

Supplemental Materials

Mplus Syntax for Model RI-LPCPM-M5 (Table 3)

title:

data: file = REM tst asc grd w-trkSchID 21APR2021.dat;

```

usevar = acase1_1 acase2_1 acase3_1 acase4_1 acase5_1 acase6_1
         acase1_2 acase2_2 acase3_2 acase4_2 acase5_2 acase6_2
         acase1_3 acase2_3 acase3_3 acase4_3 acase5_3 acase6_3
         acase1_4 acase2_4 acase3_4 acase4_4 acase5_4 acase6_4
         acase1_5 acase2_5 acase3_5 acase4_5 acase5_5 acase6_5
         gma_jz5 gma_jz6 gma_jz7 gma_jz8 gma_jz9 ;
missing = all (-999);

```

! Note standardize variables in relation to Wave 1 Mean and variances

DEFINE:

```

GMA_JZ5 = -1 * (( GMA_JZ5 -3.091 ) / 0.825**.5 );
GMA_JZ6 = -1 * (( GMA_JZ6 -3.172 ) / 0.874**.5 );
GMA_JZ7 = -1 * (( GMA_JZ7 -3.358 ) / 0.885**.5 );
GMA_JZ8 = -1 * (( GMA_JZ8 -3.292 ) / 0.908**.5 );
GMA_JZ9 = -1 * (( GMA_JZ9 -3.230 ) / 0.991**.5 );
FGES_1 = (( FGES_1 - 1000.000 ) / 100);
FGES_2 = (( FGES_2 - 1000.000 ) / 100);
FGES_3 = (( FGES_3 - 1000.627 ) / 100);
FGES_4 = (( FGES_4 - 1000.071 ) / 100);
FGES_5 = (( FGES_5 - 1000.000 ) / 100);
GMA_JZ4 = -1 * (( GMA_JZ4 -2.588 ) / 1.013**.5 );
GDE_JZ4 = -1 * (( GDE_JZ4 -2.660 ) / 0.770**.5 );

```

```

ACASE1_1 = (ACASE1_1 - 3.145 ) / 1.383**.5;
ACASE2_1 = (ACASE2_1 - 3.674 ) / 0.852**.5;
ACASE3_1 = (ACASE3_1 - 3.759 ) / 0.914**.5;
ACASE4_1 = (ACASE4_1 - 3.264 ) / 1.228**.5;
ACASE5_1 = (ACASE5_1 - 3.483 ) / 1.243**.5;
ACASE6_1 = (ACASE6_1 - 3.512 ) / 0.994**.5;

```

```

ACASE1_2 = (ACASE1_2 - 3.145 ) / 1.383**.5;
ACASE2_2 = (ACASE2_2 - 3.674 ) / 0.852**.5;
ACASE3_2 = (ACASE3_2 - 3.759 ) / 0.914**.5;
ACASE4_2 = (ACASE4_2 - 3.264 ) / 1.228**.5;
ACASE5_2 = (ACASE5_2 - 3.483 ) / 1.243**.5;
ACASE6_2 = (ACASE6_2 - 3.512 ) / 0.994**.5;

```

```

ACASE1_3 = (ACASE1_3 - 3.145 ) / 1.383**.5;
ACASE2_3 = (ACASE2_3 - 3.674 ) / 0.852**.5;
ACASE3_3 = (ACASE3_3 - 3.759 ) / 0.914**.5;
ACASE4_3 = (ACASE4_3 - 3.264 ) / 1.228**.5;
ACASE5_3 = (ACASE5_3 - 3.483 ) / 1.243**.5;
ACASE6_3 = (ACASE6_3 - 3.512 ) / 0.994**.5;

```

```

ACASE1_4 = (ACASE1_4 - 3.145 ) / 1.383**.5;
ACASE2_4 = (ACASE2_4 - 3.674 ) / 0.852**.5;
ACASE3_4 = (ACASE3_4 - 3.759 ) / 0.914**.5;
ACASE4_4 = (ACASE4_4 - 3.264 ) / 1.228**.5;
ACASE5_4 = (ACASE5_4 - 3.483 ) / 1.243**.5;
ACASE6_4 = (ACASE6_4 - 3.512 ) / 0.994**.5;

```

ACASE1_5 = (ACASE1_5 - 3.145) / 1.383**.5;
 ACASE2_5 = (ACASE2_5 - 3.674) / 0.852**.5;
 ACASE3_5 = (ACASE3_5 - 3.759) / 0.914**.5;
 ACASE4_5 = (ACASE4_5 - 3.264) / 1.228**.5;
 ACASE5_5 = (ACASE5_5 - 3.483) / 1.243**.5;
 ACASE6_5 = (ACASE6_5 - 3.512) / 0.994**.5;

analysis:
 ESTIMATOR = MLR;
 starts = 100;
 model:
 ! Note: latent self-concept factors x1-x5;
 x1 by acase1_1@.84 (1)
 acase2_1-acase6_1 (x2-x6);
 x2 by acase1_2@.84 (1)
 acase2_2-acase6_2 (x2-x6);
 x3 by acase1_3@.84 (1)
 acase2_3-acase6_3 (x2-x6);
 x4 by acase1_4@.84 (1)
 acase2_4-acase6_4 (x2-x6);
 x5 by acase1_5@.84 (1)
 acase2_5-acase6_5 (x2-x6);

! Note: All analyses are based on), metric (factor loading) invariance over the five waves;

!CORRELATED UNIQUENESSES;
 ACASE1_1-ACASE6_4 pwith ACASE1_2-ACASE6_5;
 ACASE1_1-ACASE6_3 pwith ACASE1_3-ACASE6_5;
 ACASE1_1-ACASE6_2 pwith ACASE1_4-ACASE6_5;
 ACASE1_1-ACASE6_1 pwith ACASE1_5-ACASE6_5;

!!!!!!! iX factors fixed factor loadings = 1 on auto-regressive (MSC) X factors;
 MSC1 by X1@1;MSC2 by X2@1;MSC3 by X3@1;MSC4 by X4@1;MSC5 by X5@1;

!!!Constrain x & x (MSC) factors to have zero variance & intercepts;
 X1-x5@0; [x1-x5@0];

!!

! autogression model

!!

! stability cgrades scores
 cgrade2 on cgrade1(StbGrd);
 cgrade3 on cgrade2(StbGrd);
 cgrade4 on cgrade3(StbGrd);
 cgrade5 on cgrade4(StbGrd);

! stability self-concept
 MSC2 on MSC1(StbMSC);
 MSC3 on MSC2(StbMSC);
 MSC4 on MSC3(StbMSC);
 MSC5 on MSC4(StbMSC);

! Note Lag2 stability cgrades scores
 cgrade3 on cgrade1(StbGrd2);

cgrade4 on cgrade2(StbGrd2);
 cgrade5 on cgrade3(StbGrd2);

!Lag2 stability self-concept
 MSC3 on MSC1(StbMSC2);
 MSC4 on MSC2(StbMSC2);
 MSC5 on MSC3(StbMSC2);

! Note Lag1 XP impact cgrades;
 ! Note Lag1 XP impact self-concept;
 cgrade2 on MSC1 (Xpath6) ;
 cgrade3 on MSC2 (Xpath6) ;
 cgrade4 on MSC3 (Xpath6) ;
 cgrade5 on MSC4 (Xpath6) ;

!!

! contemporaneous Reciprocal effects
 !!!

!contemporaneous REM MSC2 on cgrade;
 MSC2 on cgrade2 (CNTMP4) ;
 MSC3 on cgrade3 (CNTMP4) ;
 MSC4 on cgrade4 (CNTMP4) ;
 MSC5 on cgrade5 (CNTMP4) ;

! Note !correlated residuals within waves;
 !!!<<these should be zero when have Contemporaneous Recipicol Effects>>!!

msc1 WITH cgrade1*0;
 ! Note msc2-msc5 PWITH cgrade2-cgrade5*0;

! Note variances within wave;
 MSC1 cgrade1;
 MSC2 cgrade2;
 MSC3 cgrade3;
 MSC4 cgrade4;
 MSC5 cgrade5;

!!

! Note trait factors--for RI-CLPMs; Create within-person centered variables;

! Note transform raw scores into single-item latent factors for manifest variables;
 cgrade1 by gma_jz5@1; gma_jz5@0;
 cgrade2 by gma_jz6@1; gma_jz6@0;
 cgrade3 by gma_jz7@1; gma_jz7@0;
 cgrade4 by gma_jz8@1; gma_jz8@0;
 cgrade5 by gma_jz9@1; gma_jz9@0;

! Note trait factor for grades
 TRgrade by GMA_JZ5-GMA_JZ9@1;

! Note Trait Factor for self-concept

! Note !X factors fixed factor loadngs = 1 on global X Trat factors;

TRMSC by X1-X5@1;
 TRMSC (VTRMSC); !VT = variance of X trait factor;

TRMSC TRgrade WITH TRMSC TRgrade;
 TRMSC TRgrade WITH MSC1-MSC5@0 cgrade1-cgrade5@0;

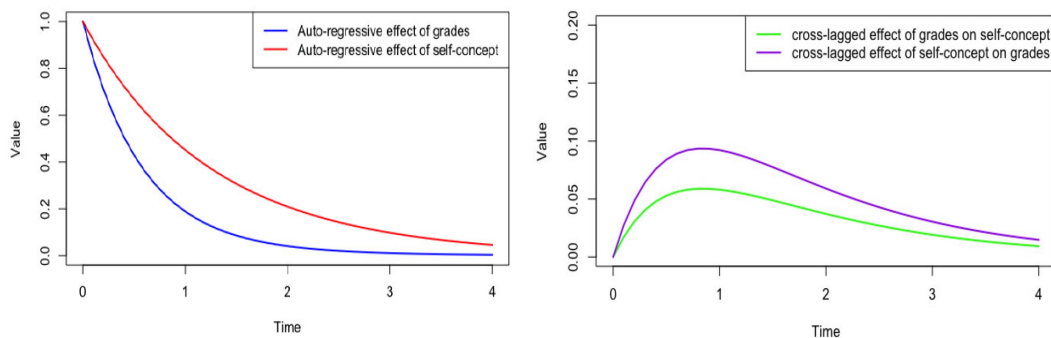
Chicken-Egg Conundrum

4

[TRMSC@0]; [TRgrade@0];
[MSC2-MSC5@0]; [cgrade2-cgrade5@0];
[MSC1@0];
[cgrade1@0];
output: sampstat standardized stdyx tech4 cinterval svalues; mODINDICES(ALL)

Supplemental Materials

Testing the continuous time model (CTM) with our data.



The continuous time model (CTM) is an evolving statistical model. Although CTMs have only been applied to evaluate how cross-lag panel effects vary over time (e.g., Hecht & Zitzmann, 2021; Kuiper et al., 2018; Lohmann, Zitzmann, Voelke & Hecht, 2022; Vogel et al., 2018), treating time as a continuous variable has theoretically important implications potentially relevant to our research. In order to juxtapose our extension to traditional approaches to CLPMs with CTMs, we reanalyzed our data with a CTMs, explicitly modeling time as a continuous rather than a discrete variable

We evaluated our data with the continuous time model available in the R package (Driver, Oud & Voelke, 2019; see the syntax for this analysis at the end of this section). The most relevant results from this analysis are the graphs of how the auto-regressive paths and particularly the cross-paths vary with time. For our data, the time interval between the five waves is always one year.

The CTM model is based on the assumption that the effects for adjacent waves are the same across waves (i.e., $W1 \rightarrow W2 = W2 \rightarrow W3$, etc.). This assumption might be problematic, particularly for developmental studies where the pattern of results is hypothesized to change with maturity (e.g., $ASC \rightarrow ACH$ path becomes stronger with maturity with very young children). However, our invariance tests demonstrate that this assumption is reasonable for our data based on adolescents.

The CTM model also assumes that Lag0 cross-paths are necessarily zero and that there is necessarily a steep decline in the extrapolated size of cross-lagged effects from Lag1 to Lag0. Thus, within the CTM model, it is impossible for the cross-lag effects to peak at some points between Lag0 and Lag1. However, from the perspective of our study, this limitation in the CTM is problematic as this is precisely what we want to test—that the peak of the $ACH \rightarrow ASC$ falls somewhere between Lag0 and Lag1, and may even be very close to Lag0. Hence, the CTM is unable to test our study's central prediction.

The CTM Lag1 effects are similar to our results for models with no Lag0 effects in that $ASC \rightarrow ACH$ paths are larger than the $ACH \rightarrow ASC$ paths. These results are surprising in that previous research and theory suggest that it should be the other way around. However, when we included Lag0 effects in our model, our results showed that the $ACH \rightarrow ASC$ paths were larger than the $ASC \rightarrow ACH$ paths. Consistent with theory and a priori predictions, we interpret these results to mean that the peak effect of $ACH \rightarrow ASC$ falls somewhere between Lag0 and Lag1. Again, we emphasize that it is not possible to test this prediction with CTMs using our data.

The limitation of the CTM is that there is no data in our study with a time interval of less than one year. Indeed, Voelke et al. (2012) warn that researchers should be cautious in extrapolating to unobserved intervals. This is particularly true for extrapolating results to the Lag0 to Lag1 interval. Thus, the CTM model can never have a peak effect within the Lag0 and Lag1 interval (i.e., less than one year). However, with sufficiently fine-grained data (with very short intervals of weeks or even days), the CTM model (as well as the various CLPMs) could test whether the optimal time interval is less than one year. Indeed, it is well-

recognized that the CTM and CLPMs provide similar information for fixed time intervals (e.g., Voelkle et al., 2018). . Hence the main advantage of the CTM is when the time intervals are varying and may not be the same for all participants, a situation not easily handled with traditional CLPMs (e.g., Voelkle et al., 2018).

Driver, C. C., Oud, J. H. L., & Voelkle, M. C. (2019). *ctsem*: Continuous time structural equation modelling (Version 2.9.6) [Computer software]. <https://cran.r-project.org/package=ctsem>.

Driver, C. C., & Voelkle, M. C. (2018). Hierarchical Bayesian continuous time dynamic modeling. *Psychological Methods*, 23, 774–799. <https://doi.org/10.1037/met0000168>

```
library(tidyverse)
library( lme4 )
library( ctsem )
ctm_data <- read.csv("ctm_data.csv")

### Step 1: Set up the model

# number of processes (=latent variables)
F <- 2

# number of manifest variables
I <- F

## define model parameters
# abbreviations:
# SC ... self-concept
# CGRADE ... grades
# GR}SC ... effect of GR on SC
# SC}GR ... effect of SC on GR

# drift matrix
A <- matrix( c("a_GR","a_GR}SC","a_SC}GR","a_SC"), nrow=F, ncol=F )

# diffusion covariance matrix (parameter names consistent with output, not input)
Q <- matrix( c("var_GR","cov_GR_SC",0,"var_SC"), nrow=F, ncol=F )

# continuous-time intercepts
b <- matrix( c("b_GR","b_SC"), nrow=F, ncol=1 )

# long-range ("lr") covariance matrix of continuous-time intercepts
# (parameter names consistent with output, not input)
Sigma.b.lr <- matrix( c("varblr_GR","covblr_GR_SC",0,"varblr_SC"), nrow=F, ncol=F )

## elements for direct mapping of manifest variables onto one latent variable each (no measurement model)

# set all intercepts of manifest variables to 0
manifestmeans <- matrix( 0, nrow=I, ncol=1 )

# set measurement error covariance matrix to 0
manifestvar <- matrix( 0, nrow=I, ncol=I )

# loading matrix: each item loads on one latent variable
Lambda <- diag( I )
library(ctsemOMX)
## set up model
m <- ctModel( n.latent = F,
              latentNames = c("GR","SC"), # set names of latent variables
              n.manifest = I,
              manifestNames = c("CGRADE","SC"), # names of manifest variables
              # as in data set
              DRIFT = A,
```

```

DIFFUSION = Q,
CINT = b,
TRAITVAR = Sigtab.lr,
LAMBDA = Lambda,
MANIFESTMEANS = manifestmeans,
MANIFESTVAR = manifestvar,
Tpoints = 5, # number of measurement occasions as in data set
type = "omx" ) # for frequentist estimation

r <- ctFit( dat = ctm_data,
            ctmodelobj = m,
            dataform = "long",
            stationary = "all" ) # stationary assumption

### Step 4: view results

smr <- summary( r )
print( smr$ctparameters )

### Step 5 (optional): transform parameters
# (e.g., to compare frequentist to Bayesian estimates)

# smr$TRAITVAR is the estimated long-range covariance matrix (in ctsem version 2.7.6)
Sigtab.lr <- smr$TRAITVAR

# transform Sigtab.lr to covariance matrix of continuous-time intercepts (Sigtab)
A <- smr$DRIFT
Sigtab <- A %%% Sigtab.lr %%% t(A)

b

### plot

require(ctsem)
nlatent=2 #number of latent processes
dt=seq(0,4,.1) #vector of time intervals

#Basic continuous time parameters

# DRIFT=matrix(c(-.4,0,.2,-.2),nrow=nlatent,ncol=nlatent)
DRIFT = smr$DRIFT
# CINT<-matrix(c(0.000007242396,-0.000006140918),ncol=1)
CINT = smr$CINT
# DIFFUSION=matrix(c(2,-1,-1,3),nrow=nlatent,ncol=nlatent) # in covariance form (Q matrix)
DIFFUSION = smr$DIFFUSION
#implied discrete DRIFT (auto and cross regression matrix) given time intervals
discreteDRIFT=array(unlist(lapply(dt,function(x) {
  expm(DRIFT * x)
})),dim=c(nlatent,nlatent,length(dt)))

# Create the plot
plot(dt, discreteDRIFT[1,1,], type='l', lwd=2, col='blue',
      ylim=c(min(discreteDRIFT), max(discreteDRIFT)),
      xlab="Time", ylab="Value")

# Add the red line
lines(dt, discreteDRIFT[2,2,], type='l', lwd=2, col='red')

# Add a legend
legend("topright",
      legend=c("Auto-regressive effect of grades", "Auto-regressive effect of self-concept"),
      col=c("blue", "red"),
      lwd=2)

# Create the plot
plot(dt, discreteDRIFT[2,1,],type='l',lwd=2,col='green',
      ylim=c(0,0.2), xlab="Time", ylab="Value")

points(dt, discreteDRIFT[1,2,],type='l',lwd=2,col='purple')

# Add a legend
legend("topright",

```

Chicken-Egg Conundrum

8

```
legend=c("cross-lagged effect of grades on self-concept", "cross-lagged effect of self-concept on  
grades"),  
col=c("green", "purple"),  
lwd=2)
```