

## Repeated Measures Data – Random Coefficients Models

The most common applications of random coefficients models are those where a linear relationship is assumed between the outcome variable of interest and time, for example test-day data in dairy cows. Usually, how the outcome variables differ between “treatment” groups are of interest. For example, the effect of BST on milk production in dairy cows.

In the textbook they go over examples of a linear random coefficients model and a polynomial random coefficients model. However, the data they use for the linear random coefficient model is not available from their website. So we will cover the Polynomial random coefficients model for now and find another dataset to go over a linear random coefficient model later.

### Polynomial random coefficients model

This study involved 45 children suffering from either solid lump tumor cancer (18) or leukemia (27). Antibody levels to a herpes virus were measured during hospital visits during chemotherapy treatment. Treatment ranged from one month to three years and the time between treatments varied among the children. The objective of the study was to determine whether virus antibody levels were affected by chemotherapy treatment and whether any change was related to type of cancer. The herpes virus antibody was present in all children in the study and it’s known that the average level of herpes virus antibody decreases with age. The book presents plots of individual patients for herpes virus antibodies over time. The plots indicate that the levels of antibody fluctuate widely in some children. The non-linear relationship of virus level with time indicates that a model using polynomials of times should be considered because we want to assess whether there is a time trend, or whether the trend varies across treatment groups.

A polynomial model is built up by adding polynomials of increasing order to the model one at a time. Time is included both as fixed effects and random coefficients. The initial linear model fitted is:

Fixed effects: type of cancer, age, time

Random coefficients: patient(intercepts), patient\*time (slopes):

```
OPTIONS LS=80;
filename ep 'i:\kathy mixed model\lyall.dat';
DATA a; INFILE ep;
INPUT pat age agecat month month2 month3 month4 virus type $;

PROC MIXED; CLASS type pat;
MODEL virus=age type month/ S DDFM=SATTERTH;
RANDOM int month/ SUB=pat TYPE=UN;
run;
```

Model Information

Data Set WORK.A  
 Dependent Variable virus  
 Covariance Structure Unstructured  
 Subject Effect pat  
 Estimation Method REML  
 Residual Variance Method Profile  
 Fixed Effects SE Method Model-Based  
 Degrees of Freedom Method Satterthwaite

Class	Levels	Values
type	2	AL ST
pat	44	3 5 13 61 63 65 67 69 71 73 77 79 81 85 87 91 93 95 97 101 103 105 107 109 113 115 117 119 123 127 129 141 142 143 144 145 146 147 148 149 150 151 152 155

Dimensions

Covariance Parameters	4
Columns in X	5
Columns in Z Per Subject	2
Subjects	44
Max Obs Per Subject	33

Number of Observations

Number of Observations Read	625
Number of Observations Used	625

Covariance Parameter Estimates

Cov Parm	Subject	Estimate
UN(1,1)	pat	0.4433
UN(2,1)	pat	0.01326
UN(2,2)	pat	0.004238
Residual		0.5640

Fit Statistics

-2 Res Log Likelihood	1588.4
AIC (smaller is better)	1596.4
AICC (smaller is better)	1596.4
BIC (smaller is better)	1603.5

Null Model Likelihood Ratio Test

DF	Chi-Square	Pr > ChiSq
3	465.66	<.0001

Solution for Fixed Effects

Effect	type	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept		3.6544	0.2331	47.3	15.68	<.0001
age		-0.04570	0.03653	43.9	-1.25	0.2176
type	AL	-0.2341	0.2465	43.8	-0.95	0.3475
type	ST	0	.	.	.	.
month		-0.03161	0.01324	16.3	-2.39	0.0293

The variance components corresponding to the patient and patient\*time random coefficients are both positive, indicating that there is more variation between the regression lines for each patient than expected by chance. In other words, patients vary in their rates of decay. So we now go ahead and add the quadratic time effects to both the fixed and random coefficients.

```
PROC MIXED; CLASS type pat;  
MODEL virus=age type month month2/ S DDFM=SATTERTH;  
RANDOM int month month2/ SUB=pat TYPE=UN;  
run;
```

Covariance Parameter Estimates

Cov Parm	Subject	Estimate
UN(1,1)	pat	0.5864
UN(2,1)	pat	-0.04333
UN(2,2)	pat	0.02451
UN(3,1)	pat	0.001586
UN(3,2)	pat	-0.00072
UN(3,3)	pat	0.000022
Residual		0.5275

Fit Statistics

-2 Res Log Likelihood	1583.4
AIC (smaller is better)	1597.4
AICC (smaller is better)	1597.6
BIC (smaller is better)	1609.9

Null Model Likelihood Ratio Test

DF	Chi-Square	Pr > ChiSq
6	482.42	<.0001

Solution for Fixed Effects

Effect	type	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept		3.7011	0.2417	48.5	15.32	<.0001
age		-0.05071	0.03695	43.5	-1.37	0.1770
type	AL	-0.08073	0.2485	42.6	-0.32	0.7469
type	ST	0	.	.	.	.
month		-0.08140	0.02987	18	-2.72	0.0139
month2		0.002468	0.001004	14.2	2.46	0.0274

Type 3 Tests of Fixed Effects

Effect	Num DF	Den DF	F Value	Pr > F
age	1	43.5	1.88	0.1770
type	1	42.6	0.11	0.7469
month	1	18	7.42	0.0139
month2	1	14.2	6.04	0.0274

Again, the three variance components (patient, patient\*time, and patient\*time<sup>2</sup>) are all positive, indicating more variation between the quadratic curves for each patient than expected by chance. Also, the month2 fixed effect was significant. So we go ahead and fit the cubic term for both fixed and random.

```
PROC MIXED; CLASS type pat;
MODEL virus=age type month month2 month3/ S DDFM=SATTERTH;
RANDOM int month month2 month3/ SUB=pat TYPE=UN;
run;
```

WARNING: Stopped because of infinite likelihood.

Covariance Parameter Values  
At Last Iteration

Cov Parm	Subject	Estimate
UN(1,1)	pat	0.4271
UN(2,1)	pat	0.02673
UN(2,2)	pat	0.02403
UN(3,1)	pat	-0.00196
UN(3,2)	pat	-0.00130
UN(3,3)	pat	0.000087
UN(4,1)	pat	0.000051
UN(4,2)	pat	0.000015
UN(4,3)	pat	-1.26E-6
UN(4,4)	pat	2.121E-8
Residual		0.5238

In other words, the model did not converge trying to include the cubic variance component. When we look at the estimates of the covariance parameter values from the last interaction performed, it appears that the time-cubed variance component was heading toward zero. So we will run the model dropping the month3 term from the random statement, but still including the month3 fixed effect.

```
PROC MIXED; CLASS type pat;
MODEL virus=age type month month2 month3/ S DDFM=SATTERTH;
```

```
RANDOM int month month2/ SUB=pat TYPE=UN;
run;
```

Cov Parm	Parameter Subject	Estimates Estimate
UN(1,1)	pat	0.5960
UN(2,1)	pat	-0.04470
UN(2,2)	pat	0.02356
UN(3,1)	pat	0.001705
UN(3,2)	pat	-0.00071
UN(3,3)	pat	0.000022
Residual		0.5258

Fit Statistics

-2 Res Log Likelihood	1597.5
AIC (smaller is better)	1611.5
AICC (smaller is better)	1611.7
BIC (smaller is better)	1624.0

Null Model Likelihood Ratio Test

DF	Chi-Square	Pr > ChiSq
6	464.77	<.0001

Solution for Fixed Effects

Effect	type	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept		3.7385	0.2427	50	15.41	<.0001
age		-0.04852	0.03683	43.3	-1.32	0.1946
type	AL	-0.06019	0.2485	43	-0.24	0.8098
type	ST	0	.	.	.	.
month		-0.1182	0.03533	39.6	-3.35	0.0018
month2		0.006543	0.002345	123	2.79	0.0061
month3		-0.00011	0.000055	79.5	-1.93	0.0569

Type 3 Tests of Fixed Effects

Effect	Num DF	Den DF	F Value	Pr > F
age	1	43.3	1.74	0.1946
type	1	43	0.06	0.8098
month	1	39.6	11.20	0.0018
month2	1	123	7.78	0.0061
month3	1	79.5	3.73	0.0569

The time3 fixed effect was almost significant ( $p=.0569$ ), so we will run a model with a time4 fixed effect term added.

```
PROC MIXED; CLASS type pat;
MODEL virus=age type month month2 month3 month4/ S DDFM=SATTERTH;
RANDOM int month month2/ SUB=pat TYPE=UN;
run;
```

Covariance Parameter Estimates

Cov Parm	Subject	Estimate
UN(1,1)	pat	0.5729
UN(2,1)	pat	-0.03886
UN(2,2)	pat	0.02148
UN(3,1)	pat	0.001537
UN(3,2)	pat	-0.00066
UN(3,3)	pat	0.000022
Residual		0.5235

Fit Statistics

-2 Res Log Likelihood	1616.1
AIC (smaller is better)	1630.1
AICC (smaller is better)	1630.3
BIC (smaller is better)	1642.6

Null Model Likelihood Ratio Test

DF	Chi-Square	Pr > ChiSq
6	464.67	<.0001

Solution for Fixed Effects

Effect	type	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept		3.8012	0.2423	51.4	15.69	<.0001
age		-0.04334	0.03673	44	-1.18	0.2444
type	AL	-0.05877	0.2468	43.3	-0.24	0.8129
type	ST	0	.	.	.	.
month		-0.1908	0.04753	144	-4.01	<.0001
month2		0.01777	0.005493	497	3.24	0.0013
month3		-0.00064	0.000241	490	-2.64	0.0086
month4		7.455E-6	3.33E-6	565	2.24	0.0256

Type 3 Tests of Fixed Effects

Effect	Num DF	Den DF	F Value	Pr > F
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age	1	44	1.39	0.2444
type	1	43.3	0.06	0.8129
month	1	144	16.12	<.0001
month2	1	497	10.47	0.0013
month3	1	490	6.97	0.0086
month4	1	565	5.01	0.0256

From our analysis, the fixed quartic term (month4) was significant. In the book, they said they did not have a significant quartic term, so did not continue. I went and added a month5 term to the dataset and ran the model with the quintic term (month5)

```
PROC MIXED; CLASS type pat;  
MODEL virus=age type month month2 month3 month4 month5/ S  
DDFM=SATTERTH;  
RANDOM int month month2/ SUB=pat TYPE=UN;  
run;
```

Covariance Parameter Estimates

Cov Parm	Subject	Estimate
UN(1,1)	pat	0.5930
UN(2,1)	pat	-0.04490
UN(2,2)	pat	0.02364
UN(3,1)	pat	0.001770
UN(3,2)	pat	-0.00075
UN(3,3)	pat	0.000025
Residual		0.5200

Fit Statistics

-2 Res Log Likelihood	1643.2
AIC (smaller is better)	1657.2
AICC (smaller is better)	1657.3
BIC (smaller is better)	1669.7

Null Model Likelihood Ratio Test

DF	Chi-Square	Pr > ChiSq
6	465.04	<.0001

Solution for Fixed Effects

Effect	type	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept		3.7651	0.2462	52.9	15.29	<.0001
age		-0.04517	0.03693	44	-1.22	0.2277
type	AL	-0.05772	0.2476	43.2	-0.23	0.8167
type	ST	0	.	.	.	.
month		-0.1373	0.06920	332	-1.98	0.0480
month2		0.005511	0.01239	558	0.44	0.6566
month3		0.000340	0.000902	497	0.38	0.7068
month4		-0.00002	0.000028	438	-0.85	0.3957
month5		3.303E-7	0	0	.	.

Type 3 Tests of Fixed Effects

Effect	Num DF	Den DF	F Value	Pr > F
age	1	44	1.50	0.2277
type	1	43.2	0.05	0.8167
month	1	332	3.94	0.0480
month2	1	558	0.20	0.6566
month3	1	497	0.14	0.7068
month4	1	438	0.72	0.3957
month5	1	425	1.28	0.2585

We see that a fixed quintic effect was not significant, so we'll stop with the previous model and go ahead and test for interactions between time and type of cancer.

```
PROC MIXED; CLASS type pat;
MODEL virus=age type month month2 month3 month4 type*month type*month2
type*month3 type*month4/
S DDFM=SATTERTH;
RANDOM int month month2/ SUB=pat TYPE=UN;
run;
```

WARNING: Stopped because of infinite likelihood.

Covariance Parameter Values  
 At Last Iteration

Cov Parm	Subject	Estimate
UN(1,1)	pat	0.4143
UN(2,1)	pat	0.02576
UN(2,2)	pat	0.008990
UN(3,1)	pat	-0.00103
UN(3,2)	pat	-0.00020
UN(3,3)	pat	6.402E-6
Residual		0.5096

Again, with this more complex model, we run into a problem with the month3 variance component heading toward zero. So we will back up a step and run a model without month4 included as a fixed effect.

```
PROC MIXED; CLASS type pat;
MODEL virus=age type month month2 month3 type*month type*month2
type*month3/
```



```
S DDFM=SATTERTH;
RANDOM int month month2/ SUB=pat TYPE=UN;
run;
```

Covariance Parameter Estimates

Cov Parm	Subject	Estimate
UN(1,1)	pat	0.5972
UN(2,1)	pat	-0.04689
UN(2,2)	pat	0.02376
UN(3,1)	pat	0.001740
UN(3,2)	pat	-0.00071
UN(3,3)	pat	0.000022
Residual		0.5248

Fit Statistics

-2 Res Log Likelihood	1618.4
AIC (smaller is better)	1632.4
AICC (smaller is better)	1632.5
BIC (smaller is better)	1644.9

Null Model Likelihood Ratio Test

DF	Chi-Square	Pr > ChiSq
6	463.50	<.0001

Solution for Fixed Effects

Effect	type	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept		3.9512	0.2794	56.3	14.14	<.0001
age		-0.04903	0.03665	43.5	-1.34	0.1879
type	AL	-0.3603	0.3058	45.8	-1.18	0.2448
type	ST	0	.	.	.	.
month		-0.2079	0.1296	410	-1.60	0.1094
month2		0.006063	0.02236	579	0.27	0.7864
month3		0.000253	0.001083	558	0.23	0.8157
month*type	AL	0.1303	0.1360	299	0.96	0.3388
month*type	ST	0	.	.	.	.
month2*type	AL	-0.00134	0.02250	582	-0.06	0.9524
month2*type	ST	0	.	.	.	.
month3*type	AL	-0.00034	0.001085	560	-0.31	0.7544
month3*type	ST	0	.	.	.	.

Type 3 Tests of Fixed Effects

Effect	Num DF	Den DF	F Value	Pr > F
age	1	43.5	1.79	0.1879
type	1	45.8	1.39	0.2448
month	1	299	4.40	0.0367
month2	1	581	0.23	0.6320
month3	1	560	0.02	0.8786
month*type	1	299	0.92	0.3388
month2*type	1	582	0.00	0.9524
month3*type	1	560	0.10	0.7544

There are no significant interactions between time effects and cancer type. Therefore, we can reasonably assume that changes in antibody level are similar for the two cancer types. We can also test for interactions between time effects and age.

```
PROC MIXED; CLASS type pat;  
MODEL virus=age type month month2 month3 age*month age*month2  
age*month3/ S;  
RANDOM int month month2/ SUB=pat TYPE=UN;  
run;
```

Covariance Parameter Estimates		
Cov Parm	Subject	Estimate
UN(1,1)	pat	0.6206
UN(2,1)	pat	-0.05316
UN(2,2)	pat	0.02614
UN(3,1)	pat	0.002006
UN(3,2)	pat	-0.00080
UN(3,3)	pat	0.000026
Residual		0.5248

Fit Statistics	
-2 Res Log Likelihood	1639.9
AIC (smaller is better)	1653.9
AICC (smaller is better)	1654.1
BIC (smaller is better)	1666.4

Null Model Likelihood Ratio Test		
DF	Chi-Square	Pr > ChiSq
6	458.47	<.0001

Solution for Fixed Effects

Effect	type	Estimate	Standard Error	DF	t Value	Pr >  t
Intercept		3.7860	0.2688	42	14.09	<.0001
age		-0.06084	0.04618	490	-1.32	0.1883
type	AL	-0.05328	0.2488	490	-0.21	0.8306
type	ST	0	.	.	.	.
month		-0.1463	0.06602	42	-2.22	0.0321
month2		0.008624	0.004999	42	1.73	0.0919
month3		-0.00015	0.000129	490	-1.19	0.2332
age*month		0.006353	0.01331	490	0.48	0.6332
age*month2		-0.00049	0.001087	490	-0.45	0.6552
age*month3		0.000011	0.000029	490	0.38	0.7016

Type 3 Tests of Fixed Effects

Effect	Num DF	Den DF	F Value	Pr > F
age	1	490	1.74	0.1883
type	1	490	0.05	0.8306
month	1	42	4.91	0.0321
month2	1	42	2.98	0.0919
month3	1	490	1.42	0.2332
age*month	1	490	0.23	0.6332
age*month2	1	490	0.20	0.6552
age*month3	1	490	0.15	0.7016

There also does not appear to be a significant age\*time interaction and the overall age effect was not significant in any of the models that we tested. However, because it is known that average antibody levels decrease with age, age should be retained in the model. However, we can drop the age\*time interactions.