Online Appendix to accompany:

Sterba, S.K. (2016) Interpreting and testing interactions in conditional mixture models. *Applied Developmental Science*, 20, 29–43.

Table of Contents: Part 1. Mplus syntax for conditional mixtures in Empirical Examples 1 and 2. Part 2. Pedagogical explanations of conversions used in Equations (2) and (3)

Part 1.

Syntax for Example 1: Product-term mixture (LCGA) syntax including probing simple slopes for two 2-way interactions.

DATA: FILE = example1.dat;
DEFINE: ga=arrest*gender; sa=arrest*supportc; !create product terms
VARIABLE: NAMES ARE y1-y3 gender absub supportc arrest; !list variables in order from dataset
USEVARIABLES ARE y1-y3 gender absub supportc arrest sa ga; !list variables used in analysis
CATEGORICAL ARE y1-y3; Ist categorical outcomes
MISSING ARE . ; !specify missing data code
CLASSES=class(3); !specify name for latent categorical variable (here, class)
specify desired number of classes (here, 3)
ANALYSIS: type = mixture; !specify that model is a mixture
estimator=ml; starts=200 20; algorithm=integration;
MODEL
%overall%
Begress latent class on each predictor and product term: see equations (8) and (10)
Parameters that are used in constructing simple slopes are given a label in parentheses, e.g. (BG1)
I abels in () are arbitrary and are chosen by user
Parameters in the last class (here class 3) are fixed -0 for identification & are not mentioned in code
class#1 on absub.
class#1 on gender (BG1):
class#1 on support; (BS1).
class#1 on arrest (BA1):
class#1 on sa (BSA1):
class#1 on ga (BGA1):
class#2 on absub;
class#2 on gender (BG2);
class#2 on supportc (BS2);
class#2 on arrest (BA2);
class#2 on sa (BSA2);
class#2 on ga (BGA2);
int by y1-y3@1; !specify intercept
lin by y1@0 y2@1 y3@2; !specify linear slope
[y1\$1-y3\$1@0]; litem thresholds fixed to 0 over time
int@0; lin@0; int with lin@0; !no random effects for growth coefficients
%class#1% [int lin]: lallow growth factor means to differ across class: (equation (7))
%class#2% [int lin];
%class#3% [int lin];
ssis_ai ssis_au ssig_ai ssig_au
sszs_ar sszs_au sszg_ar sszg_au;;deciare names or simple slopes to be formed

ss1s_a1=(BS1+BSA1*1); !class 1 (vs. 3): simple slope of support where arrest=1
ss1s_a0=(BS1+BSA1*0); ! class 1 (vs. 3): simple slope of support where arrest=0
ss1g_a1=(BG1+BGA1*1); !class 1 (vs. 3): simple slope of gender where arrest=1
ss1g_a0=(BG1+BGA1*0); !class 1 (vs. 3): simple slope of gender where arrest=0
ss2s_a1=(BS2+BSA2*1); !class 2 (vs. 3): simple slope of support where arrest=1

ss2s_a0=(BS2+BSA2*0); ! class 2 (vs. 3): simple slope of support where arrest=0 ss2g_a1=(BG2+BGA2*1); !class 2 (vs. 3): simple slope of gender where arrest=1 ss2g_a0=(BG2+BGA2*0); class 2 (vs. 3): simple slope of gender where arrest=0 PLOT: TYPE IS PLOT1 PLOT2 PLOT3; SERIES IS y1-y3(*); !request plots

Note: If one does not want to probe simple slopes, the MODEL CONSTRAINT statement can be deleted. Wald tests described in the paper were implemented using MODEL TEST statements. For instance, to obtain the test result in Table 2 row 2, add the following MODEL TEST statement to the above code, right before the PLOT statement: MODEL TEST: BS1=0; BS2=0; Finally, note that gender=1 for males and gender=0 for females in Example 1.

Syntax for Example 1: Multiple-group mixture (LCGA) syntax.

Note that the below MG code produces results that pertain to arrest=0 for syntax under the *%overall% statement. To obtain %overall% results for arrest=1 change the blue 2 to 1.* DATA: FILE = example1.dat; VARIABLE: NAMES ARE y1-y3 gender absub supportc arrest; USEVARIABLES ARE y1-y3 gender absub supportc arrest; CATEGORICAL ARE y1-y3; MISSING ARE .; CLASSES = cg (2) class (3);!specify artificial name for grouping variable (here, cg) with # of observed groups (here, 2) specify name for latent categorical variable (here, class) with desired # of classes (here, 3) KNOWNCLASS = cg (arrest=0 arrest= 1): !relate artificial name for grouping variable (here, cg) to name of grouping variable in dataset (arrest) !list lowest value (here, 0) first followed by higher value (here, 1) ANALYSIS: type = mixture: estimator=ml; starts=200 20; algorithm=integration; MODEL: %overall% class on cg absub gender supportc; !see equations (9) & (11) [cg#1@0.082]; !could estimate--here fixed at observed proportion of arrest; see equation (11) int by y1-y3@1; !specify intercept lin by y1@0 y2@1 y3@2; !specify linear slope [y1\$1-y3\$1@0]; litem thresholds fixed to 0 over time int@0; lin@0; int with lin@0; lno random effects for growth coefficients MODEL class: %class#1% [int lin]; !allow growth factor means to differ across class (equation (7)) %class#2% [int lin]; %class#3% [int lin]; MODEL cq: !specifying %cg#2% here asks for %overall% results, above, to pertain to arrest=0 %ca#2% class on gender supportc;!specify effects on class that differ across observed group (eqn. (9)) Note. One may want to use manual start values, in addition to random start values, to ensure that

this model and the Example 1 PT mixture both have the same class ordering.

Syntax for Example 2: Product term mixture (LCA) syntax including probing simple slopes for a 3-way interaction.

DATA: file is example2.dat;
DEFINE: !create product terms
agemale=age male, blackmale=black*male;
aceblack-ace*black:
ayebiack-aye biack,
VARIABLE: NAMES ARE v1-v9 age male black:
USEVARIABLES ARE v1-v9 age male black
aremale blackmale areblack amb.
CATEGORICAL ARE v1-v9: llist categorical outcomes
CLASSES=class(4): (specify name for latent categorical variable (here, class)
Ispecify desired number of classes (here, 4)
ANALYSIS: type=mixture: !specify that model is a mixture
starts=200 20; estimator=ml;
MODEL:
%overall%
Regress latent class on each predictor and product term; see equations (13) and (10)
Parameters that are used in constructing simple slopes are given a label in parentheses, e.g., (B bm1).
Labels in () are arbitrary and are chosen by user.
Parameters in the last class (here class 4) are fixed =0 for identification & are not mentioned in code
class on male black;
class#1 on blackmale (B_bm1);
class#1 on agemale (B_am1);
class#1 on age (B_a1);
class#1 on ageblack (B_ab1);
class#1 on amb (B_abm1);
class#2 on blackmale (B_bm2);
class#2 on agemale (B_am2);
class#2 on age (B_a2);
class#2 on ageblack (B_ab2);
class#2 on amb (B_abm2);
class#3 on blackmale (B_bm3);
class#3 on age (B, a3);
class#3 on ageblack (B_ab3):
class#3 on amb (B_abm3);
% close #1% [u1\$1 v0\$1]; clow and example thresholds for the 0 items to differ serves close (eq. (12))
$\frac{1}{2}$
% class#2 $%$ [y1\$1-y9\$1], % class#3% [y1\$1-y9\$1].
% class# $3%$ [y 1 $%$ 1 - y 3 $%$ 1], % class# 4% [y 1 $\%$ 1 - y 0 $\%$ 1].
7001233#470 [y141 y341],
MODEL CONSTRAINT: NEW (
s1a_b1m1 s1a_b1m0 s2a_b1m1 s2a_b1m0
s3a_b1m1 s3a_b1m0 s1a_b0m1 s1a_b0m0
s2a_b0m1 s2a_b0m0 s3a_b0m1 s3a_b0m0); !declare names of simple slopes to be formed and tested
class 1 vs. 4: simple slope of age at chosen values of race and gender
s1a_b1m1=(b_a1 + b_ab1*1 + b_am1*1 + b_abm1*1*1);!simple slope for black males
s1a_b0m1=(b_a1 + b_ab1*0 + b_am1*1 + b_abm1*1*0);!simple slope for white males
s1a_b1m0=(b_a1 + b_ab1*1 + b_am1*0 + b_abm1*0*1);!simple slope for black females

s1a_b0m0=(b_a1 + b_ab1*0 + b_am1*0 + b_abm1*0*0);!simple slope for white females

!class 3 vs. 4: simple slope of age at chosen values of race and gender s3a_b1m1=(b_a3 + b_ab3*1 + b_am3*1 + b_abm3*1*1); !simple slope for black males s3a_b0m1=(b_a3 + b_ab3*0 + b_am3*1 + b_abm3*1*0); !simple slope for white males s3a_b1m0=(b_a3 + b_ab3*1 + b_am3*0 + b_abm3*0*1); !simple slope for black females s3a_b0m0=(b_a3 + b_ab3*0 + b_am3*0 + b_abm3*0*0); !simple slope for white females

PLOT: TYPE=PLOT1 PLOT2 PLOT3; SERIES IS y1-y9(*);

Note: If one does not want to probe simple slopes the MODEL CONSTRAINT statement can be deleted.

Syntax for Example 2: Multiple-group mixture (LCA) syntax including probing simple slopes for a 3-way interaction.

Note that the below MG code produces results that pertain to male=0 for syntax under the % overall% statement. To obtain % overall% results for male = 1 change the blue 2 to 1 and (optionally, also change the red label for the simple slopes from 0 to 1). DATA: file is example2.dat; DEFINE: ageblack=age*black; VARIABLE: NAMES ARE y1-y9 male black age; USEVARIABLES ARE y1-y9 age male black ageblack; CATEGORICAL ARE y1-y9; CLASSES = cg (2) class(4);specify artificial name for grouping variable (here, cg) with # of observed groups (here, 2) specify name for latent categorical variable (here, class) with desired # of classes (here, 4) KNOWNCLASS= cg (male=0 male=1); Irelate artificial name for grouping variable (here, cg) to name of grouping variable in dataset (male) !list lowest value (here, 0) first followed by higher value (here, 1) ANALYSIS: type=mixture; starts=200 20; estimator=ml; MODEL: %overall% class on cg black; !see equations (14) & (11) class#1 on age (b a1); class#1 on ageblack (b ab1); class#2 on age (b a2); class#2 on ageblack (b ab2); class#3 on age (b_a3); class#3 on ageblack (b ab3); [cg#1@0.048]; !could estimate--here fixed at observed proportion of boys; see equation (11) MODEL class: %class#1% [y1\$1-y9\$1]; !allow endorsement thresholds for the 9 items to differ across class (eqn. (12)) %class#2% [v1\$1-v9\$1]; %class#3% [v1\$1-v9\$1]; %class#4% [y1\$1-y9\$1];

MODEL cg: !specifying %cg#2% asks for %overall% results, above, to pertain to male=0 %cg#2% class on age black ageblack; !specify effects on class that differ across obs. group (eqn. (14))
MODEL CONSTRAINT:
NEW (s1a_b0m <mark>0</mark> s1a_b1m <mark>0</mark>
s2a_b0m0 s2a_b1m0
s3a_b0m0 s3a_b1m0); !declare names of simple slopes to be formed and tested
s1a_b1m0=(b_a1+b_ab1*1); !class 1 vs. 4: simple slope of age for black females
s1a_b0m0=(b_a1+b_ab1*0); !class 1 vs. 4: simple slope of age for white females
s2a_b1m0=(b_a2+b_ab2*1); !class 2 vs. 4: simple slope of age for black females
s2a_b0m0=(b_a2+b_ab2*0); !class 2 vs. 4: simple slope of age for white females
s3a_b1m0=(b_a3+b_ab3*1); !class 3 vs. 4: simple slope of age for black females
s3a b0m0=(b a3+b ab3*0); !class 3 vs. 4: simple slope of age for white females

Note: One may want to use manual start values, in addition to random start values, to ensure that this model and the Example 2 PT mixture both have the same class ordering. Also, if one does not want to probe simple slopes the MODEL CONSTRAINT statement can be deleted.

Part. II.

Explanation for Equation (2):

$$\frac{p(c_i = k \mid x_{1i} = x_{2i} = 0)}{p(c_i = K \mid x_{1i} = x_{2i} = 0)} = \frac{\frac{exp(\beta_0^{(k)} + \beta_1^{(k)}0 + \beta_2^{(k)}0)}{\sum_{k=1}^{K} exp(\beta_0^{(k)} + \beta_1^{(k)}0 + \beta_2^{(k)}0)} = \frac{exp(\beta_0^{(k)})}{exp(0)} = exp(\beta_0^{(k)})$$

Where the coefficients in the reference (Kth) class are fixed to 0 for identification.

Explanation for Equation (3):

$$\frac{p(c_{i} = k \mid x_{1i} + 1, x_{2i})}{p(c_{i} = K \mid x_{1i} + 1, x_{2i})} / \frac{p(c_{i} = k \mid x_{1i}, x_{2i})}{p(c_{i} = K \mid x_{1i}, x_{2i})} = \\
\frac{\frac{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}(x_{1i} + 1) + \beta_{2}^{(k)}x_{2i})}{\sum_{k=1}^{K} exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}(x_{1i} + 1) + \beta_{2}^{(k)}x_{2i})} / \frac{\frac{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}x_{1i} + \beta_{2}^{(k)}x_{2i})}{\sum_{k=1}^{K} exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}(x_{1i} + 1) + \beta_{2}^{(k)}x_{2i})} = \\
\frac{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}(x_{1i} + 1) + \beta_{2}^{(k)}x_{2i})}{\sum_{k=1}^{K} exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}x_{1i} + \beta_{2}^{(k)}x_{2i})} = \\
\frac{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}(x_{1i} + 1) + \beta_{2}^{(k)}x_{2i})}{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}x_{1i} + \beta_{2}^{(k)}x_{2i})} = \\
\frac{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}(x_{1i} + 1) + \beta_{2}^{(k)}x_{2i})}{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}x_{1i} + \beta_{2}^{(k)}x_{2i})} = \\
\frac{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}(x_{1i} + 1) + \beta_{2}^{(k)}x_{2i})}{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}x_{1i} + \beta_{2}^{(k)}x_{2i})} = \\
\frac{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}(x_{1i} + 1) + \beta_{2}^{(k)}x_{2i})}{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}x_{1i} + \beta_{2}^{(k)}x_{2i})} = \\
\frac{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}(x_{1i} + 1) + \beta_{2}^{(k)}x_{2i})}{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}x_{1i}) exp(\beta_{1}^{(k)}) exp(\beta_{2}^{(k)}x_{2i})}} = \\
\frac{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}x_{1i} + \beta_{2}^{(k)}x_{2i})}{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}x_{1i}) exp(\beta_{2}^{(k)}x_{2i})}} = \\
\frac{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}x_{2i}) exp(\beta_{1}^{(k)}x_{2i})}{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}x_{2i}) exp(\beta_{2}^{(k)}x_{2i})}} = \\
\frac{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}x_{2i}) exp(\beta_{2}^{(k)}x_{2i})}{exp(\beta_{1}^{(k)}x_{1i}) exp(\beta_{2}^{(k)}x_{2i})} exp(\beta_{2}^{(k)}x_{2i})} = \\
\frac{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}x_{2i}) exp(\beta_{2}^{(k)}x_{2i})}{exp(\beta_{1}^{(k)}x_{2i}) exp(\beta_{2}^{(k)}x_{2i})} exp(\beta_{2}^{(k)}x_{2i})} = \\
\frac{exp(\beta_{0}^{(k)} + \beta_{1}^{(k)}x_{2i}) exp(\beta_{2}^{(k)}x_{2i})}{exp(\beta_{1}^{(k)}x_{2i}) exp(\beta_{2}^{(k)}x_{2i})} exp(\beta_{2}^{(k)}x_{2i})} exp(\beta_{2}^{(k)}x_{2i}) exp(\beta_{2}^{(k)}x_{2i}) exp(\beta_{2}^{(k)}x_{2i}) exp(\beta_{2}^{(k)}x_{2i}) exp(\beta_{2}^{(k)}x_{2i})} exp(\beta_{2}^{(k)}x_{2i}) exp(\beta_{2}$$

Where the coefficients in the reference (Kth) class are fixed to 0 for identification.