Longitudinal Study on Crack-Cocaine Use and Crack-Cocaine Dependence: Application of Latent Growth Mixture Modeling

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I. Introduction

• Growth Model (GM) or Latent Growth Model (LGM) :

assumes that the observed growth trajectories are a sample from a population of individuals with a single average growth trajectory.

-- Capture one form of heterogeneity: individual differences in growth trajectory

• Latent Growth Mixture Model (LGMM): the sample is derived from a population that has a finite mixture of sub-populations, each of which has its own unique growth trajectory.

-- Capture two forms of heterogeneity: 1) individual differences in growth trajectory; and 2) heterogeneity in classes of growth trajectories.

II. LGMM model specification

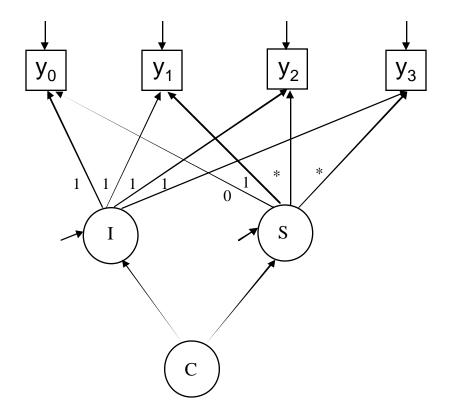
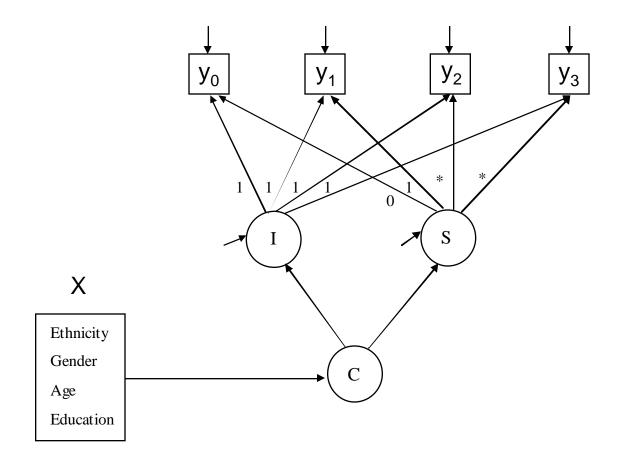
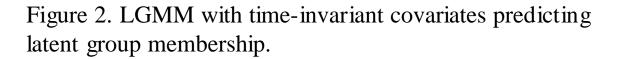


Figure 1. LGMM without covariates





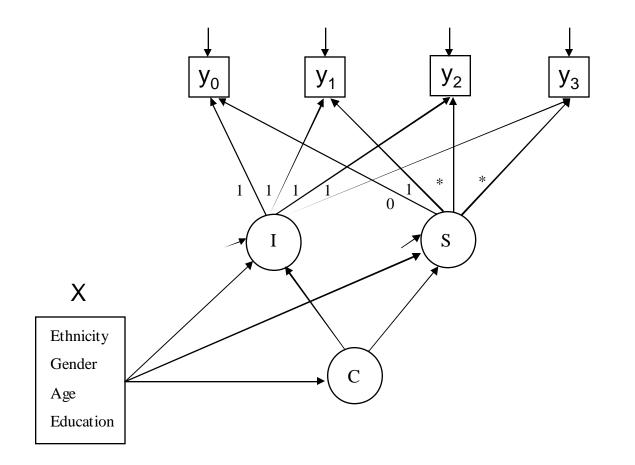


Figure 3. LGMM with time-invariant covariates having a direct influence growth factors

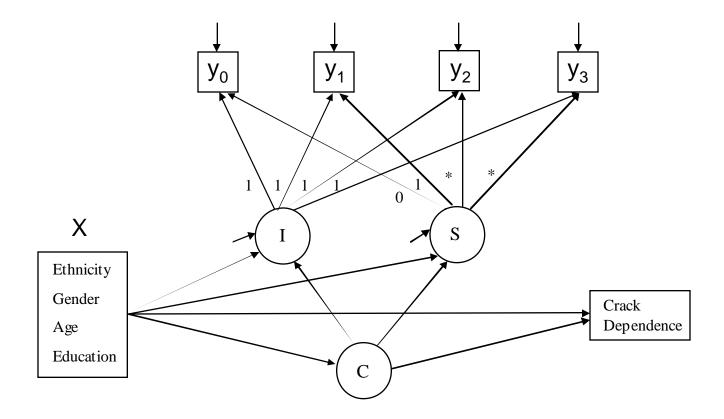


Figure 4. Adding a distal outcome measure into the Model

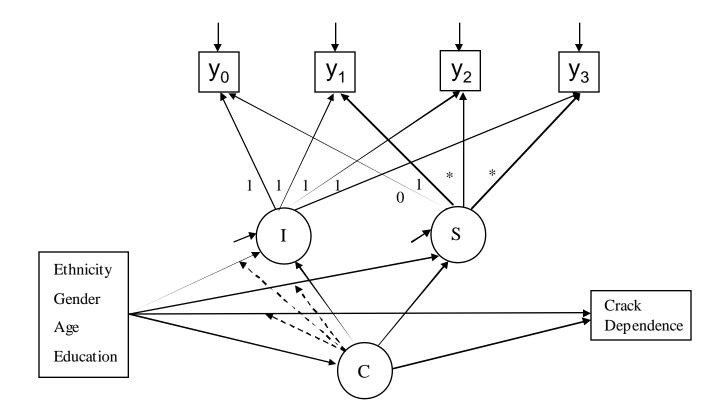


Figure 5. The effects of covariates on growth factors and the distal outcome vary across latent trajectory groups.

III. Deciding on the No. of Latent Trajectory Groups

- 1) AIC, BIC, ABIC.
- 2) Lo-Mendel-Rubin likelihood ratio (LMR LR) test (Lo, Mendel & Rubin, 2001).
- 3) Residual diagnostics based on pseudo-clasess (Wang, Brown & Bandeen-Roche, 2002).
- 4) Skewness & kurtosis (SK) test (Muthen & Asparouhov, 2002).
- 5) Bootstrap likelihood ratio (BLRT) test (Nylund & Muthen, 2006).
- 6) Precision of group classification.
- 7) Usefulness of the latent classes in practice (e.g., group size and association with theoretically related external criteria).

IV. Example

• **Sample**: A sample of 430 crack-cocaine users interviewed in a 3year observation period (1996-1999) in a natural history study in Dayton, Ohio was used for the study.

• **Outcome measure**: Repeated measures of crack-cocaine use frequency measured on a 6-point scale:

- 1 less than 4 times per month;
- 2 about 1 time a week,
- 3 about 2-6 times a week,
- 4 about 1 time a day almost every day,
- 5 about 2-3 times a day almost every day, and
- 6 about 4 or more times a day almost every day).

At the follow-up interviews, 0 (i.e., no use) was added to the response options.

• Covariates:

- Gender (1-Male; 0-Female)
- Blac (1-Black; 0-Whtie)
- Age
- Education

• Distal Outcome:

-DSM-IV Crack-cocaine dependence (1-Yes; 0-No)

•Results:

	No. of Classes				
	1	2	3	4	5
AIC	5893.31	5820.714	5705.70	5636.16	5623.60
BIC	5958.33	5918.245	5835.74	5798.71	5826.89
Entropy	-	0.57	0.81	0.85	.85
LMR LR (P-value)	-	0.0088	0.0001	0.0033	0.5423
BLRT (P-value)	-	0.0000	0.0000	0.0000	0.0000

Table 1. Deciding on the number of latent trajectory classes (n=430)

Selected Results of 4-Class Model

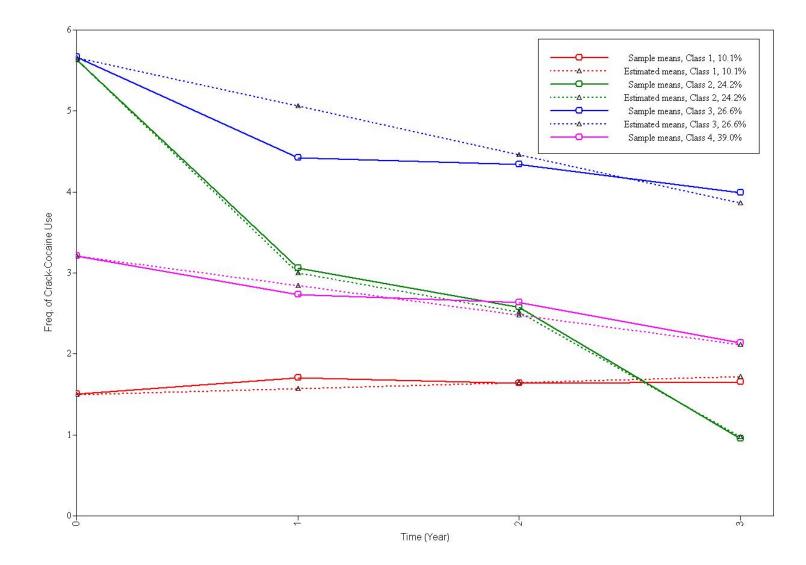
CLASSIFICATION OF INDIVIDUALS BASED ON THEIR MOST LIKELY LATENT CLASS MEMBERSHIP

Class Counts and Proportions

Latent Classes 1 49 0.11395 2 96 0.22326 3 122 0.28372 4 163 0.37907

Average Latent Class Probabilities for Most Likely Latent Class Membership (Row) by Latent Class (Column)

	1	2	3	4
1	0.877	0.000	0.000	0.123
2	0.000	0.867	0.132	0.000
3	0.000	0.168	0.832	0.001
4	0.003	0.003	0.002	0.992



	Estimates	S.E.	Est./S.E.
DD44CR ON			
BLACK	-1.135	0.385	-2.947
MALE	-0.356	0.286	-1.244
AGE	0.012	0.019	0.639
EDU	0.116	0.096	1.203
S WITH			
I	-0.022	0.038	-0.594
Means			
I	1.499	0.000	0.000
S	0.073	0.000	0.000
Thresholds			
DD44CR\$1	0.229	0.599	0.383

		Estimates	S.E.	Est./S.E.
S				
ΥO		0.000	0.000	0.000
Yl		1.000	0.000	0.000
Y2		1.183	0.133	8.880
Y3		1.770	0.222	7.964
DD44CR	ON			
BLACK		-1.135	0.385	-2.947
MALE		-0.356	0.286	-1.244
AGE		0.012	0.019	0.639
EDU		0.116	0.096	1.203
S W	ITH			
I		-0.022	0.038	-0.594
Means				
I		5.637	0.073	77.445
S		-2.636	0.405	-6.511
Thresholds				
DD44CR\$	1	1.236	1.179	1.048

	Estimates	S.E.	Est./S.E.
DD44CR ON			
BLACK	-1.135	0.385	-2.947
MALE	-0.356	0.286	-1.244
AGE	0.012	0.019	0.639
EDU	0.116	0.096	1.203
S WITH			
I			
	-0.022 0.03	38 -0	.594
Means			
I	5.658	0.069	82.582
S	-0.599	0.195	-3.079
Thresholds			
DD44CR\$1	-1.783	0.440	-4.049

	Estimates	S.E.	Est./S.E.
DD44CR ON			
BLACK	-1.135	0.385	-2.947
MALE	-0.356	0.286	-1.244
AGE	0.012	0.019	0.639
EDU	0.116	0.096	1.203
S WITH			
I	-0.022	0.038	-0.594
Means			
I	3.211	0.042	76.567
S	-0.366	0.050	-7.381
Thresholds			
DD44CR\$1	-0.347	0.313	-1.110

Results of Multinomial Logit Model

		Estimates	S.E.	Est./S.E.
C#1	ON			
BLACK		-0.300	0.391	-0.768
MALE		0.433	0.402	1.079
AGE		-0.044	0.029	-1.525
EDU		-0.134	0.144	-0.931
C#2	ON			
BLACK		0.157	0.389	0.404
MALE		0.183	0.296	0.619
AGE		-0.027	0.020	-1.378
EDU		-0.126	0.109	-1.157
C#3	ON			
BLACK		1.227	0.363	3.384
MALE		0.139	0.295	0.469
AGE		0.007	0.022	0.335
EDU		-0.087	0.100	-0.875
Intercepts	3			
C#1		-1.514	0.396	-3.821
C#2		-0.688	0.308	-2.234
C#3		-1.317	0.483	-2.727

Discussion

• The LGMM is a useful approach for longitudinal studies

• Challenges

- -- Deciding on the number of latent classes ...
- -- Problem with non-normally distributed repeated measures ...
- -- Mplus vs. SAS Proc Traj