Dynamic Structural Equation Modeling of Intensive Longitudinal Data Using Mplus Version 8

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Part 6

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Overview

- DSEM output options and plots
- Subject-specific variances
- Unevenly spaced and individual-specific times of observations
- Two-level DAFS and WNFS
- TVEM - time varying effects models
- Three level AR(1) models: within day v.s. between day autoregressive modeling

DSEM output options

- residual option: model estimated means, variance and autocorrelations for the observed variables
- residual(cluster) option: model estimated and cluster/subject specific means, variance and autocorrelations for the observed variables
- tech4 and tech4(cluster) options: model estimated quantities for the latent variables
- stand and stand(cluster) options: standardized model estimates and standardized cluster specific model estimates
- The option with (cluster) also provides the average across cluster quantities for the cluster specific estimates - applies for residual/tech4/stand
- The (cluster) option new also for none-DSEM models
- All of the above are based on Yule-Walker and require stationarity of the autoregressive part of the model
- HTML clickable output

DSEM output example

```
VARIABLE:    NAMES = y xl x2 c;
             WITHIN = x1;
             BETWEEN = x2;
             CLUSTER = c;
             LAGGED = y(1);
DATA:        FILE = a.dat;
ANALYSIS:    TYPE = TWOLEVEL RANDOM;
             ESTIMATOR = BAYES;
             PROCESSORS = 2;
MODEL:       %WITHIN%
             sl | y ON xl;
             s2 | y ON y&1;
             s3 | y;
             %BETWEEN%
             y sl-s3 ON x2;
OUTPUT:      STANDARDIZED(CLUSTER) RESIDUAL(CLUSTER) FSCOMPARISON;
PLOT:        TYPE = PLOT3;
SAVEDATA:    STDDISTRIBUTION = 1.dat;
             SAVE = fs(200);
             FILE = 2.dat;
             BPARAMETER = 3.dat;
```

DSEM output example: htm output

Mplus - [gb00o.htm]

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OUTPUT SECTIONS

Input Instructions
Input Warnings And Errors
Summary Of Analysis
Summary Of Data
Covariance Coverage Of Data
Univariate Sample Statistics
Model Warnings And Errors
Model Fit Information
Model Results
Standardized Model Results
R-square
Within-level Standardized Model Results For Cluster 1
Within-level R-square For Cluster 1
Within-level Standardized Model Results For Cluster 2
Within-level R-square For Cluster 2
Within-level Standardized Model Results For Cluster 3
```

DSEM output example: standardized model results

STDYX Standardization

	Estimate	Posterior S.D.	One-Tailed P-Value	95% C.I. Lower 2.5%	95% C.I. Upper 2.5%	Significance
Within-Level Standardized Estimates Averaged Over Clusters						
S1 | Y ON						
X1	0.438	0.007	0.000	0.427	0.454	*
S2 | Y ON						
Y&1	0.247	0.007	0.000	0.232	0.260	*
S3 |						
Y	0.452	0.009	0.000	0.427	0.464	*
Between Level						
S1 ON						
X2	0.359	0.065	0.000	0.208	0.459	*
S2 ON						
X2	0.682	0.045	0.000	0.586	0.758	*
S3 ON						
X2	0.335	0.059	0.000	0.192	0.442	*
Means						
Y	0.181	0.103	0.035	-0.005	0.393	
Intercepts						
S1	0.898	0.118	0.000	0.676	1.111	*
S2	1.219	0.114	0.000	0.969	1.406	*

DSEM output example: cluster specific standardized results

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```
WITHIN-LEVEL R-SQUARE FOR CLUSTER 1

                                Posterior  One-Tailed         95% C.I.
    Variable        Estimate       S.D.      P-Value   Lower 2.5%  Upper 2.5%

    Y                  0.607      0.097      0.000      0.460       0.871


WITHIN-LEVEL STANDARDIZED MODEL RESULTS FOR CLUSTER 2


STDYX Standardization

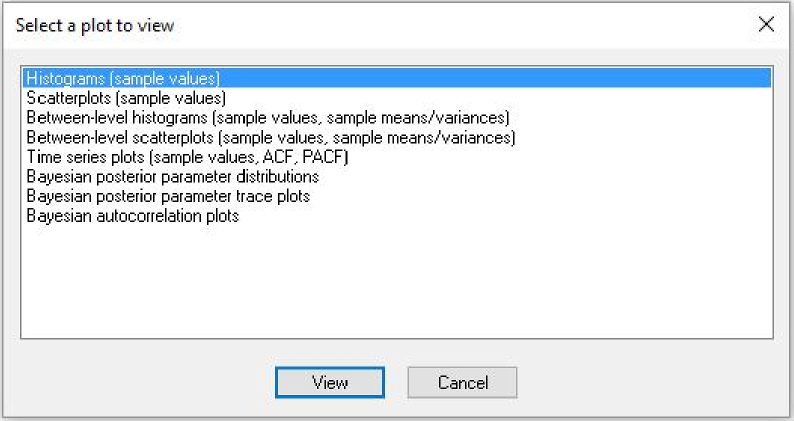
                                Posterior  One-Tailed         95% C.I.
                    Estimate       S.D.      P-Value   Lower 2.5%  Upper 2.5%  Significance
 S1 | Y ON
    X1                 0.539      0.064      0.000      0.398       0.647      *

 S2 | Y ON
    Y&1                0.250      0.070      0.000      0.108       0.388      *

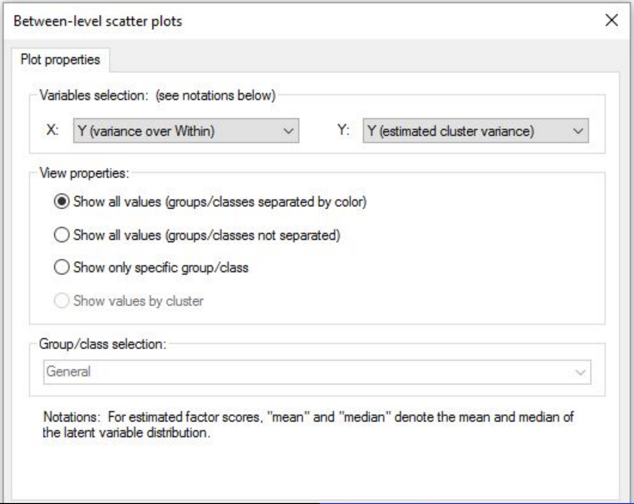
 S3 |
    Y                  0.610      0.075      0.000      0.471       0.768      *


STDY Standardization
```

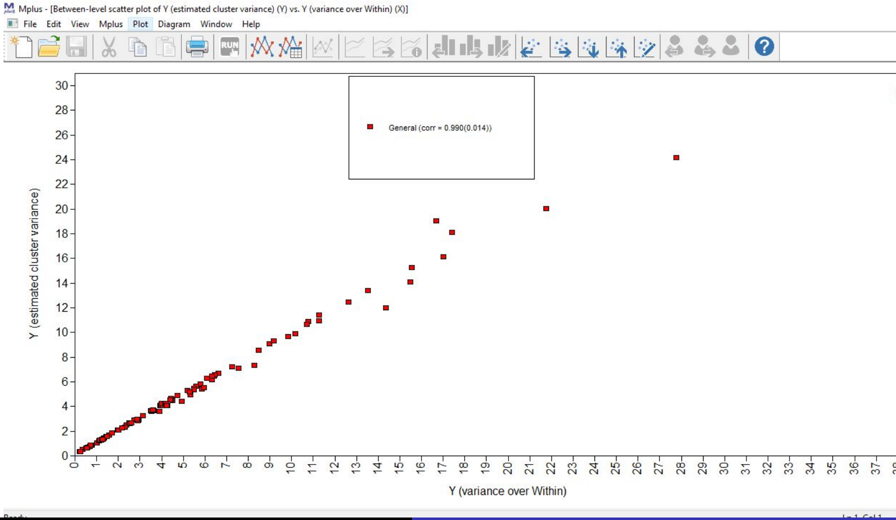
DSEM plots: plot menu



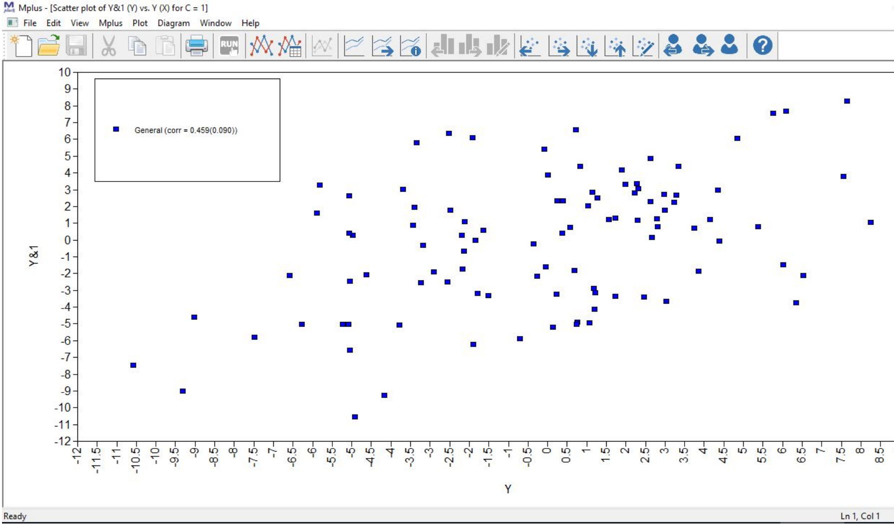
DSEM plots: plotting model estimated v.s. observed cluster specific statistic



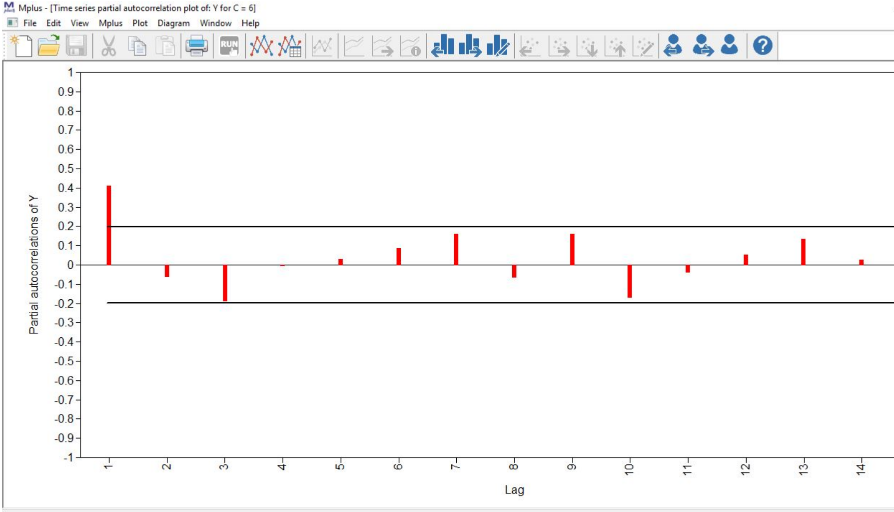
DSEM plots: plotting model estimated v.s. observed cluster specific variances



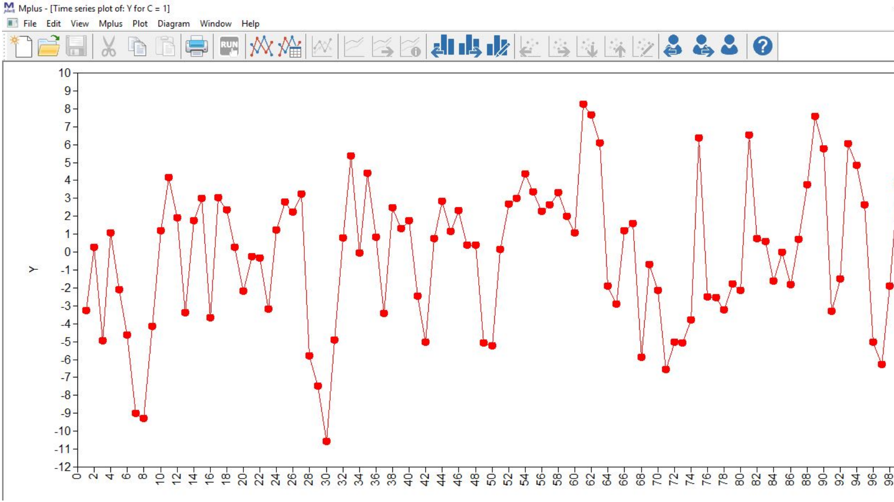
DSEM plots: cluster specific plots



DSEM plots: subject specific partial autocorrelation function



DSEM plots: subject specific time series plots



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Subject specific variance

- Jongerling J, Laurenceau J.P., Hamaker E. (2015). A Multilevel AR(1) Model: Allowing for Inter-Individual Differences in Trait-Scores, Inertia, and Innovation Variance. Multivariate Behav Res. 50(3), 334-349.
- In this paper it is shown that if subject specific variances are ignored - the structural parameters can be slightly biased. This does not happen in regular two-level models.

$$Y_{it} = \mu_i + \varepsilon_{it}$$

$$\varepsilon_{it} = r_i \varepsilon_{i,t-1} + \xi_{it}$$

$$v_i = Log(Var(\xi_{it}))$$

- The bias depends on how high the correlation is between r_i and v_i

Subject specific variance -results

Table: Comparing the estimation with random variance and without random variance (non-random variance): Bias(coverage)

parameter	$Cov(r_i, v_i)$	random variance	non-random variance
$E(r_i)$	high	.001(.97)	.040(.35)
$E(r_i)$	medium	.001(.98)	.028(.65)
$E(r_i)$	low	.001(.97)	.017(.83)
$E(r_i)$	none	.001(.96)	.007(.92)
$Var(r_i)$	high	.001(.97)	-.012(.47)
$Var(r_i)$	medium	.001(.93)	-.007(.78)
$Var(r_i)$	low	.001(.93)	-.004(.88)
$Var(r_i)$	none	.001(.94)	-.001(.91)

Subject specific variance - results

More detailed method for evaluation of model estimation

$$SMSE = \sqrt{(1/N)\sum_i (\hat{r}_i - r_i)^2}$$

$Cov(r_i, v_i)$	random variance	non-random variance
high	.255	.346
medium	.293	.329
low	.300	.316
none	.300	.310

Subject specific variance - conclusions

- Looking at the parameter estimates alone may not be enough when comparing estimation methods. Distortion of structural parameters due to ignoring subject specific variance is not simple shift in the autoregressive parameter. Error is actually doubled when looking at the random effects SMSE.
- Even in standard two-level models, using cluster specific variance is important if we use SMSE as a criterion
- Subject specific variance extracts more information from the data, yields more accurate estimation
- More simulations are needed to evaluate this issue in multivariate setting - study the effect of subject specific covariance.

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Subject-specific times of observations

- The basic model assumes that observations are taken at equally spaced time.
- If times are subject-specific we slice the time grid in sufficiently refined grid and enter missing data for the times where observation is not taken.
- For example if several observations are taken during the day, and at different times for each individual, we slice the day in 24 hour periods and place the corresponding observations in the hour slots.
- Data from the next simulation looks like this for day 1 for individual 1.

Subject-specific times of observations: subject 1 day 1

yl	y2	y3	y4	y5	T	ID
999	999	999	999	999	1	1
999	999	999	999	999	2	1
999	999	999	999	999	3	1
999	999	999	999	999	4	1
999	999	999	999	999	5	1
999	999	999	999	999	6	1
999	999	999	999	999	7	1
999	999	999	999	999	8	1
999	999	999	999	999	9	1
999	999	999	999	999	10	1
999	999	999	999	999	11	1
999	999	999	999	999	12	1
5.026193	0.327383	1.017519	0.701296	-0.55917	13	1
999	999	999	999	999	14	1
1.628885	1.652829	2.324074	1.800932	4.013447	15	1
999	999	999	999	999	16	1
4.376545	1.652831	2.098822	6.188234	2.913506	17	1
1.534865	0.631455	-0.29779	2.798775	1.37025	18	1
0.359654	1.476764	-0.43374	0.348777	1.382437	19	1
999	999	999	999	999	20	1
999	999	999	999	999	21	1
999	999	999	999	999	22	1
999	999	999	999	999	23	1
999	999	999	999	999	24	1

Subject-specific times of observations - simulation study

```
MONTECARLO:          NAMES = yl-y5 u;
                     NOBSERVATIONS = 30000;
                     NREPS = 100;
                     NCSIZES = 1;
                     CSIZES = 100(300);
                     CATEGORICAL = u; ! u is used to give the same missingness for all y1-y5
                     GENERATE = u(1);
                     WITHIN = u;
                     MISSING = y1-y5;
MODEL MISSING:       [yl-y5@-15];
                     yl-y5 ON u@30;
ANALYSIS:            TYPE = TWOLEVEL;
                     ESTIMATOR = BAYES;
                     BITERATIONS = 10000(500);
                     PROCESSORS = 2;
MODEL MONTECARLO:    %WITHIN%
                     [u$1*-0.83]; ! Probit of -.83 gives 20% present and 80% missing
                     f BY yl-y5*1 (& 1);
                     yl-y5*1;
                     f ON f&1*0.4;
                     %BETWEEN%
                     fb BY yl-y5*0.5;
                     fb@l;
                     yl-y5*0.2;
```

Table: Two-level DAFS AR(1) with subject-specific times - simulation study results

percentage missing values	$\hat{\phi}$ (coverage) $\phi = 0.4$	convergence rate	comp time per replication in min
.80	.39(.95)	100%	1.5
.85	.39(.90)	95%	2.5
.90	.35(.46)	55%	10
.95	.34(.55)	55%	18

Quality of the estimation deteriorates as the amount of inserted missing data exceeds 90%. Note that this missing data is imputed by the MCMC estimation, leading to large amount of imputed quantities. It works well with 80% and 85% missing data.

Subject-specific times of observations

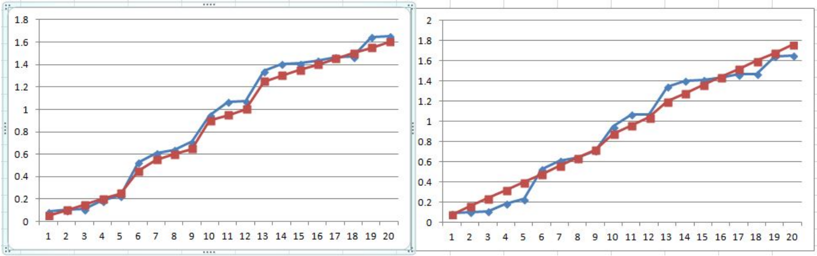
- Information contained in the unequal distances in the observations would be extracted well using the 80% to 85% missing values, eliminating the need for continuous time modeling
- Tinterval command will setup the missing data for you, given the precise times of observations and an approximation value δ
- Tinterval = $t(\delta)$ means that the continuous time variable t is replaced by the nearest integer $[t/\delta]$. There are complications if the nearest integers is the same for two or more different observations times t. Special algorithm to resolve this issue.

Subject-specific times of observations

- Split the time axis in bins of size δ. Then place each observation in the correct bin. Repeat these steps until each bin contains no more than 1 observation
  - find a bin with more than 1 observations
  - locate the nearest empty bin (look up or down)
  - move one of the extra observation to fill in the the empty bin but keep order of the observations so the extra observation bumps the rest of the observations towards the empty bin
- Mplus will warn you if the shifting process yields a discrepancy between t/δ and new time bigger than 5. Lower the δ value to resolve this.
- Fill in the remaining bins with missing values and set the time as T=1,2, ... and T is the bin number.
- Other algorithms are possible. Make your own discritzation algorithm and use Mplus with integer times.

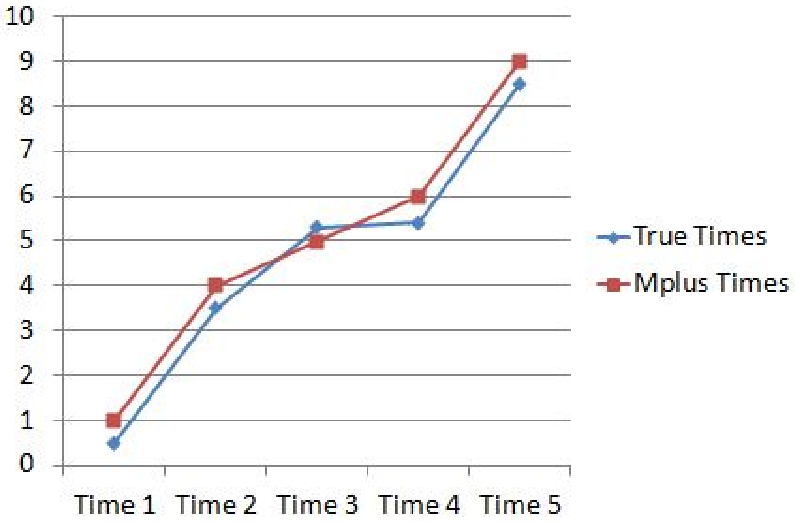
Tinterval command comparison

Tinterval(0.05) v.s. Tinterval(0.08), Blue=true times, Red=Mplus generated times



Similar plots can be produced with real data sets to evaluate the Tinterval approxmation for real data.

Tinterval command illustration



Simulation study with varying δ

Table: Two-level AR(1) with subject-specific times. Estimates and coverage for ϕ and amount of missing data m_2 during the analysis, tinterval=δ

m	δ	$\phi = 0.8$	m_2
.80	1	.80(.91)	.80
.80	2	.81(.31)	.58
.80	3	.83(.00)	.38
.80	4	.84(.00)	.18
.80	5	.86(.00)	.05
.80	10	.92(.00)	.00
.95	1	.80(.85)	.95
.95	2	.81(.57)	.90
.95	3	.82(.20)	.85
.95	4	.83(.00)	.80
.95	5	.84(.00)	.74
.95	10	.88(.00)	.49

Subject-specific times of observations

- Tinterval command is not perfect. It is an approximate solution for the continuous process.
- The main question is how to choose δ. Three considerations:
  - Choose scale that is natural to help with interpretation of model and results - hour, day, week
  - Choose scale that does not produce more than 90% missing data, around 80% unless lower is appropriate
  - Smaller values yield better approximations but also more missing data
  - TVEM models / Cross-classified DSEM: small δ will lead to too many time specific random effects

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Simulation Study - Twolevel DAFS Lag 3 model

```
montecarlo:
    names = y1-y5;
    NOBS = 10000;
    NREP = 100;
    NCSIZES = 1;
    CSIZES = 100(100);

ANALYSIS:   TYPE IS TWOLEVEL;
            estimator=bayes;
            biter=(500); proc=2;

model montecarlo:
    %within%
    f by y1-y5*1 (& 3);
    y1-y5*1;
    f@1;
    f on f&1*0.4 f&2*0.2 f&3*0.1;

    %between%
    fb by y1-y5*0.5; fb@1; y1-y5*0.2;
```

Results - Twolevel DAFS Lag 3 model

F BY							
Y1	1.000	0.9992	0.0134	0.0120	0.0002	0.900	1.000
Y2	1.000	1.0010	0.0127	0.0120	0.0002	0.950	1.000
Y3	1.000	1.0001	0.0138	0.0120	0.0002	0.910	1.000
Y4	1.000	0.9997	0.0128	0.0120	0.0002	0.930	1.000
Y5	1.000	0.9988	0.0134	0.0119	0.0002	0.910	1.000
F ON							
F&1	0.400	0.4024	0.0121	0.0123	0.0002	0.980	1.000
F&2	0.200	0.1983	0.0143	0.0139	0.0002	0.950	1.000
F&3	0.100	0.0997	0.0138	0.0126	0.0002	0.910	1.000

Note that the choice of these coefficients for simulation study purposes is tricky as you need to preserve the stationarity of the model, otherwise the data will explode. Simple rule: if all are positive and the sum is less than 1 the process is stationary. The exact stationarity condition involves finding the roots of a polynomial of degree L.

Simulation Study - Twolevel WNFS Lag 5 model

```
montecarlo:
    names = y1-y5;
    NOBS = 10000;
    NREP = 100;
    NCSIZES = 1;
    CSIZES = 100(100);

ANALYSIS:   TYPE IS TWOLEVEL;
            estimator=bayes;
            biter=(500); proc=2;

model montecarlo:
    %within%
    f by y1-y5*1 (& 5);
    y1-y5*1;
    f@1;
    y1-y5 on f&1*0.4 f&2*0.2 f&3*0.3 f&4*0.2 f&5*0.1;

    %between%
    fb by y1-y5*0.5; fb@1; y1-y5*0.2;
```

Results - Twolevel WNFS Lag 5 model

Y1	ON							
F&1		0.400	0.4012	0.0155	0.0160	0.0002	0.960	1.000
F&2		0.200	0.1989	0.0168	0.0161	0.0003	0.940	1.000
F&3		0.300	0.3021	0.0145	0.0165	0.0002	0.980	1.000
F&4		0.200	0.1998	0.0179	0.0167	0.0003	0.950	1.000
F&5		0.100	0.0985	0.0155	0.0164	0.0002	0.960	1.000

Note that the choice of these coefficients for simulation study purposes is NOT tricky: WNFS is always stationary.

Simulation Study - Twolevel DAFS-WNFS Combo Lag 1 model - ARMA(1,1) factor

```
montecarlo:
    names = y1-y5;
    NOBS = 10000;
    NREP = 100;
    NCSIZES = 1;
    CSIZES = 100(100);

ANALYSIS:     TYPE IS TWOLEVEL;
              estimator=bayes;
              biter=(500); proc=2;

model montecarlo:
    %within%
    f by y1-y5*1 (& 1);
    y1-y5*1;
    f@1;
    f on f&1*0.4;
    y1-y5 on f&1*0.6;

    %between%
    fb by y1-y5*0.5; fb@1; y1-y5*0.2;
```

Results - Twolevel DAFS-WNFS Combo Lag 1 model - ARMA(1,1) factor

F	ON							
F&1		0.400	0.3992	0.0154	0.0139	0.0002	0.930	1.000
Y1	ON							
F&1		0.600	0.5980	0.0216	0.0218	0.0005	0.970	1.000
Y2	ON							
F&1		0.600	0.6020	0.0207	0.0220	0.0004	0.990	1.000
Y3	ON							
F&1		0.600	0.5999	0.0208	0.0219	0.0004	0.980	1.000
Y4	ON							
F&1		0.600	0.6006	0.0215	0.0219	0.0005	0.940	1.000
Y5	ON							
F&1		0.600	0.5985	0.0231	0.0219	0.0005	0.920	1.000

Note that this is counterintuitive from SEM perspective, but not from time series perspective. The model is essentially a factor analysis model with ARMA(1,1) factor

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Two-level MEAR(1) TVEM - simulated example

- General TVEM framework: multivariate, multilevel, time-series, continuous and categorical dependent variables.
- Consider the following example N=500, T=50: Two-level MEAR(1) with covariate with time specific mean and regression coefficient

$$Y_{it} = \mu_t + Y_i + \beta_t X_{it} + f_{it} + \varepsilon_{it}$$

$$f_{it} = \phi f_{i,t-1} + \xi_{it}$$

$$\mu_t = f_1(t) = log(t)$$

$$\beta_t = f_2(t) = a + bt + ct^2 = 0.001 \cdot t \cdot (50 - t)$$

- $f_1(t)$ and $f_2(t)$ are arbitrary functions of t used for data generation

Type of TVEM models

- Non-parametric cross-classified: Exploratory TVEM-DSEM, no parametric shape included in the model. The random effect μ_t and β_t are modeled as normally distributed random effects
- Semi-parametric cross-classified: TVEM-DSEM, parametric shape included in the model as well as residual random effects. The random effects μ_t and β_t are modeled as normally distributed random effects which include parametric curves for the means of the random effects
- Parametric two-level: TVEM-DSEM, parametric shape included in the model. The random effects μ_t and β_t are modeled as normally distributed random effects with zero variance, only parametric curve for the the random effect mean. Typically such a model is estimated as two-level DSEM rather than cross-classified.

Exploratory TVEM-DSEM

```
variable:
names are y x t c;
within=x;
cluster=c t;

analysis:  type = cross random;
estimator=bayes; biter=(5000); process=2;

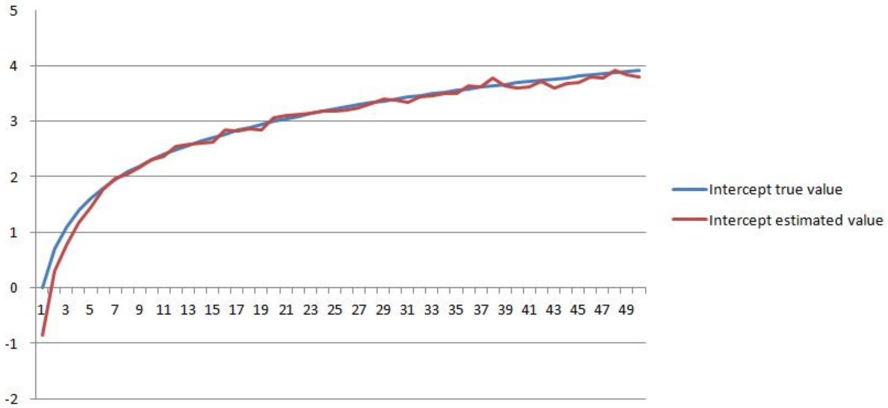
model:
%within%
y*0.5; eta by y@1 (&1);
eta on eta&1*0.5; eta*1.2;
s | y on x;

%between t%
y; s; [s*0];

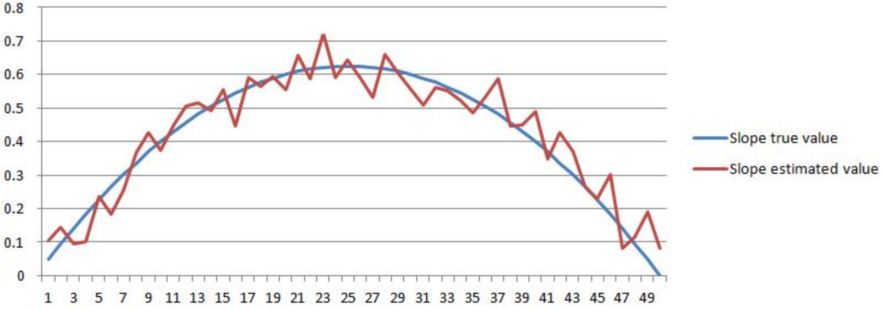
%between c%
y*0.5; [y*0]; s@0; [s@0];

savedata: file is TVEM3.dat; save=FS(2000);
```

Exploratory TVEM-DSEM results



Exploratory TVEM-DSEM results



Semi-parametric TVEM-DSEM

```
variable:
names are y x t c;
within=x;
cluster=c t;
usevar=y x x1 x2 x3;
between=(t) x1 x2 x3;

define: x1=log(t); x2=0.05*t; x3=0.001*t*t;

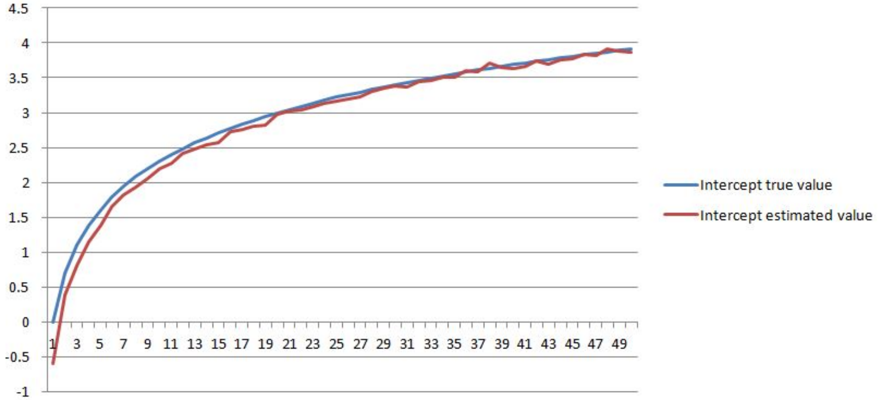
analysis:  type=cross random;
estimator=bayes; biter=(5000); process=2;

model:
%within%
y*0.5; eta by y@1 (&1);
eta on eta&1*0.5; eta*1.2;
s | y on x;

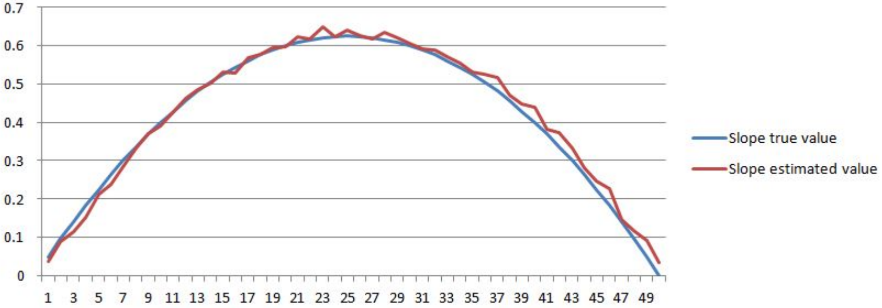
%between t%
y; s; [s*0]; y on x1*1; s on x2*1 x3*-1;

%between c%
y*0.5; [y*0]; s@0; [s@0];
```

Semi-parametric TVEM-DSEM results



Semi-parametric TVEM-DSEM results



Parametric: TVEM-DSEM - two level model

```
variable:
names are y x t c;
within=x x1 x2 x3;
cluster=c;
usevar=y x x1 x2 x3;

define: x1=log(t); x2=0.05*t*x; x3=0.001*t*t*x;

analysis:  type = twolevel random;
estimator=bayes; biter=(10000); process=2;

model:
%within%
y*0.5; eta by y@1 (&1);
eta on eta&1*0.5; eta*1.2;
y on x*0 x1*1 x2*1 x3*-1;

%between%
y*0.5; [y*0];
```

Overview

- DSEM output options and plots
- Subject-specific variances
- Unevenly spaced and individual-specific times of observations
- Two-level DAFS and WNFS
- TVEM - time varying effects models
- **Three level AR(1) models: within day v.s. between day autoregressive modeling**

Three-level AR(1) model

- Y_{idt} is the observed value for individual i on day d at time t

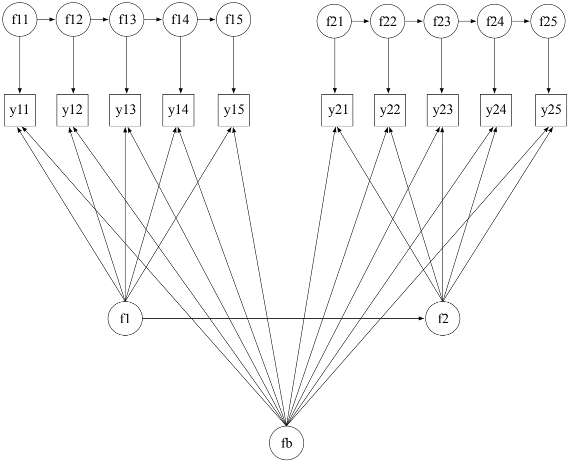
$$Y_{idt} = \mu + Y_i + E_{it} + F_{id} + G_{idt}$$

$$G_{idt} = \rho_1 G_{id,t-1} + \varepsilon_{1,idt}$$

$$F_{id} = \rho_2 F_{i,d-1} + \varepsilon_{2,id}$$

- Two type of autocorrelation parameter, ρ_1 is the autocorrelation within the day, ρ_2 is the autocorrelation between the days
- Maybe take out E_{it}?
- Model has 7 parameters: 4 variances, 2 autocorrelations, 1 intercept
- Data consists of 100 individuals, observed for 100 days, with 10 observations per day
- Model the additional level in wide format either on within or between (whichever has smaller width)

Three-level AR(1) model



Three-level AR(1) model - simulation study

```
MONTECARLO:           NAMES = yl-y10;
                      NOBSERVATIONS = 10000;
                      NREPS = 100;
                      NCSIZES = 1;
                      CSIZES = 100(100);
ANALYSIS:             TYPE = TWOLEVEL;
                      ESTIMATOR=BAYES;
                      BITERATIONS=(500);
                      PROCESSORS=2;
MODEL MONTECARLO:     %WITHIN%
                      f BY yl-y10@1 (&1);
                      yl-y10@0.01;
                      f1 BY yl@1; f2 BY y2@1; f3 BY y3@1;
                      f4 BY y4@1; f5 BY y5@1; f6 BY y6@l;
                      f7 BY y7@1; f8 BY y8@1; f9 BY y9@l;
                      f10 BY y10@l;
                      f1-f1*1 (1);
                      f*0.5;
                      f ON f&1*0.3;
                      f2-f10 pon f1-f9*0.5 (2);
                      f WITH f10@0;
                      %BETWEEN%
                      fb BY yl-y10@1;
                      fb*0.4;
                      yl-y10*0.1;
                      [V1-V10*0] (3);
```

Three-level AR(1) model - simulation study results

	Population	Estimates Average	Std. Dev.	S.E. Average	M.S.E.	95% Cover	% Sig Cover
Within Level							
F ON							
F&1	0.300	0.2955	0.0133	0.0150	0.0002	0.970	1.000
F2 ON							
F1	0.500	0.4993	0.0042	0.0040	0.0000	0.940	1.000
Variances							
F1	1.000	1.0007	0.0049	0.0049	0.0000	0.930	1.000
Residual Variances							
F	0.500	0.4994	0.0150	0.0126	0.0002	0.880	1.000
Between Level							
Intercepts							
Y1	0.000	0.0037	0.0855	0.0572	0.0072	0.810	0.190
Variances							
FB	0.400	0.4310	0.0570	0.0658	0.0042	0.970	1.000
Residual Variances							
Y1	0.100	0.1007	0.0058	0.0051	0.0000	0.940	1.000

Three-level AR(1) model with subject-specific times of observations

- Using 50% missing data. Approximately 5 randomly spaced times of observations per day
- 5 observations a bit too low to obtain good autocorrelation parameter. Needs much longer MCMC estimation.
- Add the commands:
  missing=y1-y10;
  model missing: [y1-y10*0];

Three-level AR(1) model with subject-specific times of observations - simulation results

	Population	Estimates Average	Std. Dev.	S.E. Average	M.S.E.	95% Cover	% Sig Cover
Within Level							
F ON							
F&1	0.300	0.2864	0.0210	0.0166	0.0006	0.810	1.000
F2 ON							
Fl	0.500	0.4428	0.0540	0.0188	0.0062	0.360	1.000
Variances							
Fl	1.000	1.0444	0.0429	0.0159	0.0038	0.450	1.000
Residual Variances							
F	0.500	0.4694	0.0307	0.0189	0.0019	0.560	1.000
Between Level							
Intercepts							
Y1	0.000	0.0097	0.0665	0.0589	0.0045	0.890	0.110
Variances							
FB	0.400	0.3821	0.0640	0.0608	0.0044	0.940	1.000
Residual Variances							
Y1	0.100	0.0925	0.0098	0.0057	0.0002	0.660	1.000

New models coming in future Mplus release

- Residual DSEM
- Bayesian Multilevel Mixture Models
- Bayesian Multilevel Latent Transition Models with cluster specific transition probabilities
- Multilevel Mixtures of Dynamic Structural Equation Models
- Dynamic Latent Class Analysis
- Multilevel Hidden Markov Model
- Multilevel Markov Switching Autoregressive Models
- Multilevel Markov Switching DSEM Models
- These are at various stages of development.
- Asparouhov, T., Hamaker, E.L. & Muthen, B. (2017). Dynamic Latent Class Analysis, Structural Equation Modeling: A Multidisciplinary Journal, 24:2, 257-269