SAS Code for Fitting Dynamic Groups Models

In this supplement we provide SAS code and abridged output for the dynamic groups models for the two examples in the manuscript. The first example concerns school effects when examining trajectories of growth in science achievement and uses data from the Longitudinal Study of American Youth (LSAY; Miller, Hoffer, Suchner, Brown, and Nelson, 1992). The second example focuses on family effects within longitudinal data on developmental psychopathology and uses data from the Michigan Longitudinal Study (MLS; Zucker, Fitzgerald, Refior, Puttler, Pallas and Ellis, 2000).

In fitting and interpreting models using the stabilizing banded structure, we make use of the companion macro file **stableband.sas**.

Example 1: Schools as Dynamic Groups

For this analysis the data set is referred to as **canalysis** and the variables are named and defined as follows:

LSAYID	a unique ID variable identifying the student
schcode	a unique ID variable identifying the school
sci	science achievement
grade	coded as 0 = 10th grade, 1 = 11th grade, 2=12th grade.
cohort	coded as 0 = first (began 10th grade in 1987), 1 = second (began 10th grade in 1990)
year	calendar year, represented by the last two digits (e.g., 1990 is coded as 90)
cstud_fund	school-mean-centered measure of a student's fundamentalist attitudes towards science and religion (referenced in the manuscript as **studentatt**)
schmean_fund	school mean of students' fundamentalist attitudes towards science and religion (referenced in the manuscript as **schoolatt**)
cstud_ses	school-mean-centered measure of a student's socioeconomic status (referenced in the manuscript as **studentSES**)
schmean_ses	school mean of students' socioeconomic status (referenced in the manuscript as **schoolSES**)

As described in the manuscript, we fit a sequence of models to this data varying in the covariance structure at the school level and in the inclusion of student- and school-level predictors. We provide example code for all dynamic groups models; however, we present output only for the final, selected models.

All unconditional models include the same fixed effects, as stipulated in the **model** statement; likewise, all conditional models include the same fixed effects (and include additional predictors). Student-level trajectories are also allowed to differ in their intercepts and slopes (by grade) in all models, as indicated in the first **random** statement. It is in the specification of the second **random** statement, for the school-level random effects, that the models differ. Random effects of **year** are included in each model, but the structure of these random effects varies between models as indicated in the **type** option. It is important that the variable **year** is declared as a categorical variable within the **class** statement.

Fitting Unconditional Models

The following code specifies an unrestricted covariance structure for the school effects over time (note **type=un** in the second **random** statement):

```
proc mixed data=canalysis method=reml maxiter=1000 cl;
class lsayid schcode year;
model sci=grade cohort grade*cohort/solution ddfm=bw notest alpha=.05;
random intercept grade/subject=lsayid(schcode) type=un;
random year / subject=schcode type=un;
run;
```

A Toeplitz structure can be specified for time-varying school effects as follows (**type=toep**):

```
proc mixed data=canalysis method=reml maxiter=1000 cl;
class lsayid schcode year;
model sci=grade cohort grade*cohort/solution ddfm=bw notest alpha=.05;
random intercept grade/subject=lsayid(schcode) type=un;
random year / subject=schcode type=toep;
run;
```

The following code implements the CS structure (**type=cs**):

```
proc mixed data=canalysis method=reml maxiter=1000 cl;
class lsayid schcode year;
model sci=grade cohort grade*cohort/solution ddfm=bw notest alpha=.05;
random intercept grade/subject=lsayid(schcode) type=un;
random year / subject=schcode type=cs;
run;
```

The AR(1) structure is obtained as follows (**type=ar(1)**):

```
proc mixed data=canalysis method=reml maxiter=1000 cl;
class lsayid schcode year;
model sci=grade cohort grade*cohort/solution ddfm=bw notest alpha=.05;
random intercept grade/subject=lsayid(schcode) type=un;
random year / subject=schcode type=ar(1);
run;
```

And the ARMA(1,1) structure is obtained as follows (**type=arma(1,1)**):

```
proc mixed data=canalysis method=reml maxiter=1000;
class lsayid schcode year;
model sci=grade cohort grade*cohort/solution ddfm=bw notest alpha=.05;
random intercept grade/subject=lsayid(schcode) type=un;
random year / subject=schcode type=arma(1,1);
run;
```

The stabilizing banded structure is not a default structure available within SAS, so we make use of the flexibility of the **type=lin(*q*)** structure, or general linear covariance structure. With this option, *q* is the number of parameters, and the structure is determined via a matrix constructed in a data step and input through the **ldata** option. We have provided a macro, called **stableband.sas**, which automatically constructs this matrix within a data set named **sb**. The **stableband** macro can be saved to a file and read in prior to fitting the model, as shown here:

```
filename dyngrp 'C:\Users\bauer\documents\Projects\Dynamic Groups;
%include dyngrp(SB.sas);
```

(Replace the directory in the **filename** statement to the local directory in which **stableband.sas** has been saved).

Alternatively, one can simply copy-paste the syntax within **stableband.sas** to run prior to the **proc mixed** syntax. The syntax is given here:

```
%macro stableband(lag=1,Gtimes=6);
data sb;
do p = 1 to &lag. + 1;
 do i = 1 to &Gtimes.;
   array col[&Gtimes.] col1-col&Gtimes.;
   do j = 1 to &Gtimes.;
      parm = p;
        row = i;
        if p < &lag. + 1 then do;
          if (i-j) = p-1 then col[j] = 1; else col[j]=0;
        end;
        else do;
           if j <= i - &lag. then col[j] = 1; else col[j]=0;
        end;
     end;
    output;
 end;
end;
drop j i p;
run;
%mend;
```

Two arguments are required when calling the SB macro, specifically the number of time points the groups were observed (**GTimes**) and the lag at which the covariances stabilize (**lag**). For instance, in the LSAY data there are up to six time points per school, so **GTimes=6**. Our specification of the **lag** argument determines the covariance structure. If we specify that the covariances stabilize at lag 1 then *q*=2 and we will replicate the **type=cs** structure. At the other extreme, if we specify that the covariances stabilize at lag 5 then *q*=6 and we will replicate the **type=toep** structure. Since we have already fit these models, we are more interested in situations in which the covariances stabilize at an intermediate lags, that is the covariance structures referenced in the manuscript as SB(2), SB(3), and SB(4).

The SB(2) structure is fit with the following code:

```
%stableband(lag=2,Gtimes=6);
proc mixed data=canalysis method=reml maxiter=1000 cl;
class lsayid schcode year;
model sci=grade cohort grade*cohort/solution ddfm=bw notest alpha=.05;
random intercept grade / subject=lsayid(schcode) type=un;
random year / subject=schcode type=lin(3) ldata=sb;
parms
(100)
(-1.5)
(5)
(12)
(10)
(10)
(10)
/lowerb=0,.,0,0,0,0,0;
ods output covparms=covparms;
run;
```

Note that the call to the **stableband** macro precedes the **proc mixed** code, and that we specified **lag=2**. We use **type=lin(3)** to indicate that we are using the general linear covariance structure with three parameters (the lag 1 and lag 2+ covariance parameters and the variance parameter), and we use **ldata=sb** to indicate the form of the covariance structure (recall that the **stableband** macro generated the **sb** data file).

To fit the SB(3) structure, we simply modify the macro argument to **lag=3** and indicate that now q=4 in the **type=lin(*q*)** option.

```
%stableband(lag=3,Gtimes=6);
proc mixed data=canalysis method=reml maxiter=1000 cl;
class lsayid schcode year;
model sci=grade cohort grade*cohort/solution ddfm=bw notest alpha=.05;
random intercept grade / subject=lsayid(schcode) type=un;
random year / subject=schcode type=lin(4) ldata=sb;
parms
(100)
(-1.5)
(5)
(12)
(10)
(10)
(10)
(10)
/lowerb=0,.,0,0,0,0,0,0;
run;
```

Likewise, the SB(4) structure is fit with the following code:

```
%stableband(lag=4,Gtimes=6);
proc mixed data=canalysis method=reml maxiter=1000 cl;
class lsayid schcode year;
model sci=grade cohort grade*cohort/solution ddfm=bw notest alpha=.05;
random intercept grade / subject=lsayid(schcode) type=un;
random year / subject=schcode type=lin(5) ldata=sb;
parms
(100)
(-1.5)
(5)
(12)
(10)
(10)
(10)
(10)
(10)
/lowerb=0,.,0,0,0,0,0,0,0;
run;
```

In addition to the syntax options already described, the code for the SB structures makes use of the **parms** statement to specify starting values for the variance and covariance parameters. The addition of this syntax is essential to prevent SAS from using start values that would produce a non-invertible school-level covariance matrix. The start values (within parentheses) are in the order of the covariance parameters.

- The first three entries are start values for the variance of the student-level intercepts (100), covariance of student-level intercepts and slopes (-1.5), and variance of the student-level slopes (5).
- The next entry is the start value for the variance and of the school-level effects (12).
- The following *q*-1 entries correspond to the lagged covariances (which are all set to a start value of 10 here; it is important that this value be less than the variance, e.g., 10<12).
- Finally, the last entry is the start value for the time-specific residual variance (also started at 10).

The specific start values used here were loosely based on the results obtained from the **type=cs** model. Confirmation that the variance and covariance parameter start values have been ordered correctly can be obtained from the **Covariance Parameter Estimates** table produced by **proc mixed** upon running the model. The order of the start values should correspond to the order of the estimates shown in this table.

Within the **parms** statement we have also specified a lower bound of zero for all parameters other than the covariance of the student-level intercepts and slopes. This enforces positive variances and also positive covariances for the school effects. (Negative over-time covariances among school effects are unlikely but not impossible. For situations in which negative covariances are more plausible, these lower bounds could be removed).

Fitting Conditional Models

Conditional models were fit using syntax that was nearly identical to the syntax for the unconditional models, with the exception that additional fixed effects were included for the predictors in the **model** statement. That is, the model statement was modified to be

```
model sci = grade cohort grade*cohort
            cstud_fund cstud_ses
            schmean_fund schmean_ses/
            solution ddfm=bw notest alpha=.05;
```

Output from Optimally Fitting Models

As described in the manuscript, the optimally fitting covariance structure for both the unconditional and conditional models was the SB(4) structure. Abridged results from the unconditional model are shown here:

```
                              The Mixed Procedure

                               Model Information

                    Data Set                     WORK.CANALYSIS
                    Dependent Variable           sci
                    Covariance Structures        Unstructured, Linear,
                                                 Variance Components
                    Subject Effects              LSAYID(schcode), schcode
                    Estimation Method            REML
                    Residual Variance Method     Parameter
                    Fixed Effects SE Method      Model-Based
                    Degrees of Freedom Method    Between-Within


                                  Dimensions

                         Covariance Parameters             9
                         Columns in X                      4
                         Columns in Z Per Subject        304
                         Subjects                         51
                         Max Obs Per Subject             399


                            Number of Observations

                     Number of Observations Read            7756
                     Number of Observations Used            7756
                     Number of Observations Not Used           0


                               Iteration History

                 Iteration    Evaluations    -2 Res Log Like       Criterion

                         1              2     52134.85855691      0.00155910
                         2              1     52121.72942851      0.00039101
                         3              1     52112.86374848      0.00009613
                         4              1     52110.65980331      0.00002071
                         5              1     52110.20392529      0.00000200
```

```
                         6              1       52110.16348783       0.00000002
                         7              1       52110.16302501       0.00000000


                                  Convergence criteria met.


                                Covariance Parameter Estimates

            Cov Parm      Subject             Estimate     Alpha       Lower        Upper

            UN(1,1)       LSAYID(schcode)      93.7106      0.05     88.9250      98.8951
            UN(2,1)       LSAYID(schcode)      -1.2697      0.05     -2.7480       0.2087
            UN(2,2)       LSAYID(schcode)       4.7079      0.05      4.0213       5.5878
            LIN(1)        schcode              14.5683      0.05     10.0678      22.9538
            LIN(2)        schcode              13.5601      0.05      9.1585      22.1314
            LIN(3)        schcode              12.8337      0.05      8.5128      21.5499
            LIN(4)        schcode              12.2778      0.05      8.0063      21.1907
            LIN(5)        schcode              10.7946      0.05      6.6717      20.3949
            Residual                           10.1192      0.05      9.4815      10.8238


                                       Fit Statistics

                            -2 Res Log Likelihood         52110.2
                            AIC (smaller is better)       52128.2
                            AICC (smaller is better)      52128.2
                            BIC (smaller is better)       52145.5


                                 Solution for Fixed Effects

                                  Standard
  Effect           Estimate          Error       DF     t Value     Pr > |t|     Alpha        Lower        Upper

  Intercept         60.4817         0.5806       50      104.18       <.0001      0.05      59.3157      61.6478
  grade              2.4860         0.1580     7702       15.73       <.0001      0.05       2.1762       2.7957
  COHORT             1.4808         0.4795     7702        3.09       0.0020      0.05       0.5409       2.4207
  grade*COHORT      -0.6219         0.2389     7702       -2.60       0.0092      0.05      -1.0901      -0.1536
```

These estimates match the results shown in Table 3 (Model 1) of the manuscript. See the manuscript for interpretation of the fixed effects.

The student-level covariance parameter estimates are interpreted as follows:

- UN(1,1) is the variance of the student-level trajectory intercepts (variability in 10th grade science achievement)
- UN(2,1) is the covariance of the student-level intercepts and slopes
- UN(2,2) is the variance of the student-level trajectory slopes (variability in change over time)

The school-level covariance parameter estimates are interpreted as follows:

- The LIN(1) parameter estimate corresponds to the variance of the school effects.

- The LIN(2) parameter estimate corresponds to the lag 1 covariance, the LIN(3) parameter estimate corresponds to the lag 2 covariance, and the LIN(4) parameter estimate corresponds to the lag 3 covariance.
- The LIN(5) parameter estimate corresponds to the lag 4+ covariance (lag 4 and lag 5).

These values can also be used to construct the model-implied covariance and correlation matrices of the school effects. These matrices can be produced using **proc iml** within SAS. To do so, the first thing we need to do is output the values of the covariance parameter estimates produced by **proc mixed**. To do this, we re-run the model using an **ods output** statement, as follows:

```
%stableband(lag=4,Gtimes=6);
proc mixed data=canalysis method=reml maxiter=1000 cl;
class lsayid schcode year;
model sci=grade cohort grade*cohort/solution ddfm=bw notest alpha=.05;
random intercept grade / subject=lsayid(schcode) type=un gcorr;
random year / subject=schcode type=lin(5) ldata=sb;
parms
(100)
(-1.5)
(5)
(12)
(10)
(10)
(10)
(10)
(10)
/lowerb=0,.,0,0,0,0,0,0,0;
ods output covparms=covparms;
run;
```

The **ods output** statement puts the “Covariance Parameter Estimates” table of output, referenced internally by SAS as **covparms**, into a data set also called **covparms** for us to access within **proc iml**.

```
proc iml;
 use covparms;
 read all var{Estimate} where(subject="schcode") into Linq ;
 print Linq;
 Gtimes=6; stablelag=4;
 cov = J(Gtimes,Gtimes,0);
 do i = 1 to Gtimes;
   do j = 1 to Gtimes;
      lag = abs(i-j);
        if lag < NROW(linq) then do;
          cov[i,j] = linq[lag+1];
        end;
        else do;
          cov[i,j] = linq[stablelag+1];
        end;
```

```
   end;
  end;
  print cov;
  corr = inv(sqrt(diag(cov)))*cov*inv(sqrt(diag(cov)));
  print corr;
quit;
```

The snippet "**where(subject="schcode")**" selects only the school-level covariance parameter estimates. For other applications this code should be modified to reference the appropriate group-level ID variable. Additionally, the code "**Gtimes=6; stablelag=4;**" is used to define the number of time points over which the groups were observed and to define the lag at which the covariances stabilize (here lag 4). These values too should be modified to be appropriate to the specific application.

The output produced by **proc iml** is shown here:

```
                              Linq

                            14.568339
                            13.560148
                            12.833693
                            12.277768
                            10.794648


                               cov

      14.568339 13.560148 12.833693 12.277768 10.794648 10.794648
      13.560148 14.568339 13.560148 12.833693 12.277768 10.794648
      12.833693 13.560148 14.568339 13.560148 12.833693 12.277768
      12.277768 12.833693 13.560148 14.568339 13.560148 12.833693
      10.794648 12.277768 12.833693 13.560148 14.568339 13.560148
      10.794648 10.794648 12.277768 12.833693 13.560148 14.568339


                              corr

              1 0.9307957 0.8809304 0.8427706 0.7409663 0.7409663
      0.9307957         1 0.9307957 0.8809304 0.8427706 0.7409663
      0.8809304 0.9307957         1 0.9307957 0.8809304 0.8427706
      0.8427706 0.8809304 0.9307957         1 0.9307957 0.8809304
      0.7409663 0.8427706 0.8809304 0.9307957         1 0.9307957
      0.7409663 0.7409663 0.8427706 0.8809304 0.9307957         1
```

The column of values labeled "**Linq**" repeats the covariance parameter estimates at the school level. The output labeled "**cov**" and "**corr**" corresponds to the covariance and correlation matrices of the school effects, respectively. Thus we see that the correlation in the school effects between adjacent years is .93. Across two years the correlation drops to .88. Across three years, the correlation drops to .84. The correlation stabilizes at four or more years of separation at .74. Plotting these correlations produces the trend shown in Figure 2 (Model 1) of the manuscript.

The optimally fitting conditional model also used the SB(4) covariance structure for the school effects. Output for the covariance parameter estimates and fixed effects estimates match the values shown in Table 3 (Model 2):

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Alpha	Lower	Upper
UN(1,1)	LSAYID(schcode)	87.9728	0.05	83.4454	92.8807
UN(2,1)	LSAYID(schcode)	-1.4188	0.05	-2.8575	0.02002
UN(2,2)	LSAYID(schcode)	4.7040	0.05	4.0180	5.5831
LIN(1)	schcode	9.9908	0.05	6.8100	16.0757
LIN(2)	schcode	8.9921	0.05	5.9212	15.2765
LIN(3)	schcode	8.1997	0.05	5.2306	14.6766
LIN(4)	schcode	7.6346	0.05	4.7267	14.3813
LIN(5)	schcode	6.1826	0.05	3.4611	14.0573
Residual		10.1192	0.05	9.4817	10.8235

Fit Statistics

-2 Res Log Likelihood	51883.8
AIC (smaller is better)	51901.8
AICC (smaller is better)	51901.9
BIC (smaller is better)	51919.2

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|	Alpha	Lower	Upper
Intercept	60.5443	0.4953	48	122.25	<.0001	0.05	59.5485	61.5401
grade	2.4888	0.1603	7700	15.53	<.0001	0.05	2.1747	2.8030
COHORT	1.3183	0.4743	7700	2.78	0.0055	0.05	0.3885	2.2480
grade*COHORT	-0.6105	0.2440	7700	-2.50	0.0124	0.05	-1.0888	-0.1322
cstud_fund	-2.6751	0.3530	7700	-7.58	<.0001	0.05	-3.3671	-1.9831
cstud_ses	0.1253	0.01116	7700	11.23	<.0001	0.05	0.1034	0.1472
schmean_fund	-8.3805	3.9987	48	-2.10	0.0414	0.05	-16.4204	-0.3407
schmean_ses	0.1211	0.1057	48	1.15	0.2578	0.05	-0.09152	0.3337

The fixed effects are interpreted within the manuscript. The school-level covariance parameters are labeled as described for the unconditional model above. These parameters are also interpreted similarly – except that they now represent the residual (co)variances. As illustrated above, these estimates can be arrayed into a residual covariance matrix and used to construct a residual correlation matrix. These correlations can be plotted to produce the trend shown in Figure 2 (Model 2).

Example 2: Families as Dynamic Groups

For this analysis the data set is referred to as **allkidssubset** and the variables are named and defined as follows:

kidid	a unique ID variable identifying the child
family	a unique ID variable identifying the school
intscore	depression score for the child
extscore	externalizing behavior score for the child
ageyrc	age of the child in years, centered at age 14
intyear	calendar year when interview assessing child depression and externalizing behavior were conducted
kidgen	sex of the child, coded 0=female, 1=male
coa	indicator of parental history of alcohol disorder; coded 0=no, 1=yes
parentanti	indicator of parental history of antisocial personality disorder; coded 0=no, 1=yes
parentdep	indicator of parental history of depression/dysthymia; coded 0=no, 1=yes

To reduce redundancy with the documentation of the prior example, here we focus specifically on the code for the optimally fitting dynamic groups models. For this example, an AR(1) structure for time-varying family effects resulted in the best fit to the data. The unconditional model (model 1) was fit via the following code:

```
proc mixed data=allkidssubset method=reml covtest cl maxiter=1000;
class family intyear kidid;
model extscore=ageyrc ageyrc*ageyrc/solution ddfm=bw notest alpha=.05;
random intercept ageyrc ageyrc*ageyrc/subject=kidid(family) type=un;
random intyear/subject=family type=ar(1);
run;

proc mixed data=allkidssubset method=reml covtest maxiter=1000;
class family intyear kidid;
model intscore=ageyrc ageyrc*ageyrc/solution ddfm=bw notest alpha=.05;
random intercept ageyrc ageyrc*ageyrc/subject=kidid(family) type=un;
random intyear/subject=family type=ar(1);
run;
```

Note the **type=ar(1)** specification in the second **random** statement for each outcome.

The conditional model (model 2) differed in the inclusion of additional predictors, augmenting the **model** statement for each outcome:

```
proc mixed data=allkidssubset method=reml covtest cl maxiter=1000;
class family intyear kidid;
model extscore=ageyrc ageyrc*ageyrc kidgen kidgen*ageyrc
      kidgen*ageyrc*ageyrc coa parentanti parentdep/solution ddfm=bw
      notest alpha=.05;
random intercept ageyrc ageyrc*ageyrc/subject=kidid(family) type=un;
random intyear/subject=family type=ar(1);
run;

proc mixed data=allkidssubset method=reml covtest cl maxiter=1000;
class family intyear kidid;
model intscore=ageyrc ageyrc*ageyrc kidgen kidgen*ageyrc coa
      parentanti parentdep/solution ddfm=bw notest alpha=.05;
random intercept ageyrc ageyrc*ageyrc/subject=kidid(family) type=un;
random intyear/subject=family type=ar(1);
run;
```

Below we show sample output from the unconditional model for externalizing behavior:

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr Z	Alpha	Lower	Upper
UN(1,1)	kidID(family)	0.2806	0.03452	8.13	<.0001	0.05	0.2235	0.3627
UN(2,1)	kidID(family)	0.01289	0.005836	2.21	0.0272	0.05	0.001451	0.02433
UN(2,2)	kidID(family)	0.007864	0.002226	3.53	0.0002	0.05	0.004835	0.01499
UN(3,1)	kidID(family)	-0.00586	0.002918	-2.01	0.0446	0.05	-0.01158	-0.00014
UN(3,2)	kidID(family)	-0.00154	0.000633	-2.44	0.0149	0.05	-0.00278	-0.00030
UN(3,3)	kidID(family)	0.000746	0.000436	1.71	0.0437	0.05	0.000307	0.003723
Variance	family	0.1358	0.02676	5.07	<.0001	0.05	0.09552	0.2084
AR(1)	family	0.8190	0.04881	16.78	<.0001	0.05	0.7233	0.9147
Residual		0.2098	0.01059	19.81	<.0001	0.05	0.1905	0.2322

Fit Statistics

-2 Res Log Likelihood	4825.9
AIC (smaller is better)	4843.9
AICC (smaller is better)	4844.0
BIC (smaller is better)	4876.6

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|	Alpha	Lower	Upper
Intercept	0.3899	0.03339	278	11.68	<.0001	0.05	0.3242	0.4556
ageyrc	0.008677	0.008429	2182	1.03	0.3034	0.05	-0.00785	0.02521
ageyrc*ageyrc	-0.01488	0.003625	2182	-4.10	<.0001	0.05	-0.02199	-0.00777

Focusing on the covariance parameter estimates, the child-level parameters describe variability in the growth trajectories of externalizing behavior with age:

- UN(1,1) is the variance of the child-level trajectory intercepts (variability in externalizing behavior at age 14)
- UN(2,1) is the covariance of the child-level intercepts and linear slopes
- UN(2,2) is the variance of the child-level trajectory linear slopes (rates of change in externalizing behavior at age 14)
- UN(3,1) is the covariance of the child-level intercepts and quadratic slopes
- UN(3,2) is the covariance of the child-level linear and quadratic slopes
- UN(3,3) is the variance of the child-level trajectory quadratic slopes (rates of acceleration/deceleration in change over time)

The family-level covariance parameter estimates are interpreted as follows:

- The Variance parameter estimate corresponds to the variance of the family effects.
- AR(1) parameter estimate corresponds to the autocorrelation of the family effects.

The AR(1) estimate of .819 can be interpreted as the correlation of family effects across a one-year interval. Across a *n*-year interval, the correlation is implied to be $.819^n$, and one can easily compute these correlations across all of the observed intervals to produce a plot of the correlations over time.

Sample output for the conditional model for externalizing behavior is shown here:

Covariance Parameter Estimates

Cov Parm	Subject	Estimate	Standard Error	Z Value	Pr Z	Alpha	Lower	Upper
UN(1,1)	kidID(family)	0.2646	0.03094	8.55	<.0001	0.05	0.2130	0.3375
UN(2,1)	kidID(family)	0.01617	0.005313	3.04	0.0023	0.05	0.005758	0.02659
UN(2,2)	kidID(family)	0.007892	0.002114	3.73	<.0001	0.05	0.004966	0.01446
UN(3,1)	kidID(family)	-0.00725	0.002751	-2.64	0.0084	0.05	-0.01264	-0.00186
UN(3,2)	kidID(family)	-0.00107	0.000595	-1.79	0.0730	0.05	-0.00223	0.000100
UN(3,3)	kidID(family)	0.000651	0.000417	1.56	0.0595	0.05	0.000251	0.004060
Variance	family	0.08608	0.02154	4.00	<.0001	0.05	0.05565	0.1507
AR(1)	family	0.7568	0.07341	10.31	<.0001	0.05	0.6129	0.9006
Residual		0.2124	0.01069	19.87	<.0001	0.05	0.1929	0.2350

Fit Statistics

-2 Res Log Likelihood	4736.5
AIC (smaller is better)	4754.5
AICC (smaller is better)	4754.5
BIC (smaller is better)	4787.2

Solution for Fixed Effects

Effect	Estimate	Standard Error	DF	t Value	Pr > |t|	Alpha	Lower	Upper
Intercept	-0.1329	0.07039	275	-1.89	0.0601	0.05	-0.2715	0.005663

ageyrc	0.05514	0.01459	2179	3.78	0.0002	0.05	0.02653	0.08376
ageyrc*ageyrc	-0.03425	0.006716	2179	-5.10	<.0001	0.05	-0.04742	-0.02108
kidgen	0.2168	0.06173	2179	3.51	0.0005	0.05	0.09573	0.3378
ageyrc*kidgen	-0.07006	0.01723	2179	-4.07	<.0001	0.05	-0.1038	-0.03628
ageyrc*ageyrc*kidgen	0.02772	0.008011	2179	3.46	0.0005	0.05	0.01201	0.04343
coa	0.4153	0.06317	275	6.57	<.0001	0.05	0.2909	0.5396
parentanti	0.2065	0.07976	275	2.59	0.0101	0.05	0.04948	0.3635
parentdep	0.09789	0.06362	275	1.54	0.1251	0.05	-0.02736	0.2231

The covariance parameter estimates are labeled and interpreted as indicated above, with the exception that these are now residuals.

See the primary manuscript for further interpretation of these results.

References

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