

Example 3: Time-Invariant Predictors of Practice Effects (uses same data as Example 2)

In this example we will examine time-invariant predictors of individual differences in intercepts, linear slopes, and quadratic slopes representing improvement in RT (in msec) across six practice sessions. We will examine age, abstract reasoning, and education in sequential conditional (predictor) models.

SAS Code for Data Manipulation:

```
* Centering level-2 predictor variables for analysis;
DATA work.example23; SET work.example23;
    age80 = age - 80;          * Convenient value;
    reas22 = absreas - 22;     * Near sample mean;
    LABEL age80 = "age80: Age Centered (0=80)"
           reas22 = "reas22: Abstract Reasoning Centered (0=22)";
    * Make education a grouping variable for purpose of demonstration only;
    IF educyrs LE 12          THEN educgrp=1;
    ELSE IF educyrs GT 12 AND EducYrs LE 16 THEN educgrp=2;
    ELSE IF educyrs GT 16          THEN educgrp=3;
    ELSE IF educyrs = .          THEN educgrp=. ;
    LABEL educgrp = "educgrp: Education Group (1=HS, 2=BA, 3=GRAD)";

* Removing cases with missing predictors;
    IF NMISS(age80, reas22, educgrp)>0 THEN DELETE;
RUN;
```

SPSS Code for Data Manipulation:

```
* Centering level-2 predictor variables for analysis.
DATASET ACTIVATE example23 WINDOW=FRONT.
COMPUTE age80 = age - 80.
COMPUTE reas22 = absreas - 22.
VARIABLE LABELS
    age80 "age80: Age Centered (0=80)"
    reas22 "reas22: Abstract Reasoning Centered (0=22)".
* Make education a grouping variable for purpose of demonstration only.
IF educyrs LE 12          educgrp=1.
IF educyrs GT 12 AND educyrs LE 16 educgrp=2.
IF educyrs GT 16          educgrp=3.
VARIABLE LABELS educgrp "educgrp: Education Group (1=HS, 2=BA, 3=GRAD)".

* Removing cases with missing predictors.
SELECT IF (NVALID(age80, reas22, educgrp)=3).
EXECUTE.
```

STATA Code for Data Manipulation:

```
* centering level-2 predictor variables for analysis
gen age80 = age - 80
gen reas22 = absreas - 22
label variable age80 "age80: Age Centered (0=80 years)"
label variable reas22 "reas22: Abstract Reasoning Centered (0=22)"
* make education a grouping variable for purpose of demonstration only
gen educgrp=.
replace educgrp=1 if (educyrs <= 12)
replace educgrp=2 if (educyrs > 12 & educyrs <= 16)
replace educgrp=3 if (educyrs > 16)
label variable educgrp "educgrp: Education Group (1=HS, 2=BA, 3=GRAD)"

* create new variable to hold number of missing cases
* then drop cases with incomplete predictors
egen nummiss = rowmiss(age80 reas22 educgrp)
drop if nummiss>0
```

Model 3b. Random Quadratic Time Baseline (in ML now)

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

Level 2:

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

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

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

```
TITLE1 "SAS Model 3b: Random Quadratic Time Baseline in ML";
PROC MIXED DATA=work.example23 NOCLPRINT NOITPRINT COVTEST NAMELEN=100 IC METHOD=ML;
  CLASS ID session;
  MODEL nm3rt = c1sess c1sess*c1sess / SOLUTION DDFM=Satterthwaite OUTPM=work.TimePred;
  RANDOM INTERCEPT c1sess c1sess*c1sess / G GCORR V VCORR TYPE=UN SUBJECT=ID;
  REPEATED session / R TYPE=VC SUBJECT=ID; RUN;
PROC CORR NOSIMPLE DATA=work.TimePred; VAR nm3rt pred; RUN;
```

```
TITLE "SPSS Model 3b: Random Quadratic Time Baseline in ML".
MIXED nm3rt BY ID session WITH c1sess
  /METHOD = ML
  /PRINT = SOLUTION TESTCOV G R
  /FIXED = c1sess c1sess*c1sess
  /RANDOM = INTERCEPT c1sess c1sess*c1sess | SUBJECT(ID) COVTYPE(UN)
  /REPEATED = session | SUBJECT(ID) COVTYPE(ID)
  /SAVE = FIXPRED (predtime).
CORRELATIONS nm3rt predtime.
```

```
* STATA Model 3b: Random Quadratic Time Baseline in ML
xtmixed nm3rt c.c1sess c.c1sess#c.c1sess, || id: c1sess c1sess2, ///
  variance ml covariance(un) residuals(independent,t(session)),
  estat ic, n(101),
  estat recovariance, level(id),
  estimates store Baseline, // save LL for LRT
  predict predtime // save fixed-effect predicted outcomes
corr nm3rt predtime // get total r to make r2
```

STATA output:

Mixed-effects ML 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)	=	72.45
Log likelihood = -4160.8833	Prob > chi2	=	0.0000

nm3rt	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
c1sess	-120.8999	19.94803	-6.06	0.000	-159.9973 -81.80251
c.c1sess#c.c1sess	13.86561	3.398459	4.08	0.000	7.204756 20.52647
_cons	1945.85	53.58259	36.31	0.000	1840.83 2050.87

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]
id: Unstructured			
var(c1sess)	25437.86	5781.419	16293.81 39713.52
var(c1sess2)	622.8	169.99	364.7687 1063.358
var(_cons)	273306.9	40831.76	203930.4 366285.1
cov(c1sess,c1sess2)	-3837.723	968.8047	-5736.545 -1938.9
cov(c1sess,_cons)	-35261.67	11771.5	-58333.38 -12189.95
cov(c1sess2,_cons)	3845.378	1921.468	79.37031 7611.386

```

var(Residual) |      20298.2    1649.119        17310.2    23801.98
-----
LR test vs. linear regression:      chi2(6) =    891.99    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      .      -4160.883      10      8341.767      8367.918
-----
Note: N=101 used in calculating BIC

```

In ML, the #parms is ALL
parms (both sides of model).
So STATA's versions should
agree with other programs.

```

      |      nm3rt preptime
-----+-----
nm3rt |      1.0000
preptime |      0.1917      1.0000

```

R = .1917, so R² for time = .0367

The model for the means (fixed linear and quadratic session
effects so far) accounted for ~4% of the variance in RT.

Model 4a. Age as Predictor of Intercept, Linear, and Quadratic Time Slopes

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

Level 2:

$$\text{Intercept: } \beta_{0i} = \gamma_{00} + \gamma_{01}(\text{Age}_i - 80) + U_{0i}$$

$$\text{Linear: } \beta_{1i} = \gamma_{10} + \gamma_{11}(\text{Age}_i - 80) + U_{1i}$$

$$\text{Quadratic: } \beta_{2i} = \gamma_{20} + \gamma_{21}(\text{Age}_i - 80) + U_{2i}$$

```

TITLE1 "SAS Model 4a: Age as Predictor of Intercept, Linear, and Quadratic";
PROC MIXED DATA=work.example23 NOCLPRINT NOITPRINT COVTEST NAMELEN=100 IC METHOD=ML;
  CLASS ID session;
  MODEL nm3rt = clsess clsess*clsess age80 clsess*age80 clsess*clsess*age80
    / SOLUTION DDFM=Satterthwaite OUTPM=work.AgePred;
  RANDOM INTERCEPT clsess clsess*clsess / G GCORR TYPE=UN SUBJECT=ID;
  REPEATED session / TYPE=VC SUBJECT=ID;
  * Requesting additional effects for age;
  ESTIMATE "Age Effect at Session 1" age80 1 clsess*age80 0 clsess*clsess*age80 0;
  ESTIMATE "Age Effect at Session 2" age80 1 clsess*age80 1 clsess*clsess*age80 1;
  ESTIMATE "Age Effect at Session 3" age80 1 clsess*age80 2 clsess*clsess*age80 4;
  ESTIMATE "Age Effect at Session 4" age80 1 clsess*age80 3 clsess*clsess*age80 9;
  ESTIMATE "Age Effect at Session 5" age80 1 clsess*age80 4 clsess*clsess*age80 16;
  ESTIMATE "Age Effect at Session 6" age80 1 clsess*age80 5 clsess*clsess*age80 25;
RUN; PROC CORR NOSIMPLE DATA=work.AgePred; VAR nm3rt pred; RUN;

```

```

TITLE "SPSS Model 4a: Age as Predictor of Intercept, Linear, and Quadratic".
MIXED nm3rt BY ID session WITH clsess age80
  /METHOD = ML
  /PRINT = SOLUTION TESTCOV G R
  /FIXED = clsess clsess*clsess age80 clsess*age80 clsess*clsess*age80
  /RANDOM = INTERCEPT clsess clsess*clsess | SUBJECT(ID) COVTYPE(UN)
  /REPEATED = session | SUBJECT(ID) COVTYPE(ID)
  /SAVE = FIXPRED (predage)
  /TEST = "Age Effect at Session 1" age80 1 clsess*age80 0 clsess*clsess*age80 0
  /TEST = "Age Effect at Session 2" age80 1 clsess*age80 1 clsess*clsess*age80 1
  /TEST = "Age Effect at Session 3" age80 1 clsess*age80 2 clsess*clsess*age80 4
  /TEST = "Age Effect at Session 4" age80 1 clsess*age80 3 clsess*clsess*age80 9
  /TEST = "Age Effect at Session 5" age80 1 clsess*age80 4 clsess*clsess*age80 16
  /TEST = "Age Effect at Session 6" age80 1 clsess*age80 5 clsess*clsess*age80 25.
CORRELATIONS nm3rt predage.

```

```

* STATA Model 4a: Age as Predictor of Intercept, Linear, and Quadratic
xtmixed nm3rt c.c1sess c.c1sess#c.c1sess          ///
      c.age80 c.age80#c.c1sess c.age80#c.c1sess#c.c1sess,  ///
      || id: c1sess c1sess2,          ///
      variance ml covariance(un) residuals(independent,t(session)),
      estat ic, n(101),
      estat recovariance, level(id),
      estimates store age,          // save LL for LRT
      lrtest Age Baseline,          // LRT against non-age baseline
      predict predage          // save fixed-effect predicted outcomes
      margins, at(c.c1sess=(0(1)5)) dydx(c.age80) vsquish // age slope per session
      margins, at(c.c1sess=(0(1)5) c.age80=(-5 0 5)) vsquish // predictions per session
      marginsplot, name(predicted_age, replace) // plot age predictions
corr nm3rt predage          // get total r to make r2

```

STATA output:

```

Mixed-effects ML 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)      =     88.55
Log likelihood = -4155.1009          Prob > chi2        =     0.0000

```

	nm3rt	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
c1sess		-121.8325	19.66948	-6.19	0.000	-160.3839	-83.28099
c.c1sess#c.c1sess		13.97744	3.375686	4.14	0.000	7.361221	20.59367
age80		29.04954	8.377364	3.47	0.001	12.63021	45.46887
c.age80#c.c1sess		-5.594634	3.251901	-1.72	0.085	-11.96824	.7789759
c.age80#c.c1sess#c.c1sess		.6709122	.558093	1.20	0.229	-.42293	1.764754
_cons		1950.692	50.67139	38.50	0.000	1851.378	2050.006

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
id: Unstructured				
var(c1sess)	24293.61	5623.947	15432.62	38242.33 → linear var down by 4.50%
var(c1sess2)	606.3449	167.7546	352.5508	1042.84 → quad var down by 2.64%
var(_cons)	242456.1	36492.45	180516.8	325648.3 → intercept var down 11.29%
cov(c1sess,c1sess2)	-3700.505	949.404	-5561.302	-1839.707
cov(c1sess,_cons)	-29320.18	10868.45	-50621.95	-8018.411
cov(c1sess2,_cons)	3132.873	1793.883	-383.0738	6648.819
var(Residual)	20298.2	1649.119	17310.2	23801.98 → residual var not reduced

LR test vs. linear regression: chi2(6) = 857.76 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           .   -4155.101    13    8336.202    8370.198
-----+-----

```

Note: N=101 used in calculating BIC

```

.      estimates store Age,          // save LL for LRT
.      lrtest Age Baseline,          // LRT against non-age baseline

Likelihood-ratio test          LR chi2(3) =    11.56
(Assumption: Baseline nested in Age)   Prob > chi2 =    0.0090

```

Is the age model (4a) better than the baseline random quadratic model (3b)?

Yes, $-2\Delta LL = 11.6$ on $df=3$, $p=.009$

```
. predict predage                                // save fixed-effect predicted outcomes
(option xb assumed)
. margins, at(c1sess=(0(1)5)) dydx(age80) vsquish // age slope per session
```

Average marginal effects Number of obs = 606

Expression : Linear prediction, fixed portion, predict()

dy/dx w.r.t. : age80

```
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 simple
slopes for age at
each session.

		Delta-method					
		dy/dx	Std. Err.	z	P> z	[95% Conf. Interval]	
age80	_at						
	1	29.04954	8.377364	3.47	0.001	12.63021	45.46887
	2	24.12582	7.609705	3.17	0.002	9.211068	39.04056
	3	20.54392	7.459286	2.75	0.006	5.923987	35.16385
	4	18.30385	7.330177	2.50	0.013	3.936962	32.67073
	5	17.4056	7.071475	2.46	0.014	3.545761	31.26543
	6	17.84917	7.054461	2.53	0.011	4.022683	31.67566

```
. margins, at(c1sess=(0(1)5) age80=(-5 0 5)) vsquish // predictions per session
```

Adjusted predictions Number of obs = 606

Expression : Linear prediction, fixed portion, predict()

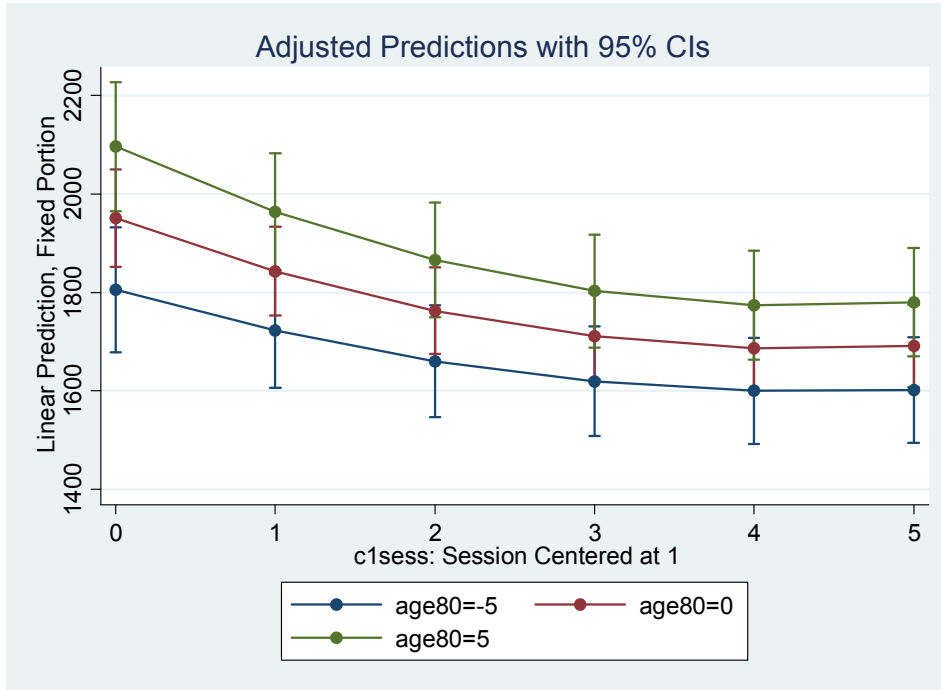
```
1._at      : c1sess      =      0
              age80      =     -5
2._at      : c1sess      =      0
              age80      =      0
3._at      : c1sess      =      0
              age80      =      5
```

(output continues for all other sessions)

		Delta-method					
		Margin	Std. Err.	z	P> z	[95% Conf. Interval]	
	_at						
	1	1805.444	64.84687	27.84	0.000	1678.347	1932.542
	2	1950.692	50.67139	38.50	0.000	1851.378	2050.006
	3	2095.94	66.62638	31.46	0.000	1965.354	2226.525
	4	1722.208	58.90463	29.24	0.000	1606.757	1837.659
	5	1842.837	46.02812	40.04	0.000	1752.623	1933.05
	6	1963.466	60.52108	32.44	0.000	1844.847	2082.085
	7	1660.217	57.74028	28.75	0.000	1547.048	1773.386
	8	1762.937	45.1183	39.07	0.000	1674.506	1851.367
	9	1865.656	59.32478	31.45	0.000	1749.382	1981.931
	10	1619.472	56.74089	28.54	0.000	1508.262	1730.682
	11	1710.991	44.33737	38.59	0.000	1624.092	1797.891
	12	1802.511	58.29796	30.92	0.000	1688.249	1916.773
	13	1599.973	54.73834	29.23	0.000	1492.688	1707.258
	14	1687.001	42.77258	39.44	0.000	1603.168	1770.834
	15	1774.029	56.24045	31.54	0.000	1663.8	1884.258
	16	1601.72	54.60664	29.33	0.000	1494.693	1708.747
	17	1690.966	42.66967	39.63	0.000	1607.335	1774.597
	18	1780.212	56.10514	31.73	0.000	1670.247	1890.176

The pattern of the interaction is shown by the simple effects of age at each session, graphed below.

```
. marginsplot, name(predicted_age, replace) // plot age predictions
```



Variables that uniquely identify margins: c1sess age80

```
. corr nm3rt predage // get total r to make r2
(obs=606)
```

	nm3rt	predage
nm3rt	1.0000	
predage	0.3269	1.0000

R = .3269, so R^2 for time+age = .1069

The fixed effects of time before accounted for ~3.7% of the variance in RT, so there is a net increase of ~7% due to age.

Model 5a. +Abstract Reasoning as Predictor of Intercept, Linear, and Quadratic Time Slopes

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

Level 2:

$$\text{Intercept: } \beta_{0i} = \gamma_{00} + \gamma_{01}(\text{Age}_i - 80) + \gamma_{02}(\text{Reason}_i - 22) + U_{0i}$$

$$\text{Linear: } \beta_{1i} = \gamma_{10} + \gamma_{11}(\text{Age}_i - 80) + \gamma_{12}(\text{Reason}_i - 22) + U_{1i}$$

$$\text{Quadratic: } \beta_{2i} = \gamma_{20} + \gamma_{21}(\text{Age}_i - 80) + \gamma_{22}(\text{Reason}_i - 22) + U_{2i}$$

```
TITLE1 "SAS Model 5a: +Reasoning as Predictor of Intercept, Linear, and Quadratic";
PROC MIXED DATA=work.example23 NOCLPRINT NOITPRINT COVTEST NAMELEN=100 IC METHOD=ML;
  CLASS ID session;
  MODEL nm3rt = c1sess c1sess*c1sess age80 c1sess*age80 c1sess*c1sess*age80
    reas22 c1sess*reas22 c1sess*c1sess*reas22
    / SOLUTION DDFM=Satterthwaite OUTPM=work.ReasPred;
  RANDOM INTERCEPT c1sess c1sess*c1sess / G GCORR TYPE=UN SUBJECT=ID;
  REPEATED session / TYPE=VC SUBJECT=ID;
RUN; PROC CORR NOSIMPLE DATA=work.ReasPred; VAR nm3rt pred; RUN;
```

TITLE "SPSS Model 5a: +Reasoning as Predictor of Intercept, Linear, and Quadratic".

```
MIXED nm3rt BY ID session WITH clsess age80 reas22
/METHOD = ML
/PRINT = SOLUTION TESTCOV G R
/FIXED = clsess clsess*csess age80 clsess*age80 clsess*csess*age80
       reas22 clsess*reas22 clsess*csess*reas22
/RANDOM = INTERCEPT clsess clsess*csess | SUBJECT(ID) COVTYPE(UN)
/REPEATED = session | SUBJECT(ID) COVTYPE(ID)
/SAVE = FIXPRED (predreas).
CORRELATIONS nm3rt predreas.
```

*** STATA Model 5a: +Reasoning as Predictor of Intercept, Linear, and Quadratic**

```
xtmixed nm3rt c.clsess c.clsess#c.clsess ///
c.age80 c.age80#c.clsess c.age80#c.clsess#c.clsess ///
c.reas22 c.reas22#c.clsess c.reas22#c.clsess#c.clsess, ///
|| id: clsess clsess2, ///
variance ml covariance(un) residuals(independent,t(session)),
estat ic, n(101),
estat recovariance, level(id),
estimates store Reas, // save LL for LRT
lrtest Reas Age, // LRT against age baseline
predict predreas // save fixed-effect predicted outcomes
corr nm3rt predreas // get total r to make r2
```

STATA output:

```
Mixed-effects ML regression      Number of obs      =      606
Group variable: id              Number of groups    =      101
                                Obs per group: min =       6
                                avg =      6.0
                                max =       6
                                Wald chi2(8)    =     103.88
                                Prob > chi2     =      0.0000

Log likelihood = -4148.8645
```

	nm3rt	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
csess		-119.7417	19.77414	-6.06	0.000	-158.4983 -80.98505
c.clsess#c.clsess		13.30362	3.36557	3.95	0.000	6.707229 19.90002
age80		22.27817	8.601751	2.59	0.010	5.419047 39.13729
c.age80#c.clsess		-6.492074	3.424732	-1.90	0.058	-13.20443 .2202772
c.age80#c.clsess#c.clsess		.9601368	.5828914	1.65	0.100	-.1823093 2.102583
reas22		-27.10041	11.11411	-2.44	0.015	-48.88366 -5.317155
c.reas22#c.clsess		-3.591742	4.425011	-0.81	0.417	-12.2646 5.081121
c.reas22#c.clsess#c.clsess		1.157537	.7531395	1.54	0.124	-.3185897 2.633663
_cons		1966.467	49.66585	39.59	0.000	1869.124 2063.811

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]
id: Unstructured			
var(csess)	24040.63	5589.24	15242.24 37917.78 → linear var down by 1.04%
var(csess2)	580.0652	164.1907	333.0729 1010.216 → quad var down by 4.33%
var(_cons)	228049.3	34467.25	169581.6 306675.4 → intercept var down by 5.94%
cov(csess,csess2)	-3618.966	937.0759	-5455.601 -1782.331
cov(csess,_cons)	-31229.47	10655.91	-52114.67 -10344.27
cov(csess2,_cons)	3748.206	1747.738	322.7024 7173.709
var(Residual)	20298.18	1649.113	17310.18 23801.94 → residual var not reduced

LR test vs. linear regression: chi2(6) = 832.43 Prob > chi2 = 0.0000

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	101	.	-4148.864	16	8329.729	8371.571

```
.      lrtest Reas Age,                // LRT against age baseline

Likelihood-ratio test                LR chi2(3) =      12.47
(Assumption: Age nested in Reas)    Prob > chi2 =      0.0059

. corr nm3rt predreas                // get total r to make r2
(obs=606)
```

Is the reasoning model (5a) better than the age model (4a)?

Yes, $-2\Delta LL = 12.5$ on $df=3$, $p=.0059$, so ΔR^2 is significant

```
-----+-----
      | nm3rt predreas
nm3rt | 1.0000
predreas | 0.4011  1.0000
```

$R = .4011$, so R^2 for time+age+reas = .1609

The fixed effects of time and age before accounted for ~10.7% of the variance in RT, so there is a net increase of ~5.4% due to reasoning.

Model 5b. Abstract Reasoning on Intercept and Linear Time Slope Only

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

Level 2:

Intercept: $\beta_{0i} = \gamma_{00} + \gamma_{01}(\text{Age}_i - 80) + \gamma_{02}(\text{Reason}_i - 22) + U_{0i}$

Linear: $\beta_{1i} = \gamma_{10} + \gamma_{11}(\text{Age}_i - 80) + \gamma_{12}(\text{Reason}_i - 22) + U_{1i}$

Quadratic: $\beta_{2i} = \gamma_{20} + \gamma_{21}(\text{Age}_i - 80) + U_{2i}$

```
TITLE1 "SAS Model 5b: Reasoning on Intercept and Linear Time Slope Only";
PROC MIXED DATA=work.example23 NOCLPRINT NOITPRINT COVTEST NAMELEN=100 IC METHOD=ML;
  CLASS ID session;
  MODEL nm3rt = clsess clsess*clsess age80 clsess*age80 clsess*clsess*age80
               reas22 clsess*reas22
               / SOLUTION DDFM=Satterthwaite OUTPM=work.ReasPred2;
  RANDOM INTERCEPT clsess clsess*clsess / G GCORR TYPE=UN SUBJECT=ID;
  REPEATED session / TYPE=VC SUBJECT=ID;
  * Requesting additional effects for reasoning instead;
  ESTIMATE "Reasoning Effect at Session 1" reas22 1 clsess*reas22 0;
  ESTIMATE "Reasoning Effect at Session 2" reas22 1 clsess*reas22 1;
  ESTIMATE "Reasoning Effect at Session 3" reas22 1 clsess*reas22 2;
  ESTIMATE "Reasoning Effect at Session 4" reas22 1 clsess*reas22 3;
  ESTIMATE "Reasoning Effect at Session 5" reas22 1 clsess*reas22 4;
  ESTIMATE "Reasoning Effect at Session 6" reas22 1 clsess*reas22 5;
RUN; PROC CORR NOSIMPLE DATA=work.ReasPred2; VAR nm3rt pred; RUN;
```

```
TITLE "SPSS Model 5b: +Reasoning as Predictor of Intercept, Linear Time Slope Only".
MIXED nm3rt BY ID session WITH clsess age80 reas22
  /METHOD = ML
  /PRINT = SOLUTION TESTCOV G R
  /FIXED = clsess clsess*clsess age80 clsess*age80 clsess*clsess*age80
           reas22 clsess*reas22
  /RANDOM = INTERCEPT clsess clsess*clsess | SUBJECT(ID) COVTYPE(UN)
  /REPEATED = session | SUBJECT(ID) COVTYPE(ID)
  /SAVE = FIXPRED (predreas2)
  /TEST = "Reasoning Effect at Session 1" reas22 1 clsess*reas22 0
  /TEST = "Reasoning Effect at Session 2" reas22 1 clsess*reas22 1
  /TEST = "Reasoning Effect at Session 3" reas22 1 clsess*reas22 2
  /TEST = "Reasoning Effect at Session 4" reas22 1 clsess*reas22 3
  /TEST = "Reasoning Effect at Session 5" reas22 1 clsess*reas22 4
  /TEST = "Reasoning Effect at Session 6" reas22 1 clsess*reas22 5.
CORRELATIONS nm3rt predreas2.
```

```
* STATA Model 5b: +Reasoning as Predictor of Intercept, Linear Time Slope Only
xtmixed nm3rt c.clsess c.clsess#c.clsess ///
  c.age80 c.age80#c.clsess c.age80#c.clsess#c.clsess ///
  c.reas22 c.reas22#c.clsess, || id: clsess clsess2, ///
  variance ml covariance(un) residuals(independent,t(session)),
  estat ic, n(101),
```



```

estat recovariance, level(id),
estimates store Reas2,          // save LL for LRT
lrtest Reas2 Age,              // LRT against age baseline
margins, at(c.c1sess=(0(1)5)) dydx(c.reas22) vsquish // reas slope per session
margins, at(c.c1sess=(0(1)5) c.reas22=(-5 0 5)) vsquish // predictions per session
marginsplot, name(predicted_reas, replace) // plot reas predictions
predict predreas2              // save fixed-effect predicted outcomes
corr nm3rt predreas2           // get total r to make r2

```

STATA output:

```

Mixed-effects ML regression              Number of obs    =      606
Group variable: id                     Number of groups  =      101
                                         Obs per group: min =       6
                                         avg =      6.0
                                         max =       6
                                         Wald chi2(7)     =    101.09
Log likelihood = -4150.032              Prob > chi2      =    0.0000

```

	nm3rt	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
	c1sess	-123.5416	19.82897	-6.23	0.000	-162.4057	-84.67758
	c.c1sess#c.c1sess	13.97744	3.375697	4.14	0.000	7.3612	20.59369
	age80	20.84705	8.561395	2.44	0.015	4.067021	37.62707
	c.age80#c.c1sess	-4.860993	3.290742	-1.48	0.140	-11.31073	1.588743
	c.age80#c.c1sess#c.c1sess	.6709122	.5580948	1.20	0.229	-.4229335	1.764758
	reas22	-32.82806	10.47071	-3.14	0.002	-53.35027	-12.30585
	c.reas22#c.c1sess	2.93618	1.241355	2.37	0.018	.5031693	5.369191
	_cons	1969.802	49.6827	39.65	0.000	1872.425	2067.178

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]		
					Relative to age-only model:
id: Unstructured					
var(c1sess)	24876.74	5713.188	15860.12	39019.37	→ linear var up by -2.40%
var(c1sess2)	606.3538	167.7562	352.557	1042.852	→ quad var not reduced
var(_cons)	228693.2	34638.71	169952.4	307736.8	→ intercept var down by 5.68%
cov(c1sess,c1sess2)	-3767.223	957.7847	-5644.446	-1889.999	
cov(c1sess,_cons)	-31963.12	10883.66	-53294.71	-10631.53	
cov(c1sess2,_cons)	3878.292	1787.961	373.9525	7382.631	
var(Residual)	20298.14	1649.108	17310.16	23801.9	→ residual var not reduced

LR test vs. linear regression: chi2(6) = 830.58 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	.	-4150.032	15	8330.064	8369.291

Note: N=101 used in calculating BIC

```

. estimates store Reas2, // save LL for LRT
. lrtest Reas2 Age, // LRT against age baseline

```

```

Likelihood-ratio test      LR chi2(2) =    10.14
(Assumption: Age nested in Reas2) Prob > chi2 =    0.0063

```

```

. margins, at(c1sess=(0(1)5)) dydx(reas22) vsquish // reas slope per session

```

```

Average marginal effects      Number of obs    =      606

```

```

Expression : Linear prediction, fixed portion, predict()

```

Is the revised reasoning model (5b) still better than the age model (4a)?

Yes, $-2\Delta LL = 10.1$ on $df=2$, $p=.006$ (so only 2.4 of the previous $-2\Delta LL$ was due to reason*quad)

dy/dx w.r.t. : reas22

```

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 simple
slopes for reasoning
at each session.

```

-----
          |      Delta-method
          |      dy/dx   Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
reas22  _at |
      1 |   -32.82806   10.47071   -3.14   0.002   -53.35027   -12.30585
      2 |   -29.89188   9.961528   -3.00   0.003   -49.41612   -10.36764
      3 |   -26.9557    9.586986   -2.81   0.005   -45.74585   -8.165552
      4 |   -24.01952   9.363252   -2.57   0.010   -42.37116   -5.667884
      5 |   -21.08334   9.301214   -2.27   0.023   -39.31338   -2.853295
      6 |   -18.14716   9.404074   -1.93   0.054   -36.57881    .2844865
-----

```

```

.      margins, at(c1sess=(0(1)5) reas22=(-5 0 5)) vsquish // predictions per session

```

```

Predictive margins                                Number of obs    =          606

```

```

Expression   : Linear prediction, fixed portion, predict()

```

```

1._at      : c1sess      =      0
              reas22      =     -5
2._at      : c1sess      =      0
              reas22      =      0
3._at      : c1sess      =      0
              reas22      =      5

```

```

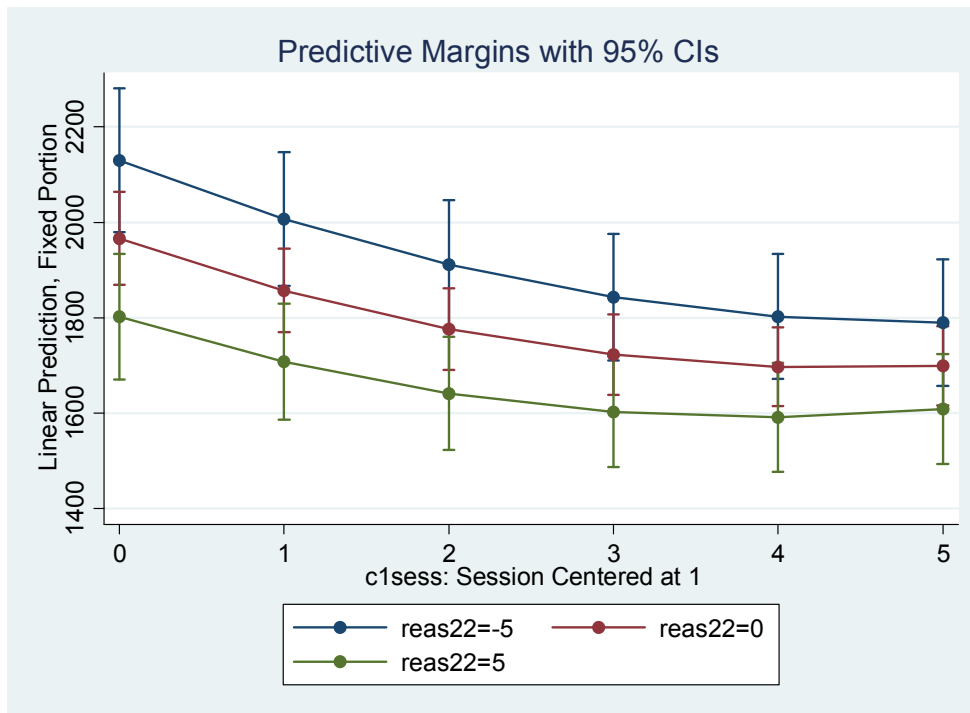
(output continues for all other sessions)

```

```

-----
          |      Delta-method
          |      Margin   Std. Err.      z    P>|z|    [95% Conf. Interval]
-----+-----
      _at |
      1 |   2130.467   76.79056   27.74   0.000    1979.96    2280.974
      2 |   1966.327   49.71952   39.55   0.000    1868.878    2063.775
      3 |   1802.186   67.29827   26.78   0.000    1670.284    1934.089
      4 |    2006.92   71.31601   28.14   0.000    1867.143    2146.697
      5 |   1857.461   44.5668    41.68   0.000    1770.112    1944.81
      6 |   1708.002   62.03248   27.53   0.000    1586.42    1829.583
      7 |   1911.105   69.07653   27.67   0.000    1775.717    2046.492
      8 |   1776.326   43.59481   40.75   0.000    1690.882    1861.771
      9 |   1641.548   60.20767   27.26   0.000    1523.543    1759.553
     10 |   1843.021   67.77101   27.19   0.000    1710.192    1975.849
     11 |   1722.923   43.0615    40.01   0.000    1638.524    1807.322
     12 |   1602.825   59.15403   27.10   0.000    1486.886    1718.765
     13 |   1802.668   66.80286   26.98   0.000    1671.736    1933.599
     14 |   1697.251   41.95444   40.45   0.000    1615.022    1779.48
     15 |   1591.834   58.16663   27.37   0.000    1477.83    1705.839
     16 |   1790.046   67.57664   26.49   0.000    1657.598    1922.494
     17 |   1699.31    42.47414   40.01   0.000    1616.062    1782.558
     18 |   1608.574   58.8501    27.33   0.000    1493.23    1723.918
-----

```



```
. marginsplot, name(predicted_reas, replace) // plot reas predictions
Variables that uniquely identify margins: c1sess reas22

. predict predreas2 // save fixed-effect predicted outcomes
(option xb assumed)

. corr nm3rt predreas2 // get total r to make r2
(obs=606)
```

	nm3rt	predre~2
nm3rt	1.0000	
predreas2	0.4001	1.0000

R = .4001, so R² for time+age+reas = .1601

So ~0.1% of the variance accounted for previously was due to reason*quad

Model 6a. +Education Group on Intercept, Linear, and Quadratic Time Slopes

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

Level 2:

$$\text{Intercept: } \beta_{0i} = \gamma_{00} + \gamma_{01}(\text{Age}_i - 80) + \gamma_{02}(\text{Reason}_i - 22) + \gamma_{03}(\text{Highvs.LowEd}_i) + \gamma_{04}(\text{Highvs.MedEd}_i) + U_{0i}$$

$$\text{Linear: } \beta_{1i} = \gamma_{10} + \gamma_{11}(\text{Age}_i - 80) + \gamma_{12}(\text{Reason}_i - 22) + \gamma_{13}(\text{Highvs.LowEd}_i) + \gamma_{14}(\text{Highvs.MedEd}_i) + U_{1i}$$

$$\text{Quadratic: } \beta_{2i} = \gamma_{20} + \gamma_{21}(\text{Age}_i - 80) + \gamma_{23}(\text{Highvs.LowEd}_i) + \gamma_{24}(\text{Highvs.MedEd}_i) + U_{2i}$$

Additional model-implied group differences:

$$\text{Medium vs. Low education intercept} = (\gamma_{00} + \gamma_{04}) - (\gamma_{00} + \gamma_{03}) = \gamma_{04} - \gamma_{03}$$

$$\text{Medium vs. Low education linear session} = (\gamma_{10} + \gamma_{14}) - (\gamma_{10} + \gamma_{13}) = \gamma_{14} - \gamma_{13}$$

$$\text{Medium vs. Low education quadratic session} = (\gamma_{20} + \gamma_{24}) - (\gamma_{20} + \gamma_{23}) = \gamma_{24} - \gamma_{23}$$

```

TITLE1 "SAS Model 6a: +Education Group on Intercept, Linear, and Quadratic";
PROC MIXED DATA=work.example23 NOCLPRINT NOITPRINT COVTEST NAMELEN=100 IC METHOD=ML;
  CLASS ID session educgrp;
  MODEL nm3rt = clsess clsess*clsess age80 clsess*age80 clsess*clsess*age80
               reas22 clsess*reas22 educgrp clsess*educgrp clsess*clsess*educgrp
               / SOLUTION DDFM=Satterthwaite OUTPM=work.EducPred;
  RANDOM INTERCEPT clsess clsess*clsess / G GCORR TYPE=UN SUBJECT=ID;
  REPEATED session / TYPE=VC SUBJECT=ID;
  * Estimating group means at first and last sessions
  LSMEANS educgrp / AT (clsess) = (0) DIFF=ALL;
  LSMEANS educgrp / AT (clsess) = (5) DIFF=ALL;
  * Contrasts between groups on intercept, linear, and quadratic slopes
  ESTIMATE "L vs. H Educ for Intercept Main Effect" educgrp -1 0 1 ;
  ESTIMATE "M vs. H Educ for Intercept Main Effect" educgrp 0 -1 1 ;
  ESTIMATE "L vs. M Educ for Intercept Main Effect" educgrp -1 1 0 ;
  ESTIMATE "L vs. H Educ for Linear Session" clsess*educgrp -1 0 1 ;
  ESTIMATE "M vs. H Educ for Linear Session" clsess*educgrp 0 -1 1 ;
  ESTIMATE "L vs. M Educ for Linear Session" clsess*educgrp -1 1 0 ;
  ESTIMATE "L vs. H Educ for Quadratic Session" clsess*clsess*educgrp -1 0 1 ;
  ESTIMATE "M vs. H Educ for Quadratic Session" clsess*clsess*educgrp 0 -1 1 ;
  ESTIMATE "L vs. M Educ for Quadratic Session" clsess*clsess*educgrp -1 1 0 ;
RUN; PROC CORR NOSIMPLE DATA=work.EducPred; VAR nm3rt pred; RUN;

```

Think of the -1 as the
"0" and the "1" as the
"1" in a dummy code.

```

TITLE "SPSS Model 6a: +Education as Predictor of Intercept, Linear, and Quadratic".
MIXED nm3rt BY ID session educgrp WITH clsess age80 reas22
  /METHOD = ML
  /PRINT = SOLUTION TESTCOV G R
  /FIXED = clsess clsess*clsess age80 clsess*age80 clsess*clsess*age80
           reas22 clsess*reas22 educgrp clsess*educgrp clsess*clsess*educgrp
  /RANDOM = INTERCEPT clsess clsess*clsess | SUBJECT(ID) COVTYPE(UN)
  /REPEATED = session | SUBJECT(ID) COVTYPE(ID)
  /SAVE = FIXPRED (prededuc)
  /EMMEANS = TABLES(educgrp) WITH (clsess=0) COMPARE(educgrp)
  /EMMEANS = TABLES(educgrp) WITH (clsess=5) COMPARE(educgrp)
  /TEST = "L vs. H Educ for for Main Effect" educgrp -1 0 1
  /TEST = "M vs. H Educ for for Main Effect" educgrp 0 -1 1
  /TEST = "L vs. M Educ for for Main Effect" educgrp -1 1 0
  /TEST = "L vs. H Educ for for Linear Session" clsess*educgrp -1 0 1
  /TEST = "M vs. H Educ for for Linear Session" clsess*educgrp 0 -1 1
  /TEST = "L vs. M Educ for for Linear Session" clsess*educgrp -1 1 0
  /TEST = "L vs. H Educ for for Quadratic Session" clsess*clsess*educgrp -1 0 1
  /TEST = "M vs. H Educ for for Quadratic Session" clsess*clsess*educgrp 0 -1 1
  /TEST = "L vs. M Educ for for Quadratic Session" clsess*clsess*educgrp -1 1 0.
CORRELATIONS nm3rt prededuc.

```

```

* STATA Model 6a: +Education Group on Intercept, Linear, and Quadratic
xtmixed nm3rt c.clsess c.clsess#c.clsess ///
  c.age80 c.age80#c.clsess c.age80#c.clsess#c.clsess ///
  c.reas22 c.reas22#c.clsess ///
  b(last).educgrp ib(last).educgrp#c.clsess ///
  ib(last).educgrp#c.clsess#c.clsess, || id: clsess clsess2, ///
  variance ml covariance(un) residuals(independent,t(session)),
  estat ic, n(101),
  estat recovariance, level(id),
  estimates store Educ,
  lrtest Educ Reas2,
  * Estimating group means at first and last sessions
  margins ib(last).educgrp, at(c.clsess=(0 5))
  * Contrasts between groups on intercept, linear, and quadratic slopes
  test 1.educgrp=3.educgrp // Low vs. High: Intercept
  test 2.educgrp=3.educgrp // Med vs. High: Intercept
  test 1.educgrp=2.educgrp // Low vs. Med: Intercept
  test 1.educgrp#c.clsess=3.educgrp#c.clsess // Low vs. High: Linear
  test 2.educgrp#c.clsess=3.educgrp#c.clsess // Med vs. High: Linear
  test 1.educgrp#c.clsess=2.educgrp#c.clsess // Low vs. Med: Linear
  test 1.educgrp#c.clsess#c.clsess=3.educgrp#c.clsess#c.clsess // Low vs. High: Quad
  test 2.educgrp#c.clsess#c.clsess=3.educgrp#c.clsess#c.clsess // Med vs. High: Quad
  test 1.educgrp#c.clsess#c.clsess=2.educgrp#c.clsess#c.clsess // Low vs. Med: Quad

```

```

contrast educgrp, // omnibus group diff on intercept
contrast educgrp#c.c1sess, // omnibus group diff on linear
contrast educgrp#c.c1sess#c.c1sess, // omnibus group diff on quadratic
margins, at(c.c1sess=(0(1)5) educgrp=(1 2 3)) vsquish // predictions per session
marginsplot, name(predicted_educ, replace) // plot educ predictions
predict prededuc // save fixed-effect predicted outcomes
corr nm3rt prededuc // get total r to make r2

```

STATA output:

Mixed-effects ML regression
Group variable: id

Number of obs = 606
Number of groups = 101
Obs per group: min = 6
 avg = 6.0
 max = 6
Wald chi2(13) = 106.94
Prob > chi2 = 0.0000

Log likelihood = -4147.6829

	nm3rt	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
	c1sess	-106.4987	40.28349	-2.64	0.008	-185.4529	-27.54452
	c.c1sess#c.c1sess	12.47966	6.848972	1.82	0.068	-.9440805	25.9034
	age80	20.28963	8.560341	2.37	0.018	3.511673	37.06759
	c.age80#c.c1sess	-4.575964	3.267261	-1.40	0.161	-10.97968	1.827749
	c.age80#c.c1sess#c.c1sess	.6176862	.5534216	1.12	0.264	-.4670003	1.702373
	reas22	-36.62127	10.76417	-3.40	0.001	-57.71865	-15.52389
	c.reas22#c.c1sess	2.978327	1.280262	2.33	0.020	.4690609	5.487594
	educgrp						
	1	-51.37682	151.0698	-0.34	0.734	-347.4683	244.7146
	2	37.64254	120.8739	0.31	0.755	-199.2659	274.5509
	educgrp#c.c1sess						
	1	-70.24589	59.07811	-1.19	0.234	-186.0368	45.54507
	2	-4.357662	48.13262	-0.09	0.928	-98.69587	89.98055
	educgrp#c.c1sess#c.c1sess						
	1	11.06526	10.03239	1.10	0.270	-8.597857	30.72837
	2	-1.464111	8.188464	-0.18	0.858	-17.51321	14.58498
	_cons	1961.886	101.7896	19.27	0.000	1762.382	2161.39

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]	
-----+-----				
id: Unstructured				
var(c1sess)	24143.68	5618.86	15300.54	38097.82 → linear var down by 2.95%
var(c1sess2)	582.0323	164.4561	334.5305	1012.648 → quad var down by 4.01%
var(_cons)	228602.6	34699.74	169776.2	307812.1 → intercept var down by 0.04%
cov(c1sess,c1sess2)	-3636.004	939.9484	-5478.269	-1793.739
cov(c1sess,_cons)	-33285.68	10917.47	-54683.52	-11887.83
cov(c1sess2,_cons)	4127.595	1789.937	619.382	7635.808

var(Residual) | 20298.12 1649.105 17310.14 23801.87 → residual var not reduced

LR test vs. linear regression: chi2(6) = 826.31 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	.	-4147.683	21	8337.366	8392.283

Note: N=101 used in calculating BIC

```
. estimates store Educ,
. lrtest Educ Reas2,
```

Is the education model (6a) better than the revised reasoning model (5b)?
 No, $-2\Delta LL = 4.7$ on $df=6$, $p = .583$

```
Likelihood-ratio test                                LR chi2(6) =      4.70
(Assumption: Reas2 nested in Educ)                   Prob > chi2 =    0.5831
```

```
. * Estimating group means at first and last sessions
. margins ib(last).educgrp, at(c1sess=(0))
Predictive margins                                Number of obs =      606
Expression   : Linear prediction, fixed portion, predict()
at           : c1sess =      0
```

		Delta-method				
		Margin	Std. Err.	z	P> z	[95% Conf. Interval]
educgrp						
1		1884.284	110.9362	16.99	0.000	1666.853 2101.715
2		1973.304	66.56898	29.64	0.000	1842.831 2103.776
3		1935.661	101.2482	19.12	0.000	1737.218 2134.104

```
. margins ib(last).educgrp, at(c1sess=(5))
Predictive margins                                Number of obs =      606
Expression   : Linear prediction, fixed portion, predict()
at           : c1sess =      5
```

		Delta-method				
		Margin	Std. Err.	z	P> z	[95% Conf. Interval]
educgrp						
1		1599.713	94.54367	16.92	0.000	1414.41 1785.015
2		1704.939	56.6088	30.12	0.000	1593.988 1815.89
3		1725.687	86.06347	20.05	0.000	1557.006 1894.369

```
. * Contrasts between groups on intercept, linear, and quadratic slopes
. test 1.educgrp=3.educgrp // Low vs. High: Intercept
( 1) [nm3rt]1.educgrp - [nm3rt]3b.educgrp = 0
    chi2( 1) =    0.12
    Prob > chi2 =    0.7338

. test 2.educgrp=3.educgrp // Med vs. High: Intercept
( 1) [nm3rt]2.educgrp - [nm3rt]3b.educgrp = 0
    chi2( 1) =    0.10
    Prob > chi2 =    0.7555

. test 1.educgrp=2.educgrp // Low vs. Med: Intercept
( 1) [nm3rt]1.educgrp - [nm3rt]2.educgrp = 0
    chi2( 1) =    0.46
    Prob > chi2 =    0.4960

. test 1.educgrp#c.c1sess=3.educgrp#c.c1sess // Low vs. High: Linear
( 1) [nm3rt]1.educgrp#c.c1sess - [nm3rt]3b.educgrp#co.c1sess = 0
    chi2( 1) =    1.41
    Prob > chi2 =    0.2344

. test 2.educgrp#c.c1sess=3.educgrp#c.c1sess // Med vs. High: Linear
( 1) [nm3rt]2.educgrp#c.c1sess - [nm3rt]3b.educgrp#co.c1sess = 0
    chi2( 1) =    0.01
    Prob > chi2 =    0.9279

. test 1.educgrp#c.c1sess=2.educgrp#c.c1sess // Low vs. Med: Linear
```

```

( 1) [nm3rt]1.educgrp#c.c1sess - [nm3rt]2.educgrp#c.c1sess = 0
      chi2( 1) =      1.69
      Prob > chi2 =    0.1939

.      test 1.educgrp#c.c1sess#c.c1sess=3.educgrp#c.c1sess#c.c1sess // Low vs. High: Quad
( 1) [nm3rt]1.educgrp#c.c1sess#c.c1sess - [nm3rt]3b.educgrp#co.c1sess#co.c1sess = 0
      chi2( 1) =      1.22
      Prob > chi2 =    0.2700

.      test 2.educgrp#c.c1sess#c.c1sess=3.educgrp#c.c1sess#c.c1sess // Med vs. High: Quad
( 1) [nm3rt]2.educgrp#c.c1sess#c.c1sess - [nm3rt]3b.educgrp#co.c1sess#co.c1sess = 0
      chi2( 1) =      0.03
      Prob > chi2 =    0.8581

.      test 1.educgrp#c.c1sess#c.c1sess=2.educgrp#c.c1sess#c.c1sess // Low vs. Med: Quad
( 1) [nm3rt]1.educgrp#c.c1sess#c.c1sess - [nm3rt]2.educgrp#c.c1sess#c.c1sess = 0
      chi2( 1) =      2.12
      Prob > chi2 =    0.1454

.      contrast educgrp, // omnibus group diff on intercept

Contrasts of marginal linear predictions
Margins      : asbalanced
-----+-----
      |      df      chi2      P>chi2
-----+-----
nm3rt  |
educgrp |      2      0.48      0.7869
-----+-----

.      contrast educgrp#c.c1sess, // omnibus group diff on linear
Contrasts of marginal linear predictions
Margins      : asbalanced
-----+-----
      |      df      chi2      P>chi2
-----+-----
nm3rt  |
educgrp#c.c1sess |      2      1.92      0.3827
-----+-----

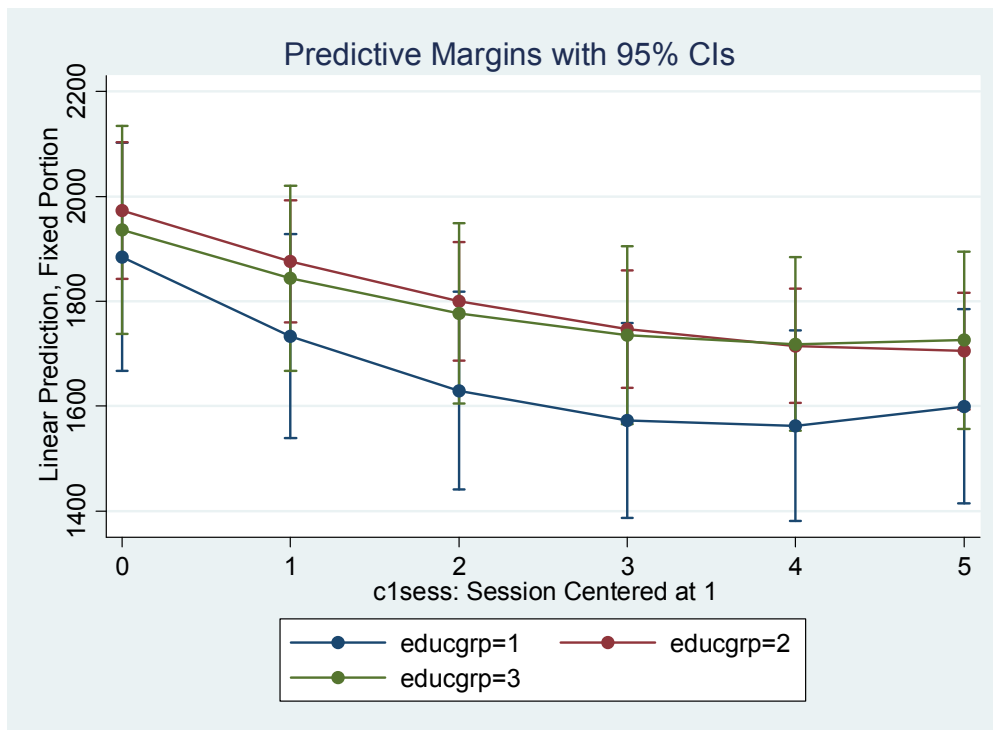
.      contrast educgrp#c.c1sess#c.c1sess, // omnibus group diff on quadratic
Contrasts of marginal linear predictions
Margins      : asbalanced
-----+-----
      |      df      chi2      P>chi2
-----+-----
nm3rt  |
educgrp#c.c1sess#c.c1sess |      2      2.18      0.3358
-----+-----

.      margins, at(c.c1sess=(0(1)5) educgrp=(1 2 3)) vsquish // predictions per session
Predictive margins      Number of obs      =      606
Expression : Linear prediction, fixed portion, predict()
1._at      : c1sess      =      0
            : educgrp      =      1
2._at      : c1sess      =      0
            : educgrp      =      2
3._at      : c1sess      =      0
            : educgrp      =      3
(output continues for all other sessions)

```

	Delta-method				[95% Conf. Interval]	
	Margin	Std. Err.	z	P> z		
_at						
1	1884.284	110.9362	16.99	0.000	1666.853	2101.715
2	1973.304	66.56898	29.64	0.000	1842.831	2103.776
3	1935.661	101.2482	19.12	0.000	1737.218	2134.104
4	1733.602	98.99478	17.51	0.000	1539.576	1927.628
5	1875.98	59.24278	31.67	0.000	1759.867	1992.094
6	1844.159	90.05891	20.48	0.000	1667.647	2020.672
7	1629.804	96.28618	16.93	0.000	1441.086	1818.521
8	1800.482	57.64972	31.23	0.000	1687.491	1913.474
9	1777.411	87.64532	20.28	0.000	1605.63	1949.193
10	1572.889	94.93902	16.57	0.000	1386.812	1758.967
11	1746.809	56.86718	30.72	0.000	1635.352	1858.267
12	1735.417	86.46259	20.07	0.000	1565.953	1904.88
13	1562.859	92.79589	16.84	0.000	1380.983	1744.736
14	1714.961	55.5437	30.88	0.000	1606.098	1823.825
15	1718.175	84.43878	20.35	0.000	1552.678	1883.672
16	1599.713	94.54367	16.92	0.000	1414.41	1785.015
17	1704.939	56.6088	30.12	0.000	1593.988	1815.89
18	1725.687	86.06347	20.05	0.000	1557.006	1894.369

```
. marginsplot, name(predicted_educ, replace) // plot educ predictions
Variables that uniquely identify margins: c1sess educgrp
```



```
. predict prededuc // save fixed-effect predicted outcomes
(option xb assumed)
```

```
. corr nm3rt prededuc // get total r to make r2
(obs=606)
```

	nm3rt prededuc	
nm3rt	1.0000	
prededuc	0.4151	1.0000

$R = .4151$, so R^2 for time+age+reas+educ = .172

The fixed effects of time, age, and reasoning before accounted for ~16.0% of the variance in RT, so there is a net increase of 1.2% due to education (which is not significant).

Simple Processing Speed – Example Conditional Models of Change Results

The extent to which individual differences in response time (RT) over six sessions for a simple processing speed test (number match three) could be predicted from baseline age, abstract reasoning, and education level was examined in a series of multilevel models (i.e., general linear mixed models) in which the six practice sessions were nested within each participant. Given the interest in comparing models differing in fixed effects, maximum likelihood (ML) was used in estimating and reporting all model parameters. The significance of new fixed effects were evaluated with individual Wald tests (i.e., of estimate / SE) as well as with likelihood ratio tests (i.e., $-2\Delta LL$), with degrees of freedom equal to the number of new fixed effects. Session (i.e., the index of time) was centered at the first occasion, age was centered at 80 years, abstract reasoning was centered at 22 (near the mean of the scale), and graduate-level education was the reference group for education level (with separate contrasts for high school or less and for bachelor's level education).

The best-fitting unconditional growth model specified quadratic decline across the six sessions (i.e., a decelerating negative function) with significant individual differences in the intercept, linear, and quadratic effects. Accordingly, effect size was evaluated via pseudo- R^2 values for the proportion reduction in each random effect variance, as well as with total R^2 , the squared correlation between the actual outcome values and the outcomes predicted by the model fixed effects. In the unconditional growth model, the fixed effects for linear and quadratic change across sessions accounted for approximately 4% of the total variation in RT.

Next, age was added as a predictor of the intercept, linear slope, and quadratic slope. The age model fit significantly better than the unconditional model as indicated by a significant likelihood ratio test, $-2\Delta LL(3) = 11.6$, $p = .009$; the AIC was lower, although the BIC was not. However, only the fixed effect of age on the intercept was significant, indicating that for every additional year of age above 80, RT at the first session was predicted to be significantly higher by 29.05 ($p = .001$). In terms of pseudo- R^2 , age accounted for 11.29% of the random intercept variance, 4.50% of the random linear slope variance, and 2.64% of the random quadratic slope variance. As expected given that baseline age is a time-invariant predictor, the residual variance was not reduced. The total cumulative R^2 from session and age was $R^2 = .11$, approximately a 7% increase due to age (which was significant, as indicated by the likelihood ratio test). Although the interactions of age with the linear and quadratic slopes were not significant, they were retained in the model to fully control for age effects before examining the effects of other predictors.

Abstract reasoning was then added as a predictor of the intercept, linear slope, and quadratic slope. The abstract reasoning model fit significantly better than the age model, $-2\Delta LL(3) = 12.5$, $p = .006$; the AIC was lower, although the BIC was not. However, only the fixed effect of reasoning on the intercept was significant. The nonsignificant effect of reasoning on the quadratic slope was then removed, revealing a significant effect of reasoning on both the intercept and linear slope, such that for every unit higher reasoning above 22, RT at the first session was expected to be lower by 32.82 and the linear rate of improvement in RT (as evaluated at the first session given the quadratic slope) was expected to be less negative by 2.94 (i.e., faster initial RT with less improvement in persons with greater reasoning). These two effects still resulted in a significant improvement in model fit over the age model, $-2\Delta LL(2) = 10.1$, $p = .006$, with a lower AIC and BIC. Reasoning accounted for 5.68% of the random intercept variance but had no measurable reduction of the random linear and quadratic slope variances. The total cumulative R^2 from session, age, and reasoning was $R^2 = .16$, approximately a 5% increase due to reasoning (which was significant, as indicated by the likelihood ratio test).

Finally, education level (high school or less, bachelor's level, or graduate level) was then added as a predictor of the intercept, linear slope, and quadratic slope. The education model did not fit significantly better than the reasoning model, $-2\Delta LL(6) = 4.7$, $p = .583$, with a higher AIC and BIC. None of the omnibus main effects of group on the intercept, linear, or quadratic slopes were significant, $\chi^2(2) < 1.92$, p 's $> .05$, and none of the pairwise group comparisons were significant as well. Education accounted for 0.04% of the random intercept variance, 2.95% of the random linear slope variance, and 4.01% of the random quadratic slope variance. The total cumulative R^2 from session, age, reasoning, and education was $R^2 = .17$, approximately a 1% increase due to education (which was not significant, as indicated by the likelihood ratio test).

(From here one might remove nonsignificant model effects and/or add other effects as needed to fully answer all research questions...)