

Further Readings On Introductory Growth Modeling

- Bijleveld, C. C. J. H., & van der Kamp, T. (1998). Longitudinal data analysis: Designs, models, and methods. Newbury Park: Sage.
- Bollen, K.A. & Curran, P.J. (2006). Latent curve models. A structural equation perspective. New York: Wiley.
- Muthén, B. & Khoo, S.T. (1998). Longitudinal studies of achievement growth using latent variable modeling. Learning and Individual Differences, Special issue: latent growth curve analysis, 10, 73-101. (#80)
- Muthén, B. & Muthén, L. (2000). The development of heavy drinking and alcohol-related problems from ages 18 to 37 in a U.S. national sample. Journal of Studies on Alcohol, 61, 290-300. (#83)
- Raudenbush, S.W. & Bryk, A.S. (2002). Hierarchical linear models: Applications and data analysis methods. Second edition. Newbury Park, CA: Sage Publications.
- Singer, J.D. & Willett, J.B. (2003). Applied longitudinal data analysis. Modeling change and event occurrence. New York, NY: Oxford University Press.
- Snijders, T. & Bosker, R. (1999). Multilevel analysis. An introduction to basic and advanced multilevel modeling. Thousand Oakes, CA: Sage Publications.

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Further Practical Issues

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Five Ways To Model Non-Linear Growth

- Estimated time scores
- Quadratic (cubic) growth model
- Fixed non-linear time scores
- Piece-wise growth modeling
- Time-varying covariates

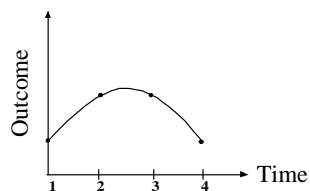
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Specifying Time Scores For Quadratic Growth Models

Quadratic growth model

$$y_{it} = \eta_{0i} + \eta_{1i} x_t + \eta_{2i} x_t^2 + \varepsilon_{it}$$

- Need three latent variables to describe a quadratic growth model: Intercept, linear slope, quadratic slope



- Linear slope time scores: 0 1 2 3
0 .1 .2 .3
- Quadratic slope time scores: 0 1 4 9
0 .01 .04 .09

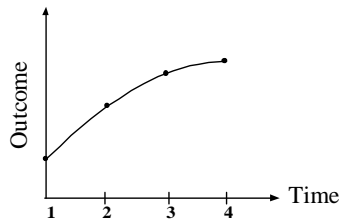
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Specifying Time Scores For Non-Linear Growth Models With Fixed Time Scores

Non-Linear Growth Models with Fixed Time scores

- Need two latent variables to describe a non-linear growth model: Intercept and slope

Growth model with a logarithmic growth curve-- $\ln(t)$

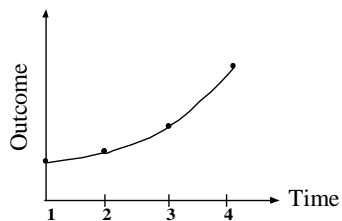


Time scores: 0 0.69 1.10 1.39

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Specifying Time Scores For Non-Linear Growth Models With Fixed Time Scores (Continued)

Growth model with an exponential growth curve-- $\exp(t-1) - 1$



Time scores: 0 1.72 6.39 19.09

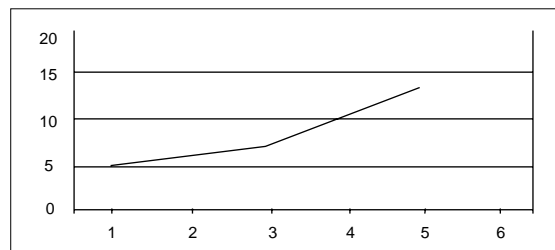
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Piecewise Growth Modeling

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Piecewise Growth Modeling

- Can be used to represent different phases of development
- Can be used to capture non-linear growth
- Each piece has its own growth factor(s)
- Each piece can have its own coefficients for covariates

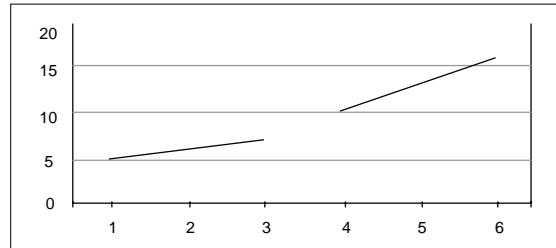


One intercept growth factor, two slope growth factors

0	1	2	2	2	2	Time scores piece 1
0	0	0	1	2	3	Time scores piece 2

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Piecewise Growth Modeling (Continued)



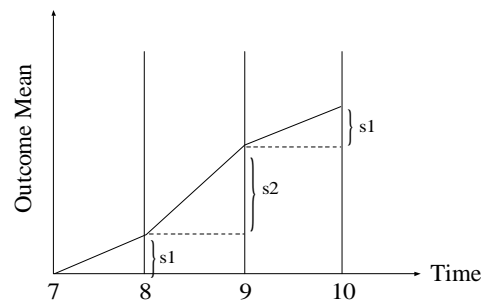
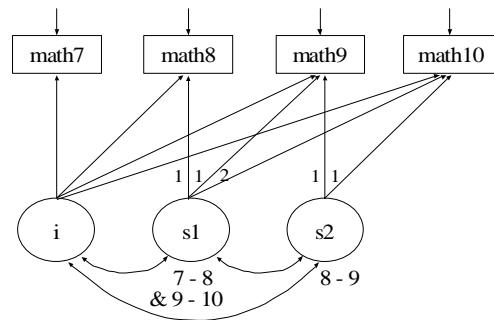
Two intercept growth factors, two slope growth factors

0 1 2

Time scores piece 1

0 1 2 Time scores piece 2

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Input For LSAY Piecewise Growth Model With Covariates

```
MODEL:      i s1 | math7@0 math8@1 math9@1 math10@2;
            i s2 | math7@0 math8@0 math9@1 math10@1;
            i s1 s2 ON mothed homeres;
```

Alternative language:

```
MODEL:      i BY math7-math10@1;
            s1 BY math7@0 math8@1 math9@1 math10@2;
            s2 BY math7@0 math8@0 math9@1 math10@1;
            [math7-math10@0];
            [i s1 s2];
            i s1 s2 ON mothed homeres;
```

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Output Excerpts LSAY Piecewise Growth Model With Covariates

n = 935

Tests of Model Fit

CHI-SQUARE TEST OF MODEL FIT

Value	11.721
Degrees of Freedom	3
P-Value	.0083

RMSEA (ROOT MEAN SQUARE ERROR OF APPROXIMATION)

Estimate	.056
90 Percent C.I.	.025 .091
Probability RMSEA <= .05	.331

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Output Excerpts LSAY Piecewise Growth Model With Covariates (Continued)

Selected Estimates

		Estimates	S.E.	Est./S.E.	Std	StdYX
I	ON					
	MOTHEd	2.127	.284	7.488	.266	.256
	HOMERES	1.389	.185	7.524	.174	.257
S1	ON					
	MOTHEd	-.126	.147	-.858	-.113	-.109
	HOMERES	.091	.096	.950	.081	.120
S2	ON					
	MOTHEd	.436	.191	2.285	.185	.178
	HOMERES	.289	.124	2.329	.123	.181

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Growth Model With Individually-Varying Times Of Observation And Random Slopes For Time-Varying Covariates

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Growth Modeling In Multilevel Terms

Time point t , individual i (two-level modeling, no clustering):

- y_{ti} : repeated measures of the outcome, e.g. math achievement
- a_{1ti} : time-related variable; e.g. grade 7-10
- a_{2ti} : time-varying covariate, e.g. math course taking
- x_i : time-invariant covariate, e.g. grade 7 expectations

Two-level analysis with individually-varying times of observation and random slopes for time-varying covariates:

$$\text{Level 1: } y_{ti} = \pi_{0i} + \pi_{1i} a_{1ti} + \pi_{2i} a_{2ti} + e_{ti}, \quad (55)$$

$$\text{Level 2: } \begin{cases} \pi_{0i} = \beta_{00} + \beta_{01} x_i + r_{0i}, \\ \pi_{1i} = \beta_{10} + \beta_{11} x_i + r_{1i}, \\ \pi_{2i} = \beta_{20} + \beta_{21} x_i + r_{2i}. \end{cases} \quad (56)$$

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Growth Modeling In Multilevel Terms (Continued)

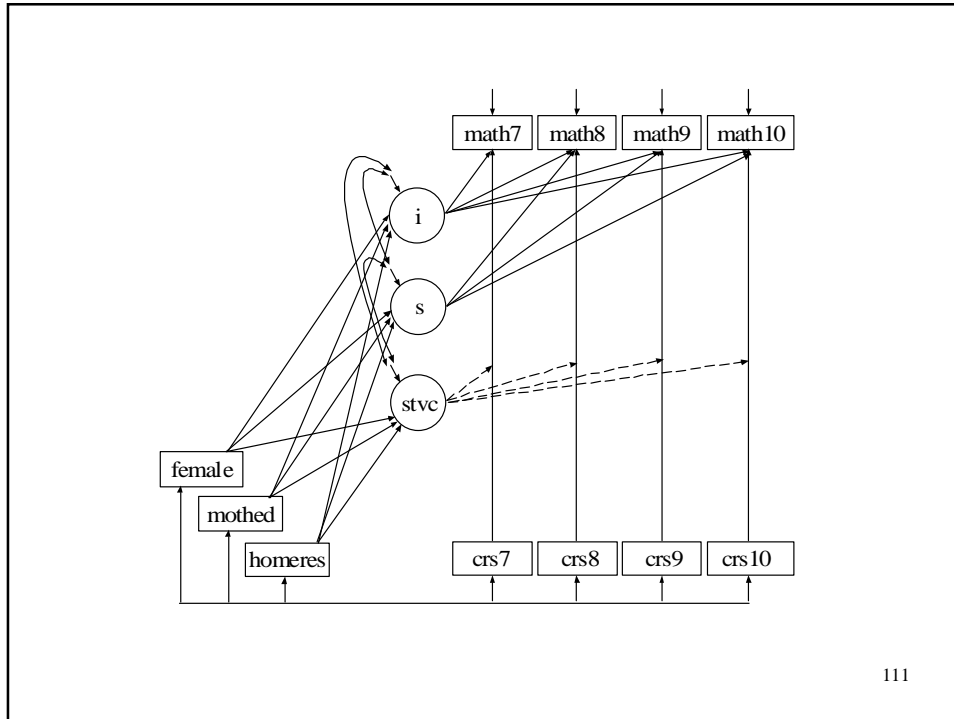
Time scores a_{1ti} read in as data (not loading parameters).

- π_{2i} possible with time-varying random slope variances
- Flexible correlation structure for $V(e) = \Theta (T \times T)$
- Regressions among random coefficients possible, e.g.

$$\pi_{1i} = \beta_{10} + \gamma_1 \pi_{0i} + \beta_{11} x_i + r_{1i}, \quad (57)$$

$$\pi_{2i} = \beta_{20} + \gamma_2 \pi_{0i} + \beta_{21} x_i + r_{2i}. \quad (58)$$

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Input For Growth Model With Individually Varying Times Of Observation

```

TITLE:      Growth model with individually varying times of
            observation and random slopes

DATA:      FILE IS lsaynew.dat;
            FORMAT IS 3F8.0 F8.4 8F8.2 3F8.0;

VARIABLE:  NAMES ARE math7 math8 math9 math10 crs7 crs8 crs9
            crs10 female mothed homeres a7-a10;

            ! crs7-crs10 = highest math course taken during each
            ! grade (0=no course, 1=low, basic, 2=average, 3=high.
            ! 4=pre-algebra, 5=algebra I, 6=geometry,
            ! 7=algebra II, 8=pre-calc, 9=calculus)

MISSING ARE ALL (9999);
CENTER = GRANDMEAN (crs7-crs10 mothed homeres);
TScores = a7-a10;

```

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Input For Growth Model With Individually Varying Times Of Observation (Continued)

```

DEFINE:      math7 = math7/10;
             math8 = math8/10;
             math9 = math9/10;
             math10 = math10/10;

ANALYSIS:    TYPE = RANDOM MISSING;
             ESTIMATOR = ML;
             MCONVERGENCE = .001;

MODEL:       i s | math7-math10 AT a7-a10;
             stvc | math7 ON crs7;
             stvc | math8 ON crs8;
             stvc | math9 ON crs9;
             stvc | math10 ON crs10;
             i ON female mothed homeres;
             s ON female mothed homeres;
             stvc ON female mothed homeres;
             i WITH s;
             stvc WITH i;
             stvc WITH s;

OUTPUT:      TECH8;

```

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Output Excerpts For Growth Model With Individually Varying Times Of Observation And Random Slopes For Time-Varying Covariates

n = 2271

Tests of Model Fit

Loglikelihood

H0 Value	-8199.311
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Information Criteria

Number of Free Parameters	22
Akaike (AIC)	16442.623
Bayesian (BIC)	16568.638
Sample-Size Adjusted BIC	16498.740
(n* = (n + 2) / 24)	

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Output Excerpts For Growth Model With Individually Varying Times Of Observation And Random Slopes For Time-Varying Covariates (Continued)

Model Results		Estimates	S.E.	Est./S.E.	
I	ON				
	FEMALE	0.187	0.036	5.247	
	MOTHEd	0.187	0.018	10.231	
	HOMERES	0.159	0.011	14.194	
S	ON				
	FEMALE	-0.025	0.012	-2.017	
	MOTHEd	0.015	0.006	2.429	
	HOMERES	0.019	0.004	4.835	
STVC	ON				
	FEMALE	-0.008	0.013	-0.590	
	MOTHEd	0.003	0.007	0.429	
	HOMERES	0.009	0.004	2.167	
I	WITH				
S		0.038	0.006	6.445	
STVC	WITH				
I		0.011	0.005	2.087	
S		0.004	0.002	2.033	115

Output Excerpts For Growth Model With Individually Varying Times Of Observation And Random Slopes For Time-Varying Covariates (Continued)

Intercepts					
	MATH7	0.000	0.000	0.000	
	MATH8	0.000	0.000	0.000	
	MATH9	0.000	0.000	0.000	
	MATH10	0.000	0.000	0.000	
	I	4.992	0.025	198.456	
	S	0.417	0.009	47.275	
	STVC	0.113	0.010	11.416	
Residual Variances					
	MATH7	0.185	0.011	16.464	
	MATH8	0.178	0.008	22.232	
	MATH9	0.156	0.008	18.497	
	MATH10	0.169	0.014	12.500	
	I	0.570	0.023	25.087	
	S	0.036	0.003	12.064	
	STVC	0.012	0.002	5.055	116

Random Slopes

- In single-level modeling random slopes β_i describe variation across individuals i ,

$$y_i = \alpha_i + \beta_i x_i + \varepsilon_i, \quad (100)$$

$$\alpha_i = \alpha + \zeta_{0i}, \quad (101)$$

$$\beta_i = \beta + \zeta_{1i}, \quad (102)$$

Resulting in heteroscedastic residual variances

$$V(y_i / x_i) = V(\beta_i) x_i^2 + \theta \quad (103)$$

- In two-level modeling random slopes β_j describe variation across clusters j

$$y_{ij} = a_j + \beta_j x_{ij} + \varepsilon_{ij}, \quad (104)$$

$$a_j = a + \zeta_{0j}, \quad (105)$$

$$\beta_j = \beta + \zeta_{1j}. \quad (106)$$

A small variance for a random slope typically leads to slow convergence of the ML-EM iterations. This suggests respecifying the slope as fixed.

Mplus allows random slopes for predictors that are

- Observed covariates
- Observed dependent variables
- Continuous latent variables

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Computational Issues For Growth Models

- Decreasing variances of the observed variables over time may make the modeling more difficult
- Scale of observed variables – keep on a similar scale
- Convergence – often related to starting values or the type of model being estimated
 - Program stops because maximum number of iterations has been reached
 - If no negative residual variances, either increase the number of iterations or use the preliminary parameter estimates as starting values
 - If there are large negative residual variances, try better starting values
 - Program stops before the maximum number of iterations has been reached
 - Check if variables are on a similar scale
 - Try new starting values
- Starting values – the most important parameters to give starting values to are residual variances and the intercept growth factor mean
- Convergence for models using the | symbol
 - Non-convergence may be caused by zero random slope variances which indicates that the slopes should be fixed rather than random

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Advanced Growth Models

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Advantages Of Growth Modeling In A Latent Variable Framework

- Flexible curve shape
- Individually-varying times of observation
- **Regressions among random effects**
- Multiple processes
- Modeling of zeroes
- Multiple populations
- Multiple indicators
- Embedded growth models
- Categorical latent variables: growth mixtures

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Regressions Among Random Effects

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Regressions Among Random Effects

Standard multilevel model (where $x_t = 0, 1, \dots, T$):

$$\text{Level 1: } y_{it} = \eta_{0i} + \eta_{1i} x_t + \varepsilon_{it}, \quad (1)$$

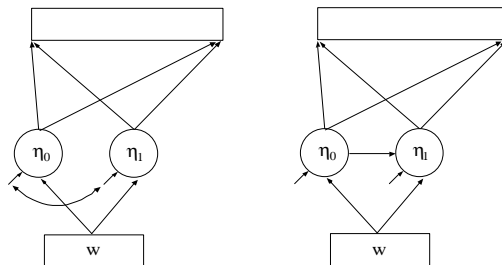
$$\text{Level 2a: } \eta_{0i} = \alpha_0 + \gamma_0 w_i + \zeta_{0i}, \quad (2)$$

$$\text{Level 2b: } \eta_{1i} = \alpha_1 + \gamma_1 w_i + \zeta_{1i}. \quad (3)$$

A useful type of model extension is to replace (3) by the regression equation

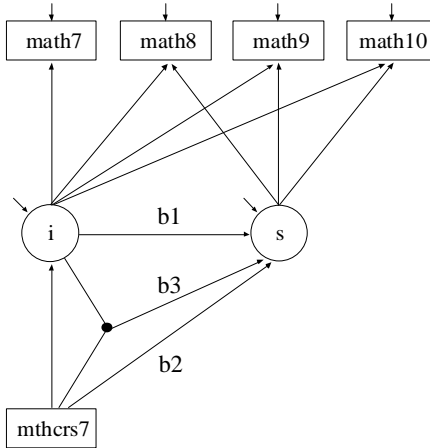
$$\eta_{1i} = \alpha + \beta \eta_{0i} + \gamma w_i + \zeta_i. \quad (4)$$

Example: Blood Pressure (Bloomqvist, 1977)



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Growth Model With An Interaction



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Input For A Growth Model With An Interaction Between A Latent And An Observed Variable

```

TITLE:    growth model with an interaction between a latent and an
          observed variable
DATA:     FILE IS lsay.dat;
VARIABLE: NAMES ARE math7 math8 math9 math10 mthcrs7;
          MISSING ARE ALL (9999);
          CENTERING = GRANDMEAN (mthcrs7);
DEFINE:   math7 = math7/10;
          math8 = math8/10;
          math9 = math9/10;
          math10 = math10/10;
ANALYSIS: TYPE=RANDOM MISSING;
MODEL:    i s | math7@0 math8@1 math9@2 math10@3;
          [math7-math10] (1);      !growth language defaults
          [i@0 s];                !overridden

          inter | i XWITH mthcrs7;
          s ON i mthcrs7 inter;
          i ON mthcrs7;
OUTPUT:   SAMPSTAT STANDARDIZED TECH1 TECH8;
    
```

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Output Excerpts Growth Model With An Interaction Between A Latent And An Observed Variable

Tests Of Model Fit

Loglikelihood		
	H0 Value	-10068.944
Information Criteria		
	Number of Free Parameters	12
	Akaike (AIC)	20161.887
	Bayesian (BIC)	20234.365
	Sample-Size Adjusted BIC	20196.236
	(n* = (n + 2) / 24)	

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Output Excerpts Growth Model With An Interaction Between A Latent And An Observed Variable (Continued)

Model Results

	Estimates	S.E.	Est./S.E.
I			
	MATH7	1.000	0.000
	MATH8	1.000	0.000
	MATH9	1.000	0.000
	MATH10	1.000	0.000
S			
	MATH7	0.000	0.000
	MATH8	1.000	0.000
	MATH9	2.000	0.000
	MATH10	3.000	0.000

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**Output Excerpts Growth Model
With An Interaction Between A Latent And
An Observed Variable (Continued)**

		Estimates	S.E.	Est./S.E.
S	ON			
	I	0.087	0.012	7.023
	INTER	-0.047	0.006	-7.301
S	ON			
	MTHCRS7	0.045	0.013	3.555
I	ON			
	MTHCRS7	0.632	0.016	40.412

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**Output Excerpts Growth Model
With An Interaction Between A Latent And
An Observed Variable (Continued)**

		Estimates	S.E.	Est./S.E.
Intercepts				
	MATH7	5.019	0.015	341.587
	MATH8	5.019	0.015	341.587
	MATH9	5.019	0.015	341.587
	MATH10	5.019	0.015	341.587
	I	0.000	0.000	0.000
	S	0.417	0.007	57.749
Residual Variances				
	MATH7	0.184	0.011	16.117
	MATH8	0.178	0.009	20.109
	MATH9	0.164	0.009	18.369
	MATH10	0.173	0.015	11.509
	I	0.528	0.018	28.935
	S	0.037	0.004	10.027

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Interpreting The Effect Of The Interaction Between Initial Status Of Growth In Math Achievement And Course Taking In Grade 6

- Model equation for slope s
 $s = a + b_1 * i + b_2 * mthcrs7 + b_3 * i * mthcrs7 + e$
or, using a moderator function (Klein & Moosbrugger, 2000) where i moderates the influence of $mthcrs7$ on s
 $s = a + b_1 * i + (b_2 + b_3 * i) * mthcrs7 + e$
- Estimated model
Unstandardized
 $s = 0.417 + 0.087 * i + (0.045 - 0.047 * i) * mthcrs7$
Standardized with respect to i and $mthcrs7$
 $s = 0.42 + 0.08 * i + (0.04 - 0.04 * i) * mthcrs7$

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Interpreting The Effect Of The Interaction Between Initial Status Of Growth In Math Achievement And Course Taking In Grade 6 (Continued)

- Interpretation of the standardized solution
At the mean of i , which is zero, the slope increases 0.04 for 1 SD increase in $mthcrs7$

At 1 SD below the mean of i , which is zero, the slope increases 0.08 for 1 SD increase in $mthcrs7$

At 1 SD above the mean of i , which is zero, the slope does not increase as a function of $mthcrs7$

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Growth Modeling With Parallel Processes

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Advantages Of Growth Modeling In A Latent Variable Framework

- Flexible curve shape
- Individually-varying times of observation
- Regressions among random effects
- **Multiple processes**
- Modeling of zeroes
- Multiple populations
- Multiple indicators
- Embedded growth models
- Categorical latent variables: growth mixtures

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Multiple Processes

- Parallel processes
- Sequential processes

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Growth Modeling With Parallel Processes

- Estimate a growth model for each process separately
 - Determine the shape of the growth curve
 - Fit model without covariates
 - Modify the model
- Joint analysis of both processes
- Add covariates

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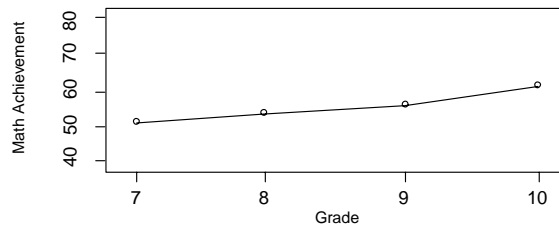
LSAY Data

The data come from the Longitudinal Study of American Youth (LSAY). Two cohorts were measured at four time points beginning in 1987. Cohort 1 was measured in Grades 10, 11, and 12. Cohort 2 was measured in Grades 7, 8, 9, and 10. Each cohort contains approximately 60 schools with approximately 60 students per school. The variables measured include math and science achievement items, math and science attitude measures, and background information from parents, teachers, and school principals. There are approximately 60 items per test with partial item overlap across grades—adaptive tests.

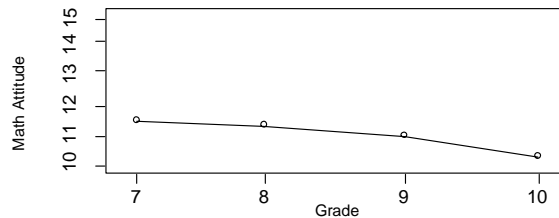
Data for the analysis include the younger females. The variables include math achievement and math attitudes from Grades 7, 8, 9, and 10 and mother's education.

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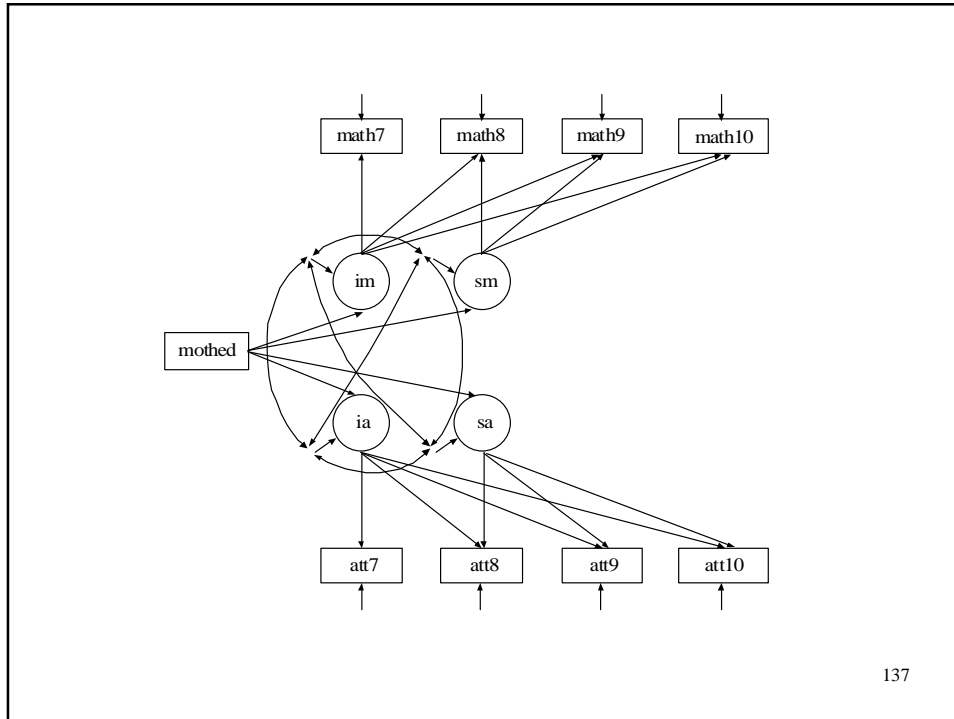
LSAY Sample Means for Math



Sample Means for Attitude Towards Math



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Input For LSAY Parallel Process Growth Model

```

TITLE:      LSAY For Younger Females With Listwise Deletion
            Parallel Process Growth Model-Math Achievement and
            Math Attitudes

DATA:       FILE IS lsay.dat;
            FORMAT IS 3f8 f8.4 8f8.2 3f8 2f8.2;

VARIABLE:   NAMES ARE cohort id school weight math7 math8 math9
            math10 att7 att8 att9 att10 gender mothed homerese
            ses3 sesq3;
            USEOBS = (gender EQ 1 AND cohort EQ 2);
            MISSING = ALL (999);
            USEVAR = math7-math10 att7-att10 mothed;

ANALYSIS:   TYPE = MEANSTRUCTURE;
  
```

Input For LSAY Parallel Process Growth Model

```
MODEL:      im sm | math7@0 math8@1 math9 math10;  
           ia sa | att7@0 att8@1 att9@2 att10@3;  
           im-sa ON mothed;
```

```
OUTPUT:     MODINDICES STANDARDIZED;
```

Alternative language:

```
im BY math7-math10@1;  
sm BY math7@0 math8@1 math9 math10;  
  
ia BY att7-att10@1;  
sa BY att7@0 att8@1 att9@2 att10@3;  
  
[math7-math10@0 att7-att10@0];  
[im sm ia sa];  
  
im-sa ON mothed;
```

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Output Excerpts LSAY Parallel Process Growth Model

n = 910

Tests of Model Fit

Chi-Square Test of Model Fit

Value	43.161
Degrees of Freedom	24
P-Value	.0095

RMSEA (Root Mean Square Error Of Approximation)

Estimate	.030
90 Percent C.I.	.015 .044
Probability RMSEA <= .05	.992

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Output Excerpts LSAY Parallel Process Growth Model (Continued)

		Estimates	S.E.	Est./S.E.	Std	StdYX
IM	ON					
	MOTHEd	2.462	.280	8.798	.311	.303
SM	ON					
	MOTHEd	.145	.066	2.195	.132	.129
IA	ON					
	MOTHEd	.053	.086	.614	.025	.024
SA	ON					
	MOTHEd	.012	.035	.346	.017	.017

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Output Excerpts LSAY Parallel Process Growth Model (Continued)

		Estimates	S.E.	Est./S.E.	Std	StdYX
SM	WITH					
	IM	3.032	.580	5.224	.350	.350
IA	WITH					
	IM	4.733	.702	6.738	.282	.282
	SM	.544	.164	3.312	.235	.235
SA	WITH					
	IM	-.276	.279	-.987	-.049	-.049
	SM	.130	.066	1.976	.168	.168
	IA	-.567	.115	-4.913	-.378	-.378

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Modeling With Zeroes

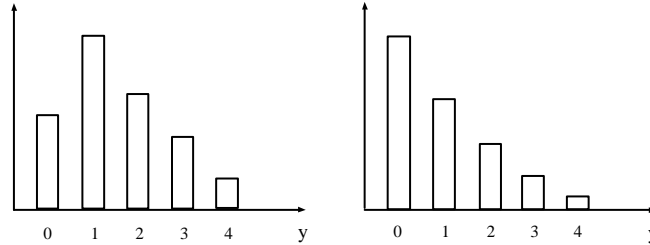
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Advantages Of Growth Modeling In A Latent Variable Framework

- Flexible curve shape
- Individually-varying times of observation
- Regressions among random effects
- Multiple processes
- **Modeling of zeroes**
- Multiple populations
- Multiple indicators
- Embedded growth models
- Categorical latent variables: growth mixtures

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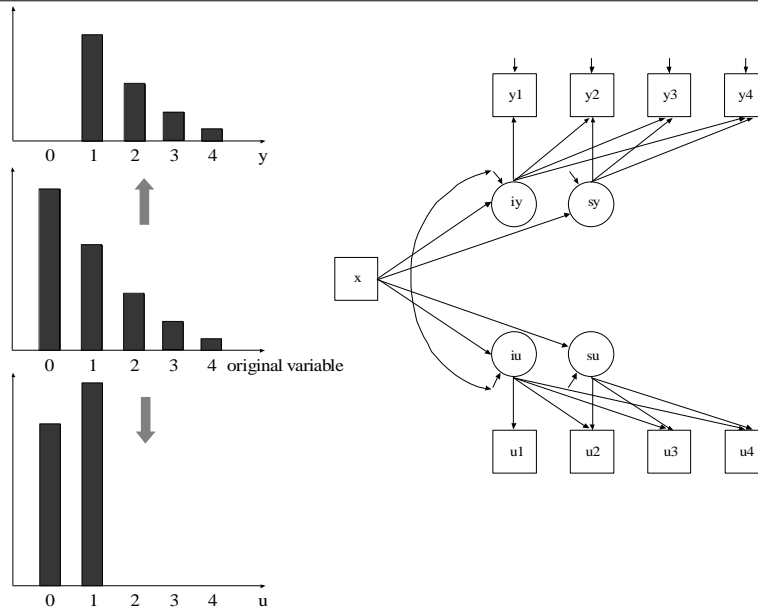
Modeling With A Preponderance Of Zeros



- Outcomes: non-normal continuous – count – categorical
- Censored-normal modeling
- Two-part (semicontinuous modeling): Duan et al. (1983), Olsen & Schafer (2001)
- Mixture models, e.g. zero-inflated (mixture) Poisson (Roeder et al., 1999), censored-inflated, mover-stayer latent transition models, growth mixture models
- Onset (survival) followed by growth: Albert & Shih (2003)

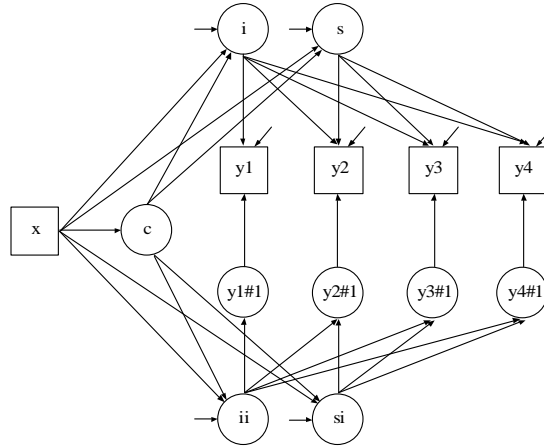
145

Two-Part (Semicontinuous) Growth Modeling



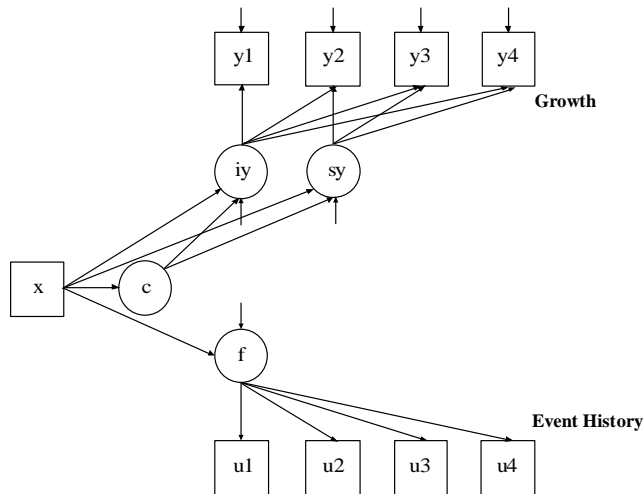
146

Inflated Growth Modeling (Two Classes At Each Time Point)



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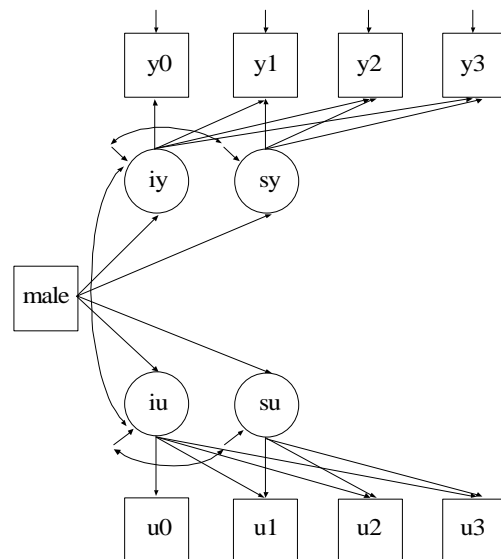
Onset (Survival) Followed By Growth



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Two-Part Growth Modeling

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Input For Step 1 Of A Two-Part Growth Model

```
TITLE:      step 1 of a two-part growth model
            Amover u   y
            >0   1   >0
            0   0   999
            999 999 999

DATA:      FILE = amp.dat;
VARIABLE:  NAMES ARE caseid
            amover0 ovrdrnk0 illdrnk0 vrydrn0
            amover1 ovrdrnk1 illdrnk1 vrydrn1
            amover2 ovrdrnk2 illdrnk2 vrydrn2
            amover3 ovrdrnk3 illdrnk3 vrydrn3
            amover4 ovrdrnk4 illdrnk4 vrydrn4
            amover5 ovrdrnk5 illdrnk5 vrydrn5
            amover6 ovrdrnk6 illdrnk6 vrydrn6
            tfq0-tfq6 v2 sex race livewith
            agedrnk0-agedrnk6 grades0-grades6;
            USEV = amover0 amover1 amover2 amover3
            sex race u0-u3 y0-y3;
            ! MISSING = ALL (999);
```

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Input For Step 1 Of A Two-Part Growth Model (Continued)

```
DEFINE:    u0 = 1;                                !binary part of variable
            IF(amover0 eq 0) THEN u0 = 0;
            IF(amover0 eq 999) THEN u0 = 999;
            y0 = amover0;                          !continuous part of variable
            IF (amover0 eq 0) THEN y0 = 999;
            u1 = 1;
            IF(amover1 eq 0) THEN u1 = 0;
            IF(amover1 eq 999) THEN u1 = 999;
            y1 = amover1;
            IF(amover1 eq 0) THEN y1 = 999;
            u2 = 1;
            IF(amover2 eq 0) THEN u2 = 0;
            IF(amover2 eq 999) THEN u2 = 999;
            y2 = amover2;
            IF(amover2 eq 0) THEN y2 = 999;
            u3 = 1;
            IF(amover3 eq 0) THEN u3 = 0;
            IF(amover3 eq 999) THEN u3 = 999;
            y3 = amover3;
            IF(amover3 eq 0) THEN y3 = 999;

ANALYSIS:  TYPE = BASIC;
SAVEDATA:  FILE = ampyu.dat;
```

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Output Excerpts Step 1 Of A Two-Part Growth Model

SAVEDATA Information

Order and format of variables

```
AMOVER0 F10.3
AMOVER1 F10.3
AMOVER2 F10.3
AMOVER3 F10.3
SEX      F10.3
RACE     F10.3
U0       F10.3
U1       F10.3
U2       F10.3
U3       F10.3
Y0       F10.3
Y1       F10.3
Y2       F10.3
Y3       F10.3
```

Save file

ampyu.dat

Save file format

14F10.3

Save file record length 1000

153

Input For Step 2 Of A Two-Part Growth Model

```
TITLE:      two-part growth model with linear growth for both
             parts
DATA:       FILE = ampyu.dat;
VARIABLE:   NAMES = amover0-amover3 sex race u0-u3 y0-y3;
             USEV = u0-u3 y0-y3 male;
             USEOBS = u0 NE 999;
             MISSING = ALL (999);
             CATEGORICAL = u0-u3;
DEFINE:     male = 2-sex;
```

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Input For Step 2 Of A Two-Part Growth Model (Continued)

```
ANALYSIS:  TYPE = MISSING;
           ESTIMATOR = ML;
           ALGORITHM = INTEGRATION;
           COVERAGE = .09;

MODEL:     iu su | u0@0 u1@0.5 u2@1.5 u3@2.5;
           iy sy | y0@0 y1@0.5 y2@1.5 y3@2.5;
           iu-sy ON male;
           ! estimate the residual covariances
           ! iu with su, iy with sy, and iu with iy
           iu WITH sy@0;
           su WITH iy-sy@0;

OUTPUT:    PATTERNS SAMPSTAT STANDARDIZED TECH1 TECH4 TECH8;

PLOT:      TYPE = PLOT3;
           SERIES = u0-u3(su) | y0-y3(sy);
```

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Output Excerpts Step 2 Of A Two-Part Growth Model

Tests of Model Fit

Loglikelihood

H0 Value	-3277.101
----------	-----------

Information Criteria

Number of Free parameters	19
Akaike (AIC)	6592.202
Bayesian (BIC)	6689.444
Sample-Size Adjusted BIC	6629.092

$(n^* = (n + 2) / 24)$

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Output Excerpts Step 2 Of A Two-Part Growth Model (Continued)

Model Results

	Estimates	S.E.	Est./S.E.	Std	StdYX
IU					
U0	1.000	0.000	0.000	2.839	0.843
U1	1.000	0.000	0.000	2.839	0.882
U2	1.000	0.000	0.000	2.839	0.926
U3	1.000	0.000	0.000	2.839	0.905
SU					
U0	0.000	0.000	0.000	0.000	0.000
U1	0.500	0.000	0.000	0.416	0.129
U2	1.500	0.000	0.000	1.249	0.407
U3	2.500	0.000	0.000	2.082	0.664

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Output Excerpts Step 2 Of A Two-Part Growth Model (Continued)

IY					
Y0	1.000	0.000	0.000	0.534	0.787
Y1	1.000	0.000	0.000	0.534	0.738
Y2	1.000	0.000	0.000	0.534	0.740
Y3	1.000	0.000	0.000	0.534	0.644
SY					
Y0	0.000	0.000	0.000	0.000	0.000
Y1	0.500	0.000	0.000	0.117	0.162
Y2	1.500	0.000	0.000	0.351	0.487
Y3	2.500	0.000	0.000	0.586	0.707

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Output Excerpts Step 2 Of A Two-Part Growth Model (Continued)

IU	ON					
	MALE	0.569	0.234	2.433	0.200	0.100
SU	ON					
	MALE	-0.181	0.119	-1.518	-0.218	-0.109
IY	ON					
	MALE	0.149	0.061	2.456	0.279	0.139
SY	ON					
	MALE	-0.068	0.038	-1.790	-0.290	-0.145
IU	WITH					
	SU	-1.144	0.326	-3.509	-0.484	-0.484
	IY	1.193	0.134	8.897	0.788	0.788
	SY	0.000	0.000	0.000	0.000	0.000
IY	WITH					
	SY	-0.039	0.019	-2.109	-0.316	-0.316
SU	WITH					
	IY	0.000	0.000	0.000	0.000	0.000
	SY	0.000	0.000	0.000	0.000	0.000 159

Output Excerpts Step 2 Of A Two-Part Growth Model (Continued)

Intercepts						
Y0		0.000	0.000	0.000	0.000	0.000
Y1		0.000	0.000	0.000	0.000	0.000
Y2		0.000	0.000	0.000	0.000	0.000
Y3		0.000	0.000	0.000	0.000	0.000
IU		0.000	0.000	0.000	0.000	0.000
SU		0.855	0.098	8.716	1.027	1.027
IY		0.232	0.059	3.901	0.435	0.435
SY		0.240	0.031	7.830	1.025	1.025
Thresholds						
U0\$1		2.655	0.206	12.877		
U1\$1		2.655	0.206	12.877		
U2\$1		2.655	0.206	12.877		
U3\$1		2.655	0.206	12.877		

Output Excerpts Step 2 Of A Two-Part Growth Model (Continued)

Residual Variances

Y0	0.175	0.032	5.470	0.175	0.380
Y1	0.266	0.029	9.159	0.266	0.509
Y2	0.238	0.027	8.810	0.238	0.457
Y3	0.269	0.054	5.014	0.269	0.392
IU	7.982	1.086	7.351	0.990	0.990
SU	0.685	0.202	3.400	0.988	0.988
IY	0.279	0.040	7.019	0.981	0.981
SY	0.054	0.017	3.224	0.979	0.979

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Output Excerpts Step 2 Of A Two-Part Growth Model (Continued)

Observed Variable R-Square

U0	0.710
U1	0.682
U2	0.650
U3	0.666
Y0	0.620
Y1	0.491
Y2	0.543
Y3	0.608

Latent Variable R-Square

IU	0.010
SU	0.012
IY	0.019
SY	0.021

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Output Excerpts Step 2 Of A Two-Part Growth Model (Continued)

Technical 4 Output

ESTIMATED MEANS FOR THE LATENT VARIABLES					
	IU	SU	IY	SY	MALE
1	0.305	0.758	0.312	0.204	0.536

ESTIMATED COVARIANCE MATRIX FOR THE LATENT VARIABLES					
	IU	SU	IY	SY	MALE
IU	8.062				
SU	-1.170	0.694			
IY	1.214	-0.007	0.285		
SY	-0.010	0.003	-0.042	0.055	
MALE	0.142	-0.045	0.037	-0.017	0.249

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Output Excerpts Step 2 Of A Two-Part Growth Model (Continued)

ESTIMATED CORRELATION MATRIX FOR THE LATENT VARIABLES					
	IU	SU	IY	SY	MALE
IU	1.000				
SU	-0.495	1.000			
IY	0.801	-0.015	1.000		
SY	-0.014	0.016	-0.336	1.000	
MALE	0.100	-0.109	0.139	-0.145	1.000

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