LTA in Mplus:
Transition probabilities influenced by covariates

Bengt Muthén & Tihomir Asparouhov

Mplus Web Notes: No. 13

July 27, 2011

1 Introduction

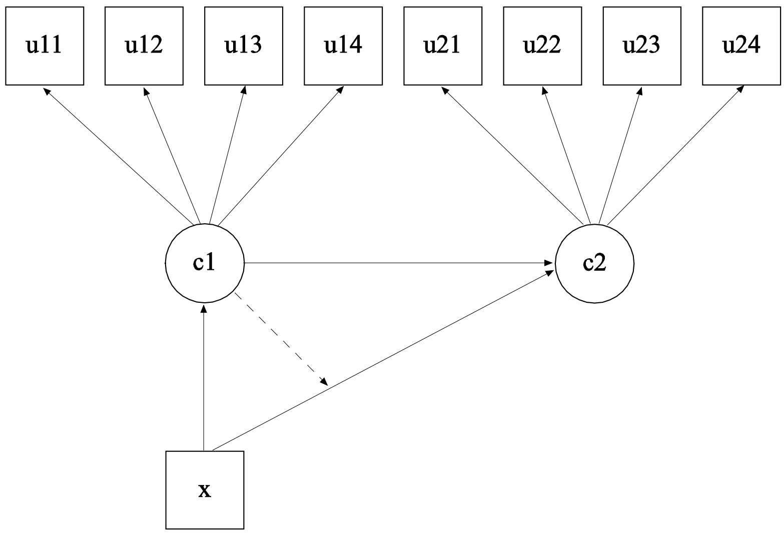
This note describes how to specify and interpret a latent transition analysis where the transition probabilities vary as a function of covariates. The Mplus parameterization is given and it is shown how to derive the transition probabilities and related odds ratios for different values of the covariates. For simplicity, a model with two time points and binary latent class indicators is considered. A first model uses a dichotomous covariate, resulting in two different transition tables. The Mplus results are compared to those of PROC LTA and shown to be equivalent. A second model uses a continuous covariate where transition tables can be derived for all the different covariate values. These two models consider latent class variables with two categories. The case of latent class variables with three categories is also outlined. The generalizations possible in Mplus are listed. Further readings with Mplus applications are suggested.

The latent transition analysis (LTA) model consists of a measurement model for the latent class variable at each time point and a structural model relating the latent class variables to each other and to covariates. The measurement parameters are typically all held invariant across time, although this is not necessary. The discussion in this note focuses on the structural part of the model.

A typical model example is shown in Figure 1 which is example 8.13 in the Mplus User's Guide (Muthén & Muthén, 1998-2010). This model indicates that the different c1 classes have different slopes for the regression of c2 on x.

Although the c2 regression is a multinomial logistic regression with a nominal dependent variable, it is useful to consider the analogous situation for a linear regression with a continuous dependent variable. For this case, assume for the

Figure 1: Latent transition model for two time points with a covariate: c1 moderating c2 regressed on x



moment that both c1 and c2 are observed variables and that c2 is continuous. The key idea is that there is an interaction between c1 and x in their influence on c2,

$$c2 = \alpha + \beta_1 \; c1 + \beta_2 \; x + \beta_3 \; c1 \times x + \epsilon, \tag{1}$$

where β_3 is the slope for the interaction. This equation can be rewritten in two equivalent ways

$$c2 = \alpha + \beta_1 \; c1 + (\beta_2 + \beta_3 \; c1) \; x + \epsilon, \tag{2}$$

$$c2 = \alpha + (\beta_1 \; + \beta_3 \; x) \; c1 + \beta_2 \; x + \epsilon, \tag{3}$$

In (2), the term $\beta_3 \; c1$ moderates the β_2 influence of x on c2. In (3), the term $\beta_3 \; x$ moderates the β_1 influence of c1 on c2. The latter formulation is shown in

Figure 2: Latent transition model for two time points with a covariate: x moderating c2 regressed on c1

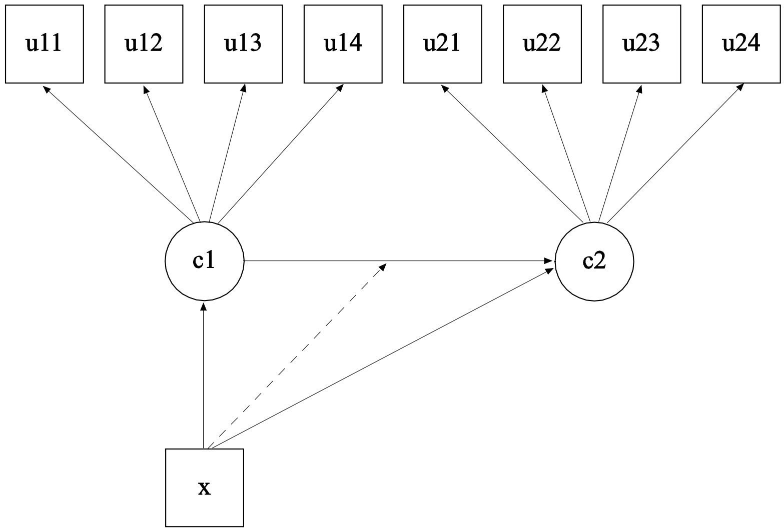


Figure 2. The key point is that the two models are equivalent. This is the case also in the current situation where c1 and c2 are latent variables and the c2 regression is a multinomial logistic regression. This note focuses on the formulation of (3) where x moderates the relationship between c1 and c2. A description is given of how the transition probabilities for the transition between c1 and c2 are affected by different values of x.

2 LTA transition modeling

Transition probabilities are conditional probabilities for c2 categories given c1 categories, where c1 and c2 refer to latent class variables at two different time points. Consider the example in Table 2 where both c1 and c2 have two categories. For each c1 row the two probabilities sum to 1. For example, for subjects in c1

Table 1: Transition probabilities

		c2	
		1	2
c1	1	0.762	0.238
	2	0.625	0.375

Table 2: Transition odds

		c2	
		1	2
c1	1	1	0.312
	2	1.667	1

class 1, the probability is 0.762 to stay in class 1 and 0.238 to transition to class 2. The transition probabilities can also be turned into odds. Using the diagonal as the reference category gives the odds of Table 2. For example, the odds of 0.312 is obtained as 0.238/0.762. This means that the odds is low to transition from class 1 to class 2.

The transition probabilities are obtained from multinomial regression of c2 on c1. As described in chapter 14 of the Mplus User's Guide, the multinomial regression of c2 on c1 is expressed via parameters in a logit metric. A technical description is given in Asparouhov and Muthén (2011). Consider Table 3 from page 447, which shows the case of three latent classes for both c1 (rows) and c2 (columns), and where a and b are logit parameters. The a parameters are intercepts and the b parameters are slopes for c2 regressed on c1. The first b parameter subscript refers to the category of the dependent variable c2 and the second subscript refers to the c1 category. In this first case, there is no covariate. For each row of c1, that is conditioning on a certain c1 category, the multinomial regression is expressed as

$$P(c2 = j|c1 = k) = e^{logit_{jk}} / \sum_{s=1}^{J} e^{logit_{sk}}, \tag{4}$$

where j refers to the column (1, 2, 3) and k refers to the row (1, 2, 3). Here, the summation is over J=3 columns. For each c2 category, the three c2 probabilities sum to one because they represent the three possible c2 outcomes. The a parameters are intercepts and the b parameters are slopes for c1. The last column of zero logits reflect the fact that the last column corresponds to the reference category of the dependent variable c2. Note that $e^0 = 1$, where the unit term is often shown in multinomial regression. Letting the last category of c2 be the reference category means that the b parameters can be interpreted as log odds when comparing category j to the last category, category J. The six logit parameters of a and b correspond to the 3×2 probabilities of the table. These are the probabilities of the unrestricted product (independent)-multinomial distribution. Equation (4) is the same as equation (4) in Lanza and Collins (2008). They also consider a grouping variable, which is handled in Mplus using the KNOWNCLASS option.

From the logits of Table 3 other cases can be derived. The case of only two categories for the two latent class variables is obtained by deleting the second column and the second row of Table 3. The table is naturally extended to more than three categories. The two latent class variables need not have the same

Table 3: Logit table for c2 regressed on c1

		c2		
		1	2	3
c1	1	a1 + b11	a2 + b21	0
	2	a1 + b12	a2 + b22	0
	3	a1	a2	0

Table 4: Logit table for c2 regressed on c1 and x: Parameterization 1

		c2		
		1	2	3
c1	1	a1 + b11 + (g1+g11) x	a2 + b21 + (g2+g21) x	0
	2	a1 + b12 + (g1+g12) x	a2 + b22 + (g2+g22) x	0
	3	a1 + g1 x	a2 + g2 x	0

number of latent classes, although this changes the definition of transitioning between classes all having the same meaning.

Adding a covariate x, two parameterizations are considered here. The first parameterization is in line with ex8.13 and is shown in Table 4, where the g parameters are slopes for the x covariate, varying over the c1 and c2 classes. This parameterization is obtained with the Mplus MODEL statement given in Table 5. The OVERALL part of the model gives the influence of x via the g1 and g2 parameters. The g11, g21, g12, and g22 parameters modify this influence. Note that the MODEL c1 part does not refer to the third (last) c1 class so that in this class the slopes are given only by g1 and g2.

The second parameterization is as in Table 6. This parameterization is obtained with the Mplus MODEL statement given in Table 7. The OVERALL

Table 5: Mplus specification of parameterization 1

MODEL:	%OVERALL% c1 ON x; c2 ON c1; c2#1 ON x (g1); c2#2 ON x (g2);
MODEL c1:	%c1#1% c2#1 ON x (g11); c2#2 ON x (g21);
	%c1#2% c2#1 ON x (g12); c2#2 ON x (g22);

Table 6: Logit table for c2 regressed on c1 and x: Parameterization 2

		c2		
		1	2	3
c1	1	a1 + b11 + g11 x	a2 + b21 + g21 x	0
	2	a1 + b12 + g12 x	a2 + b22 + g22 x	0
	3	a1 + g13 x	a2 + g23 x	0

Table 7: Mplus specification of parameterization 2

```
MODEL:        %OVERALL%
              c1 ON x;
              c2 ON c1;

MODEL c1:     %c1#1%
              c2#1 ON x (g11);
              c2#2 ON x (g21);

              %c1#2%
              c2#1 ON x (g12);
              c2#2 ON x (g22);

              %c1#3%
              c2#1 ON x (g13);
              c2#2 ON x (g23);
```

part of the model does not involve g parameters, but they are instead given in the MODEL c1 part for all three c1 classes. This second parameterization is used in the following application.

3 An application

As an illustration, a modified version of ex8.13 in the Mplus User's Guide is used. This example corresponds to Figure 1 and, equivalently, Figure 2. The two latent class variables both have two categories. For simplicity in the results discussion, the continuous covariate x has been dichotomized at zero. Of interest is the corresponding two tables of transition probabilities. As in Lanza and Collins (2008), odds ratios will also be derived for the transitions using as reference category the diagonal elements representing no transition. The data are available on the Mplus web site www.statmodel.com in connection with the online User's

Guide, Chapter 8.

The Mplus input is shown in Table 8. The dichotomization is carried out in DEFINE using the CUT option. This input uses parameterization 2 described above and not parameterization 1 which is used in the User's Guide ex8.13. In the OVERALL part of the model no c2 on x regression is specified, but the slope for x is instead given in each of the two c1 classes within MODEL c1. In the User's Guide the two slopes are estimated in the OVERALL part of the model and for the first c1 class. This means that the slope for x in the 1, 1 cell of the c1, c2 table is obtained as the sum of the OVERALL slope and the slope for the first class as indicated in Table 4. Note that the model is not identified if the c2 on x regression is specified both in the OVERALL and in the c1 class-specific parts. Other parts of the input shown in Table 8 are described in the User's Guide for ex 8.13. Across-time measurement invariance is specified by equality constraints on the logits corresponding to the conditional item probabilities. STARTS=0 is used together with starting values in order to obtain a specific ordering of the classes. In general, many random starts should be used, such as STARTS = 100 20. In some cases with several latent class variables it is also useful to reduce the default perturbation factor used to produce the random starts from STSCALE=5 to STSCALE=1.

Table 9 and Table 10 show the flexibility of being able to form new parameters to describe special results of interest. Using the MODEL CONSTRAINT command, the logit parameters of Table 6 are defined using parameter labels specified in the MODEL command. From these logit parameters, the probabilities of the 2×2 c1, c2 table are defined using the multinomial regression expression of (4). In Table 10 the probabilities are used to compute odds and odds ratios

Table 8: Input for example 8.13

TITLE:	this is an example of a LTA with a covariate and an interaction
DATA:	FILE = ex8.13.dat;
VARIABLE:	NAMES = u11-u14 u21-u24 x;
	CATEGORICAL = u11-u14 u21-u24;
	CLASSES = c1 (2) c2 (2);
DEFINE:	CUT x(0);
ANALYSIS:	TYPE = MIXTURE;
	STARTS = 0;
MODEL:	%OVERALL%
	[c2#1] (a);
	c2 ON c1 (b);
	c1 ON x;
MODEL c1:	%c1#1%
	[u11$1-u14$1*1] (1-4);
	c2 ON x (g1);
	%c1#2%
	[u11$1-u14$1*-1] (5-8);
	c2 ON x (g2);
MODEL c2:	%c2#1%
	[u21$1-u24$1*1] (1-4);
	%c2#2%
	[u21$1-u24$1*-1] (5-8);
OUTPUT:	TECH1 TECH8;

comparing the two x categories, as well as the corresponding log odds ratios.

The next set of tables show the maximum-likelihood estimates for both the model parameters and the new parameters defined in MODEL CONSTRAINT. Table 11 and Table 12 show the measurement parameters, that is, the conditional item probabilities in logit form. Table 13 - Table 16 show the corresponding probabilities (only the first output column is given). Table 17 shows the structural parameters corresponding to the a, b, and g parameters of Table 6. Table 18 shows the new parameters. This includes the tables of transition probabilities for each of the two x categories. The two tables of transition probabilities for the two x values are also shown in Table 19.

Note that the z scores for the log odds ratios of Table 18 are the same (apart from a sign change due to different reference class) as for the g parameters of Table 17. This means that the differences in the transition tables can be tested in the log odds metric simply by considering the slope of c2 on x for the two c1 classes. In other words, creating the new parameters in MODEL CONSTRAINT is not essential.

The case of a continuous covariate x presents no extra difficulties. The model specification is the same. Transition probability tables can be computed via MODEL CONSTRAINT using specific x values. For instance, the above x=0 case may correspond to the mean of x and the x=1 case may correspond to one standard deviation above the mean.

Table 9: Input for example 8.13, continued

```
MODEL CONSTRAINT:
        NEW(logx011 logx021 logx111 logx121 probx011 probx012
        probx021 probx022 probx111 probx112 probx121 probx122
        oddsx012 oddsx021 oddsx112 oddsx121 or12 or21 logor12
        logor21);
        ! define 4 logits. Note that logits are zero
        ! for the last (reference) c2 class
        ! (see UG, p. 447 table, last column):

        ! logit for x=0 and c1=1, c2=1:
        logx011 = a + b;

        ! logit for x=0 and c1=2, c2=1
        ! (see p. 447 table, last row)
        logx021 = a;

        ! logit for x=1 and c1=1, c2=1:
        logx111 = a + b + g1;

        ! logit for x=1 and c1=2, c2=1:
        logx121 = a + g2;

        ! define probabilities for the 4 c1, c2 cells
        ! for x=0:
        probx011 = exp(logx011)/(exp(logx011)+1);
        probx012 = 1/(exp(logx011)+1);
        probx021 = exp(logx021)/(exp(logx021)+1);
        probx022 = 1/(exp(logx021)+1);
        ! for x=1;
        probx111 = exp(logx111)/(exp(logx111)+1);
        probx112 = 1/(exp(logx111)+1);
        probx121 = exp(logx121)/(exp(logx121)+1);
        probx122 = 1/(exp(logx121)+1);
```

Table 10: Input for example 8.13, continued

```
! define odds with diagonal (staying in the same class) as
! the reference class
! x=0
oddsx012 = probx012/probx011;
oddsx021 = probx021/probx022;
! x= 1;
oddsx112 = probx112/probx111;
oddsx121 = probx121/probx122;

! define odds ratios for x=1 vs x=0:
! for moving from c1=1 to c2=2:
or12 = oddsx112/oddsx012;
! for moving from c1=2 to c2=1:
or21 = oddsx121/oddsx021;

logor12 = log(or12);
logor21 = log(or21);
```

Table 11: Example 8.13, model results

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Latent class pattern 1 1				
Thresholds				
u11$1	1.136	0.131	8.640	0.000
u12$1	1.136	0.112	10.123	0.000
u13$1	0.955	0.118	8.087	0.000
u14$1	1.139	0.132	8.626	0.000
u21$1	1.136	0.131	8.640	0.000
u22$1	1.136	0.112	10.123	0.000
u23$1	0.955	0.118	8.087	0.000
u24$1	1.139	0.132	8.626	0.000
Latent class pattern 1 2				
Thresholds				
u11$1	1.136	0.131	8.640	0.000
u12$1	1.136	0.112	10.123	0.000
u13$1	0.955	0.118	8.087	0.000
u14$1	1.139	0.132	8.626	0.000
u21$1	-0.953	0.115	-8.310	0.000
u22$1	-0.905	0.118	-7.643	0.000
u23$1	-0.964	0.109	-8.814	0.000
u24$1	-0.985	0.112	-8.831	0.000

Table 12: Example 8.13, model results

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Latent class pattern 2 1				
Thresholds				
u11$1	-0.953	0.115	-8.310	0.000
u12$1	-0.905	0.118	-7.643	0.000
u13$1	-0.964	0.109	-8.814	0.000
u14$1	-0.985	0.112	-8.831	0.000
u21$1	1.136	0.131	8.640	0.000
u22$1	1.136	0.112	10.123	0.000
u23$1	0.955	0.118	8.087	0.000
u24$1	1.139	0.132	8.626	0.000
Latent class pattern 2 2				
Thresholds				
u11$1	-0.953	0.115	-8.310	0.000
u12$1	-0.905	0.118	-7.643	0.000
u13$1	-0.964	0.109	-8.814	0.000
u14$1	-0.985	0.112	-8.831	0.000
u21$1	-0.953	0.115	-8.310	0.000
u22$1	-0.905	0.118	-7.643	0.000
u23$1	-0.964	0.109	-8.814	0.000
u24$1	-0.985	0.112	-8.831	0.000

Table 13: Item parameters in probability scale

	Estimate
Latent class pattern 1 1	
u11	
category 1	0.757
category 2	0.243
u12	
category 1	0.757
category 2	0.243
u13	
category 1	0.722
category 2	0.278
u14	
category 1	0.757
category 2	0.243
u21	
category 1	0.757
category 2	0.243
u22	
category 1	0.757
category 2	0.243
u23	
category 1	0.722
category 2	0.278
u24	
category 1	0.757
category 2	0.243

Table 14: Item parameters in probability scale, continued

	Estimate
Latent class pattern 1 2	
u11	
category 1	0.757
category 2	0.243
u12	
category 1	0.757
category 2	0.243
u13	
category 1	0.722
category 2	0.278
u14	
category 1	0.757
category 2	0.243
u21	
category 1	0.278
category 2	0.722
u22	
category 1	0.288
category 2	0.712
u23	
category 1	0.276
category 2	0.724
u24	
category 1	0.272
category 2	0.728

Table 15: Item parameters in probability scale, continued

	Estimate
Latent class pattern 2 1	
u11	
category 1	0.278
category 2	0.722
u12	
category 1	0.288
category 2	0.712
u13	
category 1	0.276
category 2	0.724
u14	
category 1	0.272
category 2	0.728
u21	
category 1	0.757
category 2	0.243
u22	
category 1	0.757
category 2	0.243
u23	
category 1	0.722
category 2	0.278
u24	
category 1	0.757
category 2	0.243

Table 16: Item parameters in probability scale, continued

	Estimate
Latent class pattern 2 2	
u11	
category 1	0.278
category 2	0.722
u12	
category 1	0.288
category 2	0.712
u13	
category 1	0.276
category 2	0.724
u14	
category 1	0.272
category 2	0.728
u21	
category 1	0.278
category 2	0.722
u22	
category 1	0.288
category 2	0.712
u23	
category 1	0.276
category 2	0.724
u24	
category 1	0.272
category 2	0.728

Table 17: Example 8.13, structural parameter estimates

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
Categorical latent variables				
c2#1 ON				
c1#1	-0.147	0.377	-0.389	0.697
c1#1 ON				
x	0.659	0.182	3.629	0.000
Intercepts				
c1#1	-0.431	0.187	-2.304	0.021
c2#2	-0.653	0.202	-3.230	0.001
Latent class pattern 1 1				
c2#1 ON				
x	1.963	0.359	5.473	0.000
Latent class pattern 2 1				
c2#1 ON				
x	1.163	0.298	3.904	0.000

Table 18: Example 8.13, new parameter estimates

	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value
New/additional parameters				
logx011	-0.800	0.308	-2.599	0.009
logx021	-0.653	0.202	-3.230	0.001
logx111	1.163	0.274	4.252	0.000
logx121	0.510	0.244	2.089	0.037
probx011	0.310	0.066	4.712	0.000
probx012	0.690	0.066	10.481	0.000
probx021	0.342	0.046	7.521	0.000
probx022	0.658	0.046	14.449	0.000
probx111	0.762	0.050	15.352	0.000
probx112	0.238	0.050	4.798	0.000
probx121	0.625	0.057	10.921	0.000
probx122	0.375	0.057	6.559	0.000
oddsx012	2.225	0.684	3.250	0.001
oddsx021	0.521	0.105	4.946	0.000
oddsx112	0.313	0.085	3.656	0.000
oddsx121	1.665	0.406	4.098	0.000
or12	0.140	0.050	2.789	0.005
or21	3.199	0.953	3.357	0.001
logor12	-1.963	0.359	-5.473	0.000
logor21	1.163	0.298	3.904	0.000

Table 19: Estimated transition probabilities

x=0

		c2	
		1	2
c1	1	0.310	0.690
	2	0.342	0.658

x=1

		c2	
		1	2
c1	1	0.762	0.238
	2	0.625	0.375

4 Conclusions

This web note shows the flexibility and ease of using Mplus for latent transition modeling. Estimates and tests for parameters determining the latent transition probabilities are directly obtained. As illustrated, many interesting functions of the model parameters can be expressed using MODEL CONSTRAINT. Further Mplus capabilities related to latent transition analysis include:

- testing of (partial) across-time invariance of conditional item probabilities
- binary, ordinal, nominal, continuous, and count indicators the latent classes, as well as combinations of such indicators
- latent (continuous, categorical) indicators
- mover-stayer models (second-order latent class variable)
- complex survey data (weights, clustering, stratification)
- multilevel LTA

Articles which include many Mplus applications are given in the reference list.

5 Appendix

As a comparison to the Mplus analyses, SAS PROC LTA (Lanza & Collins, 2008) was also used and provides the same results. We are indebted to Aidan Wright at PSU, for doing the PROC LTA analyses. The input is given in Table 20. The data set EX813 is the same as used in the Mplus runs except the dichotomization of x has been done and the items rescored from 0 and 1 to 1 and 2 prior to analysis.

Table 20: PROC LTA input

```
PROC LTA DATA=EX813;
NSTATUS 2;
NTIMES 2;
ITEMS u11 u12 u13 u14 u21 u22 u23 u24;
CATEGORIES 2 2 2 2;
COVARIATES1 X;
REFERENCE1 1;
COVARIATES2 X;
REFERENCE2 1 2 ;
MEASUREMENT TIMES;
SEED 564536;
CORES 2;
RUN;
```

5.1 PROC LTA output

Figure 3 - Figure 6 show the output. The odds ratios of Figure 5 agree with the or12 and or21 values in Table 18.

Figure 3: PROC LTA output

LTA-no prior-pg1.pdf

```
                                         The SAS System          18:14
Tuesday, July 26, 2011   1

        Data and Model Summary and Fit Statistics (EM Algorithm with Logistic
Regression)



Number of subjects in dataset:        1000
Number of subjects in analysis:       1000

Number of measurement items per time:    4
Response categories per item:            2 2 2 2
Number of occasions (times):             2
Number of groups in the data:            1
Number of latent statuses:               2

Logistic model for time 1:               multinomial
Number of covariates for time 1:         1
Reference status for time 1:             1

Logistic model for transitions:          multinomial
Number of covariates for transitions:    1
Reference statuses for time 1 to 2:      1 2

Rho starting values were randomly generated (seed = 564536).

Parameter restrictions: Rho (measurement) parameters were constrained to be
equal across time.

The model converged in 137 iterations.

Maximum number of iterations: 5000
Convergence method: maximum absolute deviation (MAD)
Convergence criterion:  0.000001000

=============================================
Fit statistics:
=============================================

Log-likelihood:     -5252.50
```

Figure 4: PROC LTA output

```
                                            The SAS System          18:14
Tuesday, July 26, 2011   2

                            Parameter Estimates

Delta estimates (status membership probabilities):
Status:                    1          2
  Time  1     :       0.4705     0.5295
  Time  2     :       0.4974     0.5026

Tau estimates (transition probabilities):
Time   1 latent status (rows) by
    Time   2 latent status (columns)
                           1          2
        1     :       0.5224     0.4776
        2     :       0.4751     0.5249


Rho estimates (item-response probabilities):
(All times)
  Response category:  1:
Status:                    1          2
  u11         :       0.7569     0.2782
  u12         :       0.7569     0.2879
  u13         :       0.7222     0.2761
  u14         :       0.7575     0.2718

  Response category:  2:
Status:                    1          2
  u11         :       0.2431     0.7218
  u12         :       0.2431     0.7121
  u13         :       0.2778     0.7239
  u14         :       0.2425     0.7282

Beta estimates for Delta:

Status:                    1          2
 Intercept      :  Reference     0.4307
  X           :                 -0.6586


Delta Odds Ratio estimates:

Status:                    1          2
 Intercept(odds):  Reference     1.5384
  X           :                  0.5176


Beta estimates for Tau:
Time   1 latent status (rows)
    Time   2 latent status (columns)
 Intercept      :
                           1          2
        1     :    Reference     0.7996
```

LTA-no prior-pg2.pdf

Figure 5: PROC LTA output

```
                                          The SAS System          18:14
Tuesday, July 26, 2011   3

                            Parameter Estimates

        2     :      -0.6529  Reference

  X           :
                           1          2
        1     :    Reference    -1.9626
        2     :       1.1628  Reference


Tau Odds Ratio estimates:
Time   1 latent status (rows)
    Time   2 latent status (columns)
 Intercept(odds):
                           1          2
        1     :    Reference     2.2246
        2     :       0.5205  Reference

  X           :
                           1          2
        1     :    Reference     0.1405
        2     :       3.1988  Reference
```

LTA-no prior-pg3.pdf

Figure 6: PROC LTA output

```
                                          The SAS System          18:14
Tuesday, July 26, 2011   4

                            Significance Tests

Beta parameter test (Type III) for time 1 covariates (COVARIATES1):  (based
on 2*log-likelihood)

  Covariate   Exclusion LL   Change in 2*LL    deg freedom     p-Value
-----------------------------------------------------------------------
 X            -5259.59609957      14.20001019         1      0.000164370
```

LTA-no prior-pg4.pdf

References

[1] Asparouhov, T. & Muthén, B. (2011). C on C and X. Technical appendix, www.statmodel.com.

[2] Petras, H., Masyn, K. & Ialongo, N. (2011). The developmental impact of two first grade preventive interventions on aggressive/disruptive behavior in childhood and adolescence: An application of latent transition growth mixture modeling. Accepted for publication in Prevention Science.

[3] Cho, S., Cohen, A., Kim, S. & Bottge, B. (2010). Latent transition analysis with a mixture item response theory measurement model. Applied Psychological Measurement, 34(7), 483504.

[4] Kaplan, D. (2008). An overview of Markov chain methods for the study of stage-sequential developmental processes. Developmental Psychology, 44, 457-467.

[5] Bray, B.C. (2007). Examining gambling and substance use: Applications of advanced latent class modeling techniques for cross-sectional and longitudinal data. Doctoral dissertation, Pennsylvania State University.

[6] Lanza, S.T. & Collins, L.M. (2008). A new SAS procedure for latent transition analysis: Transitions in dating and sexual risk behavior. Developmental Psychology, 44, 446-456.

[7] Muthén, B. & Muthén, L. (1998-2010). Mplus User's Guide. Sixth Edition. Los Angeles, CA: Muthén & Muthén.

[8] Nylund, K. (2007). Latent transition analysis: Modeling extensions and an application to peer victimization. Doctoral dissertation, University of California, Los Angeles.

[9] Nylund, K.L., Muthén, B., Nishina, A., Bellmore, A. & Graham, S. (2006). Stability and instability of peer victimization during middle school: Using latent transition analysis with covariates, distal outcomes, and modeling extensions. Submitted for publication.

[10] Reboussin, B.A., Reboussin, D.M., Liang, K.Y., Anthony, J.C. (1998). Latent transition modeling of progression of health-risk behavior. Multivariate Behavioral Research, 33, 457-478.