Col1	Col2	Col3	Col4	Col5	Col6
1	27905					
2		27905				
3			27905			
4				27905		
5					27905	
6						27905

Estimated G Matrix Participant

Row	Effect	ID	Col1	Col2
1	Intercept	101	253258	-12701
2	C1sess	101	-12701	2233.83

Estimated V Matrix for ID 101

Row	Col1	Col2	Col3	Col4	Col5	Col6
1	281163	240557	227856	215155	202455	189754
2	240557	257995	219623	209156	198689	188222
3	227856	219623	239295	203157	194924	186691
4	215155	209156	203157	225063	191158	185159
5	202455	198689	194924	191158	215298	183627
6	189754	188222	186691	185159	183627	210001

The **V** matrix is the total variance-covariance matrix after combining the level-2 **G** and level-1 **R** matrices. Now the variances and covariances are predicted to change based on time.

Estimated V Correlation Matrix for ID 101

Row	Col1	Col2	Col3	Col4	Col5	Col6
1	1.0000	0.8932	0.8784	0.8553	0.8229	0.7809
2	0.8932	1.0000	0.8839	0.8680	0.8430	0.8086
3	0.8784	0.8839	1.0000	0.8754	0.8588	0.8328
4	0.8553	0.8680	0.8754	1.0000	0.8684	0.8517
5	0.8229	0.8430	0.8588	0.8684	1.0000	0.8636
6	0.7809	0.8086	0.8328	0.8517	0.8636	1.0000

The **VCORR** matrix is the correlation version. The ICC is now predicted to change over time, too (and conditional on linear time).

How the V matrix variances and covariances get calculated in a random linear time model:

$$V_i \text{ matrix: Variance}[y_{\text{time}}] = \tau_{U_0}^2 + \left[(\text{Session} - 1)^2 \tau_{U_1}^2 \right] + \left[2(\text{Session} - 1) \tau_{U_{01}} \right] + \sigma_e^2$$

$$V_i \text{ matrix: Covariance}[y_A, y_B] = \tau_{U_0}^2 + \left[(A + B) \tau_{U_{01}} \right] + \left[(AB) \tau_{U_1}^2 \right]$$

Model 3a. Fixed Quadratic, Random Linear Time

$$\text{Level 1: } y_{ti} = \beta_{0i} + \beta_{1i}(\text{Session}_{ti} - 1) + \beta_{2i}(\text{Session}_{ti} - 1)^2 + e_{ti}$$

$$\text{Level 2: Intercept: } \beta_{0i} = \gamma_{00} + U_{0i}$$

$$\text{Linear Session: } \beta_{1i} = \gamma_{10} + U_{1i}$$

$$\text{Quadratic Session: } \beta_{2i} = \gamma_{20}$$

```
TITLE1 "SAS Model 3a: Fixed Quadratic, Random Linear Time";
PROC MIXED DATA=work.example23 NOCLPRINT NOITPRINT COVTEST NAMELEN=100 METHOD=REML;
  CLASS ID session;
  MODEL nm3rt = c1sess c1sess*c1sess / SOLUTION DDFM=Satterthwaite;
  RANDOM INTERCEPT c1sess / G V V CORR TYPE=UN SUBJECT=ID;
  REPEATED session / R TYPE=VC SUBJECT=ID; RUN;
```

```
TITLE "SPSS Model 3a: Fixed Quadratic, Random Linear Time".
MIXED nm3rt BY ID session WITH c1sess
  /METHOD = REML
  /PRINT = SOLUTION TESTCOV G R
  /FIXED = c1sess c1sess*c1sess
  /RANDOM = INTERCEPT c1sess | SUBJECT(ID) COVTYPE(UN)
  /REPEATED = session | SUBJECT(ID) COVTYPE(ID).
```

Interactions can be defined on the fly in SAS and SPSS using *, or in STATA using # (but only for fixed effects in STATA).

```
* STATA Model 3a: Fixed Quadratic, Random Linear Time
xtmixed nm3rt c.c1sess c.c1sess#c.c1sess, || id: c1sess, ///
  variance reml covariance(un) residuals(independent,t(session)),
  estat ic, n(101),
  estat recovariance, level(id),
  estimates store FixQuad
```

STATA output:

```
Mixed-effects REML regression                Number of obs    =      606
Group variable: id                          Number of groups =      101
                                             Obs per group:  min =       6
                                             avg =      6.0
                                             max =       6
                                             Wald chi2(2)    =     97.86
Log restricted-likelihood = -4170.7386      Prob > chi2      =     0.0000
```

nm3rt	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
c1sess	-120.8999	14.54147	-8.31	0.000	-149.4007	-92.39917
c.c1sess#c.c1sess	13.86561	2.634761	5.26	0.000	8.701578	19.02965
_cons	1945.85	52.2433	37.25	0.000	1843.455	2048.245

The fixed quadratic effect of c1sess is significant according to the Wald test (p -value for fixed effect).

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
id: Unstructured				
var(c1sess)	2332.667	551.5799	1467.501	3707.891
var(_cons)	254164	37895.62	189758.3	340429.7
cov(c1sess,_cons)	-12947.88	3620.697	-20044.31	-5851.442
var(Residual)	26175.83	1844.008	22800.05	30051.42

Relative to the random linear time model 2b, the fixed quadratic effect of session explained another ~6% of the residual variance (which made the random intercept variance increase due to its residual variance correction factor).

```
LR test vs. linear regression:      chi2(3) = 851.78  Prob > chi2 = 0.0000
```

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

```

.      estat ic, n(101),
-----+-----
Model | Obs   ll(null)   ll(model)   df       AIC       BIC
-----+-----
.      | 101           .   -4170.739     7     8355.477   8373.783
-----+-----
Note: N=101 used in calculating BIC

```

Model 3b. Random Quadratic Time (and an example of ESTIMATE/TEST/MARGINS statements)

$$\text{Level 1: } y_{ti} = \beta_{0i} + \beta_{1i}(\text{Session}_{ti} - 1) + \beta_{2i}(\text{Session}_{ti} - 1)^2 + e_{ti}$$

$$\text{Level 2: Intercept: } \beta_{0i} = \gamma_{00} + U_{0i}$$

$$\text{Linear Session: } \beta_{1i} = \gamma_{10} + U_{1i}$$

$$\text{Quadratic Session: } \beta_{2i} = \gamma_{20} + U_{2i}$$

```

TITLE1 "SAS Model 3b: Random Quadratic Time";
PROC MIXED DATA=work.example23 NOCLPRINT NOITPRINT COVTEST NAMELEN=100 METHOD=REML;
CLASS ID session;
MODEL nm3rt = c1sess c1sess*c1sess / SOLUTION DDFM=Satterthwaite;
RANDOM INTERCEPT c1sess c1sess*c1sess / G V VCORR TYPE=UN SUBJECT=ID;
REPEATED session / R TYPE=VC SUBJECT=ID;
ESTIMATE "Intercept at Session 1" intercept 1 c1sess 0 c1sess*c1sess 0;
ESTIMATE "Intercept at Session 2" intercept 1 c1sess 1 c1sess*c1sess 1;
ESTIMATE "Intercept at Session 3" intercept 1 c1sess 2 c1sess*c1sess 4;
ESTIMATE "Intercept at Session 4" intercept 1 c1sess 3 c1sess*c1sess 9;
ESTIMATE "Intercept at Session 5" intercept 1 c1sess 4 c1sess*c1sess 16;
ESTIMATE "Intercept at Session 6" intercept 1 c1sess 5 c1sess*c1sess 25;
* Predicting linear rate of change at each session (linear changes by 2*quad);
ESTIMATE "Linear Slope at Session 1" c1sess 1 c1sess*c1sess 0;
ESTIMATE "Linear Slope at Session 2" c1sess 1 c1sess*c1sess 2;
ESTIMATE "Linear Slope at Session 3" c1sess 1 c1sess*c1sess 4;
ESTIMATE "Linear Slope at Session 4" c1sess 1 c1sess*c1sess 6;
ESTIMATE "Linear Slope at Session 5" c1sess 1 c1sess*c1sess 8;
ESTIMATE "Linear Slope at Session 6" c1sess 1 c1sess*c1sess 10; RUN;

TITLE "SPSS Model 3b: Random Quadratic Time".
MIXED nm3rt BY ID session WITH c1sess
/METHOD = REML
/PRINT = SOLUTION TESTCOV G R
/FIXED = c1sess c1sess*c1sess
/RANDOM = INTERCEPT c1sess c1sess*c1sess | SUBJECT(ID) COVTYPE(UN)
/REPEATED = session | SUBJECT(ID) COVTYPE(ID)
/TEST = "Intercept at Session 1" intercept 1 c1sess 0 c1sess*c1sess 0
/TEST = "Intercept at Session 2" intercept 1 c1sess 1 c1sess*c1sess 1
/TEST = "Intercept at Session 3" intercept 1 c1sess 2 c1sess*c1sess 4
/TEST = "Intercept at Session 4" intercept 1 c1sess 3 c1sess*c1sess 9
/TEST = "Intercept at Session 5" intercept 1 c1sess 4 c1sess*c1sess 16
/TEST = "Intercept at Session 6" intercept 1 c1sess 5 c1sess*c1sess 25
/TEST = "Linear Slope at Session 1" c1sess 1 c1sess*c1sess 0
/TEST = "Linear Slope at Session 2" c1sess 1 c1sess*c1sess 2
/TEST = "Linear Slope at Session 3" c1sess 1 c1sess*c1sess 4
/TEST = "Linear Slope at Session 4" c1sess 1 c1sess*c1sess 6
/TEST = "Linear Slope at Session 5" c1sess 1 c1sess*c1sess 8
/TEST = "Linear Slope at Session 6" c1sess 1 c1sess*c1sess 10.

```

Because twice the quadratic slope is how the linear slope changes per unit time, the value for `c1sess` used in estimating the linear slope per session gets multiplied by 2.

*** STATA Model 3b: Random Quadratic Time**

```
xtmixed nm3rt c.c1sess c.c1sess#c.c1sess, || id: c1sess c1sess2, ///
variance reml covariance(un) residuals(independent,t(session)),
estat ic, n(101),
estat recovariance, level(id),
estimates store RandQuad,
lrtest RandQuad FixQuad,
margins, at(c.c1sess=(0(1)5)) vsquish // intercepts per session
marginsplot, name(predicted_means, replace) // plot intercepts
margins, at(c.c1sess=(0(1)5)) dydx(c.c1sess) vsquish // linear slope per session
marginsplot, name(change_in_linear_slope, replace) // plot quadratic effect
```

The random statement will not accept interaction terms, so we are using the c1sess2 created manually before.

STATA output:

```
Mixed-effects REML regression          Number of obs   =       606
Group variable: id                    Number of groups =       101
                                      Obs per group:  min =         6
                                      avg   =       6.0
                                      max   =         6
                                      Wald chi2(2)    =       71.74
Log restricted-likelihood = -4151.3728  Prob > chi2     =       0.0000
```

nm3rt	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
c1sess	-120.8999	20.04752	-6.03	0.000	-160.1923	-81.6075
c.c1sess#c.c1sess	13.86561	3.41541	4.06	0.000	7.171534	20.55969
_cons	1945.85	53.84993	36.13	0.000	1840.306	2051.394

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
id: Unstructured				
var(c1sess)	25839.79	5864.685	16561.42	40316.29
var(c1sess2)	634.4659	172.375	372.5198	1080.605
var(_cons)	276207.8	41445.59	205831.2	370647.1
cov(c1sess,c1sess2)	-3903.291	982.6248	-5829.2	-1977.381
cov(c1sess,_cons)	-35734.05	11947.96	-59151.62	-12316.48
cov(c1sess2,_cons)	3901.974	1950.304	79.44722	7724.5
var(Residual)	20298.19	1649.117	17310.19	23801.96

```
LR test vs. linear regression:      chi2(6) = 890.51  Prob > chi2 = 0.0000
Note: LR test is conservative and provided only for reference.
```

```
. estat ic, n(101),
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	101	.	-4151.373	10	8322.746	8348.897

Note: N=101 used in calculating BIC

```
. estimates store RandQuad,
```

```
. lrtest RandQuad FixQuad,
```

```
Likelihood-ratio test
(Assumption: FixQuad nested in RandQuad)
```

```
LR chi2(3) = 38.73
Prob > chi2 = 0.0000
```

Is the random quadratic model (3b) better than the fixed quadratic, random linear model (3a)?

Yep, $-2\Delta LL = 39$, which is bigger than the critical value of 7.82ish on $df \sim 3$ ish

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. Note: LR tests based on REML are valid only when the fixed-effects specification is identical for both models.

```

. margins, at(c1sess=(0(1)5)) vsquish // intercepts per session
Adjusted predictions Number of obs = 606
Expression : Linear prediction, fixed portion, predict()
1._at : c1sess = 0
2._at : c1sess = 1
3._at : c1sess = 2
4._at : c1sess = 3
5._at : c1sess = 4
6._at : c1sess = 5
    
```

These are the quadratic-model-predicted means per session.

	Margin	Std. Err.	z	P> z	[95% Conf. Interval]	
_at						
1	1945.85	53.84993	36.13	0.000	1840.306	2051.394
2	1838.815	48.48658	37.92	0.000	1743.784	1933.847
3	1759.512	46.99744	37.44	0.000	1667.399	1851.626
4	1707.941	45.89598	37.21	0.000	1617.986	1797.895
5	1684.1	44.23964	38.07	0.000	1597.392	1770.808
6	1687.991	44.20394	38.19	0.000	1601.352	1774.629

```

. marginsplot, name(predicted_means, replace) // plot intercepts
Variables that uniquely identify margins: c1sess
. margins, at(c1sess=(0(1)5)) dydx(c1sess) vsquish // linear slope per session
Conditional marginal effects Number of obs = 606
Expression : Linear prediction, fixed portion, predict()
dy/dx w.r.t. : c1sess
1._at : c1sess = 0
2._at : c1sess = 1
3._at : c1sess = 2
4._at : c1sess = 3
5._at : c1sess = 4
6._at : c1sess = 5
    
```

These are the instantaneous linear slopes at each session. Note how the SEs narrow towards the middle of the data.

	dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
c1sess _at						
1	-120.8999	20.04752	-6.03	0.000	-160.1923	-81.6075
2	-93.1687	13.64968	-6.83	0.000	-119.9216	-66.4158
3	-65.43747	8.002796	-8.18	0.000	-81.12266	-49.75228
4	-37.70624	5.92417	-6.36	0.000	-49.3174	-26.09508
5	-9.975015	9.973315	-1.00	0.317	-29.52235	9.572324
6	17.75621	16.03616	1.11	0.268	-13.67408	49.18651

How well do the predicted means, variances, and covariances from the random quadratic model (3b) match the original means, variances, and covariances from the saturated means model (1b)?

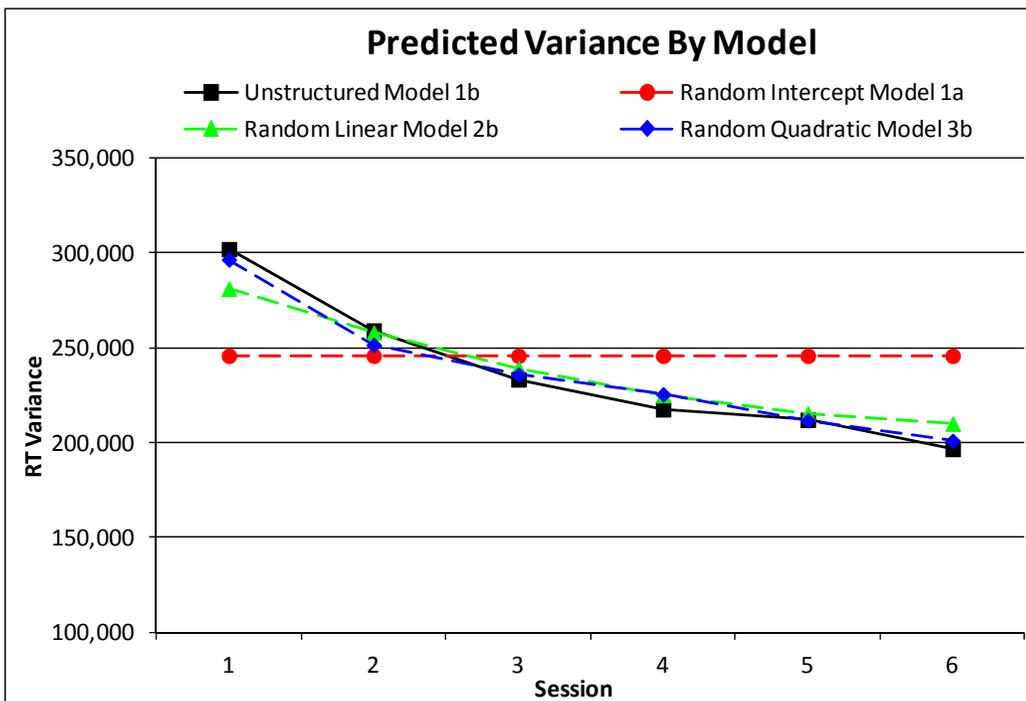
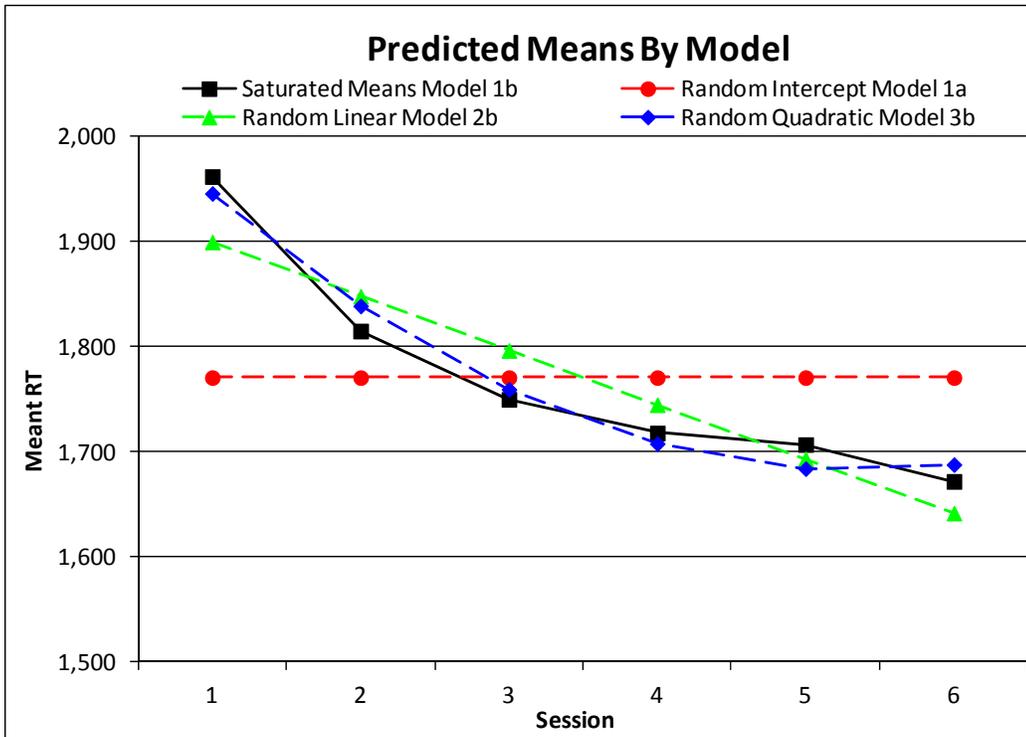
Extra SAS output not provided by STATA:

Estimated V Matrix for ID 101

Row	Col1	Col2	Col3	Col4	Col5	Col6
1	296504	244374	220346	204122	195702	195085
2	244374	251508	219312	208680	199315	191215
3	220346	219312	235842	209043	199808	187840
4	204122	208680	209043	225508	197182	184958
5	195702	199315	199808	197182	211735	182571
6	195085	191215	187840	184958	182571	200977

The **V** matrix is the total variance-covariance matrix after combining the level-2 **G** and level-1 **R** matrices. The variances and covariances are predicted to change based on time, but differently.

Figure 1



How the V matrix variances and covariances get calculated in a random quadratic time model:

Predicted Variance at Time T:

$$\text{Var}(y_T) = \sigma_e^2 + \tau_{U_0}^2 + 2*T*\tau_{U_{01}} + T^2*\tau_{U_1}^2 + 2*T^2*\tau_{U_{02}} + 2*T^3*\tau_{U_{12}} + T^4*\tau_{U_2}^2$$

Predicted Covariance between Time A and B:

$$\text{Cov}(y_A, y_B) = \tau_{U_0}^2 + (A+B)*\tau_{U_{01}} + (AB)*\tau_{U_1}^2 + (A^2+B^2)*\tau_{U_{02}} + (AB^2)+(A^2B)*\tau_{U_{12}} + (A^2B^2)*\tau_{U_2}^2$$

Simple Processing Speed – Example Unconditional Models of Change Results

Model Specification

Linear mixed models were estimated using restricted maximum likelihood (REML) in order to examine the overall pattern of and individual differences in response time over six sessions for a simple processing speed test (number match three). The significance of new fixed effects were evaluated using Wald tests, whereas the significance of new random effects was evaluated using likelihood ratio tests (i.e., $-2\Delta LL$), with degrees of freedom equal to the number of new random effects variances and covariances. The 95% confidence interval (CI) for random variation around each fixed effect was calculated as ± 1.96 standard deviations of its accompanying random variance term.

Although the six sessions were held over a period of 6–10 days, given that experience to the test (and not *time* per se) was the most likely reason for changes in response time, session was used as the metric of time (i.e., as opposed to age or day). Session was centered at the first occasion, such that the intercept represented initial status in all models. Observed mean response times (in milliseconds) estimated from a saturated means model (i.e., multivariate analysis of variance) are shown in Figure 1. The intraclass correlation from the unconditional means model (i.e., empty model; random intercept only) was calculated as .82, indicating that over 80% of the variance in number match 3 across sessions occurred between persons in mean RT. Polynomial models were then estimated to approximate the effects of practice across the six sessions, as presented below.

Polynomial Models

Polynomial models were first specified with a random intercept only. A fixed linear effect of session was significant ($p < .001$), such that average response time declined across sessions. The addition of a random linear slope (as well as a covariance between the random intercept and random linear slope) resulted in a significant improvement to the model, $-2\Delta LL(2) = 43$, $p < .001$. However, the magnitude of this linear decline was reduced in later sessions, as indicated by a significant fixed quadratic effect of session (i.e., a decelerating negative trend; $p < .001$). The addition of a random quadratic slope (and its two accompanying covariances with the random intercept and random linear slope) also resulted in a significant improvement in model fit, $-2\Delta LL(3) = 39$, $p < .001$.

The predicted means from the unconditional random quadratic polynomial model for session (i.e., without predictors) are shown in Figure 1, and model parameters using REML estimation are given in Table 1. As shown, the mean predicted response time at session 1 was 1946 ms, with a 95% CI of 916 to 2976 ms. The mean instantaneous linear rate of change at session 1 was -121 ms per session, with a 95% CI of -436 to 194 ms, indicating that not all participants were predicted to improve as evaluated at session 1. Half the mean deceleration in linear rate of change was 14 ms per session, such that the linear rate of change became less negative by 28 ms with each session. The 95% CI for the quadratic effect was of -36 to 63 ms, indicating that not all participants were predicted to decelerate in their rate of improvement across sessions.

Computing random effects confidence intervals for each random effect:

$$\text{Random Effect 95\% CI} = \text{fixed effect} \pm \left(1.96 * \sqrt{\text{Random Variance}}\right)$$

$$\text{Intercept 95\% CI} = \gamma_{00} \pm \left(1.96 * \sqrt{\tau_{U_0}^2}\right) \rightarrow 1,945.9 \pm \left(1.96 * \sqrt{276,209}\right) = 916 \text{ to } 2,976$$

$$\text{Linear Time Slope 95\% CI} = \gamma_{10} \pm \left(1.96 * \sqrt{\tau_{U_1}^2}\right) \rightarrow -120.9 \pm \left(1.96 * \sqrt{25,840}\right) = -436 \text{ to } 194$$

$$\text{Quadratic Time Slope 95\% CI} = \gamma_{20} \pm \left(1.96 * \sqrt{\tau_{U_2}^2}\right) \rightarrow 13.9 \pm \left(1.96 * \sqrt{634}\right) = -36 \text{ to } 63$$