### **PSY 9556B (Feb 5) Latent Growth Modeling**

- "Fixed" and "random" word confusion
- Simplest LGM knowing how to calculate dfs
- How many time points needed?
- Power, sample size
- Nonlinear growth quadratic
- Nonlinear growth freeing loadings
- Piecewise models
- Linear growth (different ways of scaling time)
- Associative LGM
- Higher order LGM: curve-of-factors model
- Conditional models (time-invariant, time-variant)
- Multiple groups (group covariate or multiple-groups analysis)
- Similarity between LGM and MLM
- When to use LGM, when to use MLM

#### "Fixed" and "Random" word clarification

- Fixed and random effects in MLM and LGM
  - Fixed effect: single values that estimate of population values
    - (e.g., a regression coefficient, a mean intercept or slope in LGM, MLM)
  - Random effect: provide information about the variation in the regression coefficient or intercept parameters across the clustering units
    - (e.g., variance of intercepts and slopes in LGM or MLM)
- Fixed and random factors in ANOVA
  - Fixed factor levels chosen apriori
  - Random factor: no particular interest in the levels; chosen at random
    - Best example of a random factor: persons
    - Repeated measures design
    - At least two observations nested within persons
    - Persons as a random factor is also referred to as the clustering unit or in MLM
- Mixed models
  - One fixed factor crossed with one random factor (e.g., split plot ANOVA)

# Number of Parameters and Degrees of Freedom Example: 2 time points (linear)

#### Parameters and dfs

```
Elements: (v (v+3))/2 = (2*5)/2 = 5
```

#### Parameters:

2 residuals (2 time points): left-over variance not explained by latent variables

1 mean intercept: the mean start-point of individual trajectories

1 mean slope: the mean slope (e.g., growth/learning/decrease) of individual trajectories

1 variance of the intercepts: variation in individual start-points

1 variance of the slopes: variation in individual slopes

1 correlation between intercept and slope

(note, indicator intercepts fixed at 0)

Total parameters = 7 dfs = to many parameters

# Number of Parameters and Degrees of Freedom Example: 3 time points (linear)

#### Parameters and dfs

```
Elements: (v (v+3))/2 = (3*6)/2 = 9
```

#### Parameters:

3 residuals (3 time points): left-over variance not explained by latent variables

1 mean intercept: the mean start-point of individual trajectories

1 mean slope: the mean slope (e.g., growth/learning/decrease) of individual trajectories

1 variance of the intercepts: variation in individual start-points

1 variance of the slopes: variation in individual slopes

1 correlation between intercept and slope

(note, indicator intercepts fixed at 0)

Total parameters = 
$$8$$
 dfs =  $9 - 8 = 1$ 

# Number of Parameters and Degrees of Freedom Example: 4 time points (linear + quadratic)

#### Parameters and dfs

#### **Elements:**

$$(4 (4+3))/2 = (4*7)/2 = 14$$

#### Parameters:

4 residuals (4 time points): left-over variance not explained by latent variables

1 mean intercept: the mean start-point of individual trajectories

1 mean slope: the mean slope (e.g., growth/learning/decrease) of individual trajectories

1 mean quadratic component

1 variance of the intercepts: variation in individual start-points

1 variance of the slopes: variation in individual slopes

1 variance of quadratic component

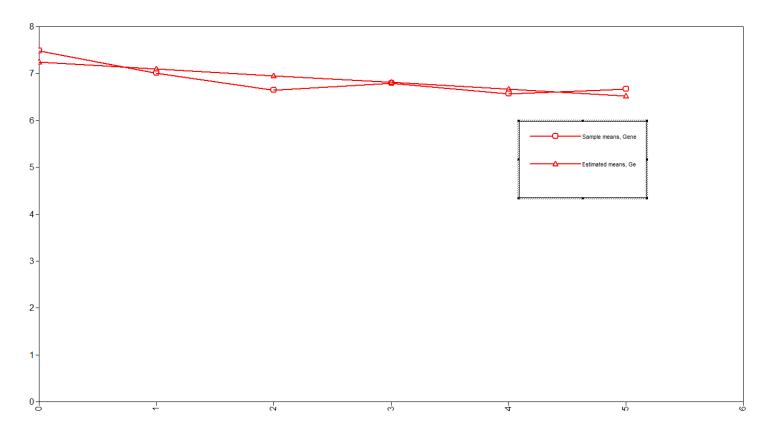
3 correlations between intercept, slope, quadratic

(note, indicator intercepts fixed at 0)

Total parameters = 
$$13$$
 dfs =  $14 - 13 = 1$ 

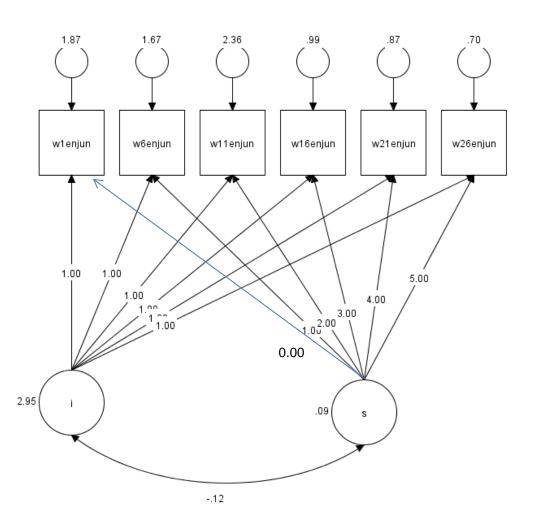
### **Example of a LGM with Five Time Points**

```
USEVARIABLES ARE wlenjun w6enjun w11enjun w16enjun w21enjun w26enjun;
model:
I S | w1enjun@0 w6enjun@1 w11enjun@2 w16enjun@3 w21enjun@4 w26enjun@5;
plot:
type=plot3;
series = w1enjun(0) w6enjun(1) w11enjun(2) w16enjun(3) w21enjun(4) w26enjun(5);
output: sampstat residual stdyx tech4 modindices;
```



## **Example of a LGM with Five Time Points**

In this figure you should also indicate the means of the latent variables: Intercept = 2.948 and Slope = 0.094

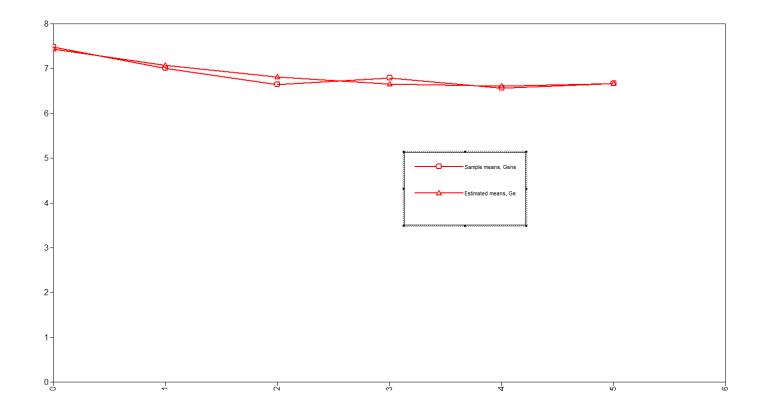


## **Example of a LGM with Five Time Points**

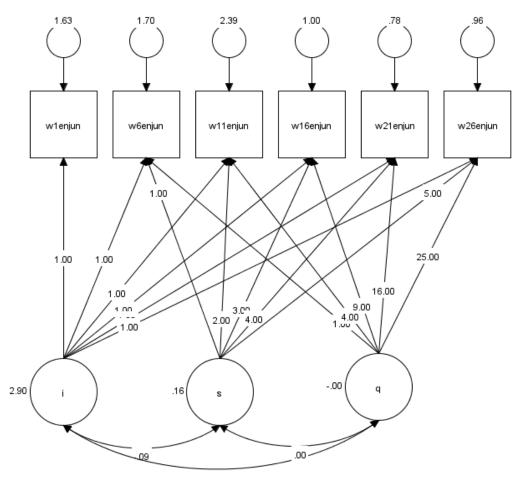
									Two-Tailed
NT	5 F D					Estimate	S.E.	Est./S.E.	P-Value
Number of	Free Parameters	11							
Loglikeli	ihood			I	 W1ENJUN	1.000	0.000	999.000	999.000
LOGITACIA	illood				WIENJUN W6ENJUN	1.000	0.000	999.000	999.000
	HO Value	-3779.045			W11ENJUN	1.000	0.000	999.000	999.000
	H1 Value	-3745.014			W16ENJUN	1.000	0.000	999.000	
	ni value	-3/45.014			W21ENJUN	1.000	0.000	999.000	
Informati	ion Criteria				W26ENJUN	1.000	0.000	999.000	999.000
111101111001	on orrection								
	Akaike (AIC)	7580.091		S	I				
	Bayesian (BIC)	7624.349			W1ENJUN	0.000	0.000	999.000	999.000
	Sample-Size Adjusted BIC	7589.443			W6ENJUN	1.000	0.000	999.000	999.000
	(n* = (n + 2) / 24)				W11ENJUN	2.000	0.000	999.000	999.000
	( ( 2) / 22)				W16ENJUN	3.000	0.000	999.000	999.000
Chi-Smar	re Test of Model Fit				W21ENJUN	4.000	0.000	999.000	999.000
CIII DQUUI	ic lest of model lit				W26ENJUN	5.000	0.000	999.000	999.000
	Value	68.063		S	WITH				
	Degrees of Freedom	16			I	-0.116	0.050	-2.300	0.021
	P-Value	0.0000							
				Mea					
RMSEA (Ro	oot Mean Square Error Of Appro	oximation)			I	7.241	0.100		0.000
					S	-0.145	0.022	-6.442	0.000
	Estimate	0.089		Tn+					
	90 Percent C.I.	0.068	0.111		ercepts W1ENJUN	0.000	0.000	999.000	999.000
	Probability RMSEA <= .05	0.002			W1ENJUN W6ENJUN	0.000	0.000	999.000	999.000
					W11ENJUN	0.000	0.000	999.000	999.000
CFI/TLI					W16ENJUN	0.000	0.000	999.000	999.000
					W21ENJUN	0.000	0.000	999.000	
	CFI	0.957			W26ENJUN	0.000	0.000	999.000	999.000
	TLI	0.960							
				Var	iances				
Chi-Squar	re Test of Model Fit for the H	Baseline Model			I	2.948	0.289	10.192	0.000
					S	0.094	0.014	6.718	0.000
	Value	1239.482		Doo	idual Variano				
	Degrees of Freedom	15			iduai variano W1ENJUN	es 1.872	0.208	9.019	0.000
	P-Value	0.0000			W1ENJUN W6ENJUN	1.666	0.166	10.026	0.000
					W11ENJUN	2.363	0.166	10.949	0.000
SRMR (Sta	andardized Root Mean Square Re	esidual)			W16ENJUN	0.992	0.099	10.068	0.000
					W21ENJUN	0.871	0.105	8.273	0.000
	Value	0.078			W26ENJUN	0.704	0.128	5.504	0.000

# **Example of a LGM with Five Time Points Adding a Quadratic Component**

```
USEVARIABLES ARE wlenjun w6enjun w11enjun w16enjun w21enjun w26enjun;
model:
I S Q| w1enjun@0 w6enjun@1 w11enjun@2 w16enjun@3 w21enjun@4 w26enjun@5;
plot:
type=plot3;
series = w1enjun(0) w6enjun(1) w11enjun(2) w16enjun(3) w21enjun(4) w26enjun(5);
output: sampstat residual stdyx tech4 modindices;
```



# **Example of a LGM with Five Time Points Adding a Quadratic Component**

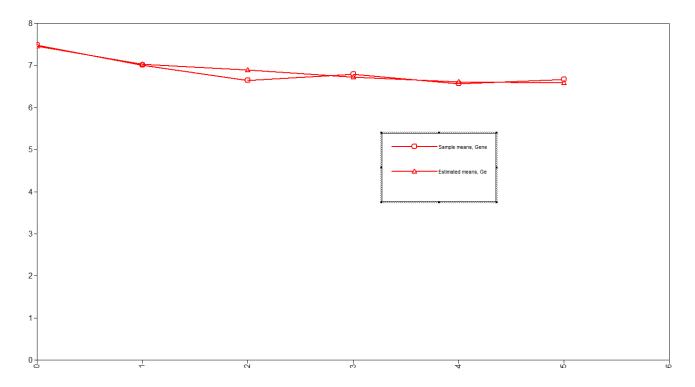


THE MODEL ESTIMATION TERMINATED NORMALLY

WARNING: THE LATENT VARIABLE COVARIANCE MATRIX (PSI) IS NOT POSITIVE DEFINITE. THIS COULD INDICATE A NEGATIVE VARIANCE/RESIDUAL VARIANCE FOR A LATENT VARIABLE, A CORRELATION GREATER OR EQUAL TO ONE BETWEEN TWO LATENT VARIABLES, OR A LINEAR DEPENDENCY AMONG MORE THAN TWO LATENT VARIABLES. CHECK THE TECH4 OUTPUT FOR MORE INFORMATION. PROBLEM INVOLVING VARIABLE Q.

# Example of a LGM with Five Time Points Time Points Free

```
USEVARIABLES ARE w1enjun w6enjun w11enjun w16enjun w21enjun w26enjun;
model:
I S | w1enjun@0 w6enjun@1 w11enjun* w16enjun* w21enjun* w26enjun*5;
plot:
type=plot3;
series = w1enjun(0) w6enjun(1) w11enjun(2) w16enjun(3) w21enjun(4) w26enjun(5);
output: sampstat residual stdyx tech4 modindices;
```

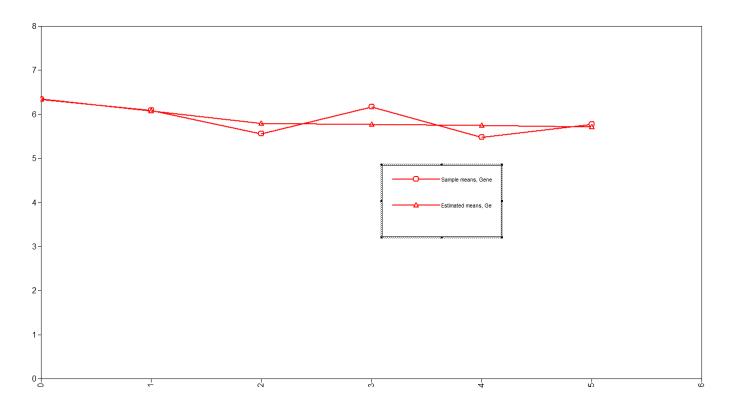


# **Example of a LGM with Five Time Points Time Points Free**

								Two-Tailed	
Number of Free Parameters	15				Estimate	S.E.	Est./S.E.	P-Value	
			I	1					
Loglikelihood			_	ENJUN	1.000	0.000	999.000	999.000	
				ENJUN	1.000	0.000	999.000	999.000	
HO Value	-3764.199		W1:	1ENJUN	1.000	0.000	999.000	999.000	
H1 Value	-3745.014		W1	6ENJUN	1.000	0.000	999.000	999.000	
			W2:	1ENJUN	1.000	0.000	999.000	999.000	
Information Criteria			W2	6ENJUN	1.000	0.000	999.000	999.000	
Akaike (AIC)	7558.398		S						
Bayesian (BIC)	7618.749			ENJUN ENJUN	0.000 1.000	0.000	999.000 999.000	999.000 999.000	
Sample-Size Adjusted BIC	7571.151			LNJUN 1ENJUN	1.304	0.000	7.525	0.000	
(n* = (n + 2) / 24)	70711101			6ENJUN	1.706	0.173	7.323	0.000	
(11 (11 - 2) / 21)				1ENJUN	1.954	0.287		0.000	
Chi-Square Test of Model Fit				6ENJUN	2.013	0.289	6.965	0.000	
oni square rest or noder ris									
Value	38.370		S	WITH					
Degrees of Freedom	12		I		-0.687	0.288	-2.383	0.017	
P-Value	0.0001		Means						
			Means I		7.452	0.108	69.287	0.000	
RMSEA (Root Mean Square Error Of App	proximation)		S		-0.429	0.100	-4.911	0.000	
			_		51123			21.020	
Estimate	0.073		Inter	cepts					
90 Percent C.I.	0.048	0.099	W11	ENJUN	0.000	0.000	999.000	999.000	
Probability RMSEA <= .05	0.065			ENJUN	0.000	0.000	999.000	999.000	
				1ENJUN	0.000	0.000		999.000	
CFI/TLI				6ENJUN	0.000	0.000	999.000	999.000	
				1ENJUN	0.000	0.000	999.000	999.000	
CFI	0.978		W2	6ENJUN	0.000	0.000	999.000	999.000	
TLI	0.973		Varia	nces					
			I	11000	3.523	0.444	7.928	0.000	
Chi-Square Test of Model Fit for the	e Baseline Model		5		0.723	0.291	2.481	0.013	
-									
Value	1239.482			ual Variano					
Degrees of Freedom	15			ENJUN	0.935	0.374	2.500	0.012	
P-Value	0.0000			ENJUN	1.869	0.177		0.000	
				1ENJUN	2.435	0.218	11.175	0.000	
SRMR (Standardized Root Mean Square	Residual)			6ENJUN	0.939	0.101		0.000	
, and a second of the secon				1ENJUN	0.774	0.111	6.946	0.000	
Value	0.030		W2	6ENJUN	0.910	0.124	7.330	0.000	
	0.000								

# Example of a LGM with Five Time Points Piecewise

```
USEVARIABLES ARE wlenjcr w6enjcr w11enjcr w16enjcr w21enjcr w26enjcr;
model:
I S1 | w1enjcr@0 w6enjcr@1 w11enjcr@2 w16enjcr@2 w21enjcr@2 w26enjcr@2;
I S2 | w1enjcr@0 w6enjcr@0 w11enjcr@0 w16enjcr@1 w21enjcr@2 w26enjcr@3;
plot:
type=plot3;
series = w1enjcr(0) w6enjcr(1) w11enjcr(2) w16enjcr(3) w21enjcr(4) w26enjcr(5);
output: sampstat residual stdyx tech4 modindices;
```



# **Example of a LGM with Five Time Points Piecewise**

Poor model

MODEL FIT	INFORMATION		
Number of	Free Parameters	15	
Loglikeli	hood		
	HO Value	-4038.467	
	H1 Value	-3997.736	
Informatio	on Criteria		
	Akaike (AIC)	8106.934	
	Bayesian (BIC)	8167.249	
	Sample-Size Adjusted BIC $(n* = (n + 2) / 24)$	8119.651	
Chi-Square	e Test of Model Fit		
	Value	81.462	
	Degrees of Freedom	12	
	P-Value	0.0000	
RMSEA (Ro	ot Mean Square Error Of App:	roximation)	
	Estimate	0.119	
	90 Percent C.I.	0.095	0.144
	Probability RMSEA <= .05	0.000	
CFI/TLI			
	CFI	0.902	
	TLI	0.877	
Chi-Square	e Test of Model Fit for the	Baseline Model	
	Value	722.674	
	Degrees of Freedom	15	
	P-Value	0.0000	
SRMR (Star	ndardized Root Mean Square I	Residual)	
	Value	0.074	

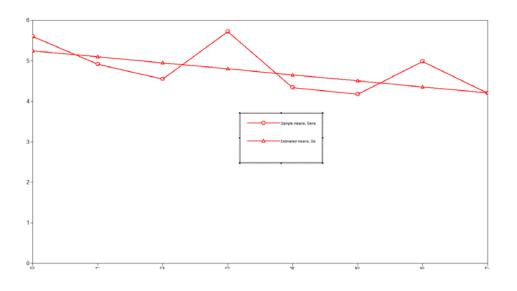
#### **Power in LGM**

- Fan (2003) showed that LGM consistently showed higher statistical power for detecting group differences in the linear growth slope than repeated measures ANOVA.
- Study done with five time points
- More research needed on the impact of number of time points

Fan, X. (2003). Power of latent growth modeling for detecting group differences in linear growth trajectory parameters. *Structural Equation Modeling: A Multidisciplinary Journal*, *10*, 380-400.

## **Alternative Ways of Scaling Slope: Drinking Example (8 time points)**

MODEL FIT	INFORMATION		
Number of	Free Parameters	13	
Loglikelih	nood		
	HO Value	-7809.924	
	H1 Value	-7736.326	
Informatio	on Criteria		
	Akaike (AIC)	15645.849	
	Bayesian (BIC)	15695.927	
	Sample-Size Adjusted BIC $(n* = (n + 2) / 24)$	15654.687	
Chi-Square	e Test of Model Fit		
	Value	147.197	
	Degrees of Freedom	31	
	P-Value	0.0000	
RMSEA (Roo	ot Mean Square Error Of Approxim	mation)	
	Estimate	0.104	
	90 Percent C.I.	0.087	0.121
	Probability RMSEA <= .05	0.000	
CFI/TLI			
	CFI	0.942	
	TLI	0.948	
Chi-Square	e Test of Model Fit for the Base	eline Model	
	Value	2027.634	
	Degrees of Freedom	28	
	P-Value	0.0000	
SRMR (Star	ndardized Root Mean Square Resid	dual)	
200000000000000000000000000000000000000	Value	0.059	



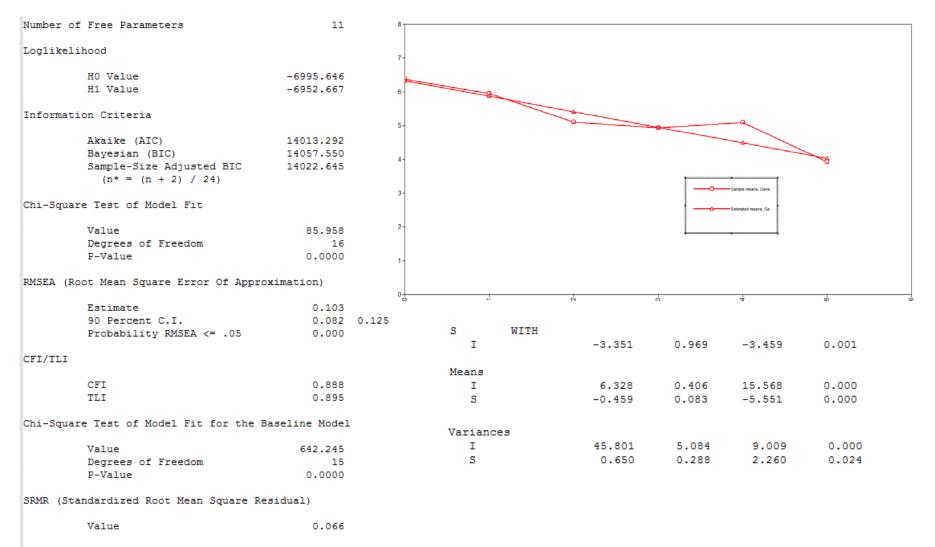
## **Alternative Ways of Scaling Slope: Drinking Example (8 time points)**

usevariables are d1 d2 d3 d4 d5 d6 d7 d8; model: i s | d1@0 d2@0.143 d3@0.286 d4@0.429 d5@0.572 d6@0.715 d7@0.858 d8@1; S WITH Ι -13.709 2.624 -5.225 0.000 Means I 5.246 0.351 14.941 0.000 S -1.038 0.348 -2.978 0.003 Variances 36.513 I 3.251 11.230 0.000 S 24.601 3.386 7.266 0.000

usevaria	bles are d1 d2 d3 d4	d5 d6 d7	d8;		usevariab	les are d1	. d2 d3 d4 d5	d6 d7 d8;	;	
model: i	. s   d1@0 d2@1 d3@2	d4@3 d5@4 (	d605 d706 d	807;	model: i	s   d10-7	d2@-6 d3@-5	d40-4 d50-	-3 d6@-2 d7	'@-1 d8@0;
S	WITH									
I	-1.959	0.375	-5.225	0.000	S	WITH				
					I		1.557	0.359	4.332	0.000
Means										
I	5.245	0.351	14.941	0.000	Means					
S	-0.148	0.050	-2.978	0.003	I		4.208	0.340	12.385	0.000
					S		-0.148	0.050	-2.978	0.003
Variances	3									
I	36.511	3.251	11.230	0.000	TT					
S	0.502	0.069	7.266	0.000	Varia	nces				
3	0.302	0.005	7.200	5.000	I		33.698	3.047	11.060	0.000
					S		0.502	0.069	7.266	0.000

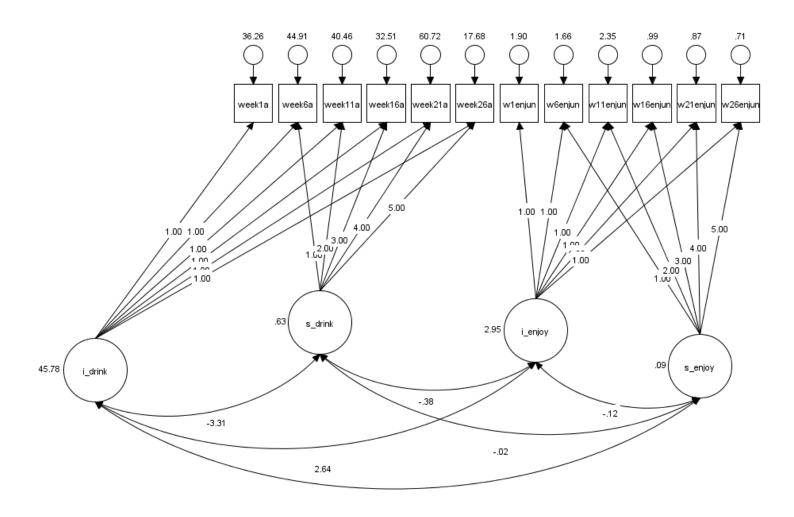
### **Associative LGM (i.e., Trajectory of Two Different Variables)**

I will investigate whether the slope in enjoying courses is associated with the slope in drinking. Here is a LGM of drinking only:



### **Associative LGM (i.e., Trajectory of Two Different Variables)**

```
USEVARIABLES ARE week1a week6a week11a week16a week21a week26a
wlenjun w6enjun w11enjun w16enjun w21enjun w26enjun;
model:
I_drink S_drink | week1a@0 week6a@1 week11a@2 week16a@3 week21a@4 week26a@5;
I_enjoy S_enjoy | w1enjun@0 w6enjun@1 w11enjun@2 w16enjun@3 w21enjun@4 w26enjun@5;
output: sampstat residual stdyx tech4 modindices;
```



## **Associative LGM (i.e., Trajectory of Two Different Variables)**

Loglikelihood						
HO Value	-10767.889					
H1 Value	-10665.836	Means				
		I DRINK	6.309	0.407	15.514	0.000
Information Criteria		S DRINK	-0.454	0.083	-5.485	0.000
		I ENJOY	7.240	0.100	72.342	0.000
Akaike (AIC)	21587.778	S ENJOY	-0.144	0.022	-6.408	0.000
Bayesian (BIC)	21692.388	_				
Sample-Size Adjusted BIC	21609.884					
(n* = (n + 2) / 24)		Variances				
		I_DRINK	45.779	5.085	9.003	0.000
Chi-Square Test of Model Fit		S_DRINK	0.631	0.287	2.201	0.028
		I ENJOY	2.949	0.290	10.181	0.000
Value	204.105	S ENJOY	0.093	0.014	6.705	0.000
Degrees of Freedom	64	_				
P-Value	0.0000					
RMSEA (Root Mean Square Error Of App	roximation)	S DRINK WITH				
		- I DRINK	-0.616	0.090	-6.833	0.000
Estimate	0.073					
90 Percent C.I.	0.062 0.084	I ENJOY WITH				
Probability RMSEA <= .05	0.000	I DRINK	0.228	0.069	3.307	0.001
		S DRINK	-0.277			0.038
CFI/TLI		5_51.21111	312.,	5.155	2.0.0	3.333
CET	0.925	S_ENJOY WITH				
CFI TLI	0.925	I DRINK	-0.013	0.089	-0.145	0.884
111	0.923	S DRINK	-0.087	0.146	-0.599	0.549
Chi-Square Test of Model Fit for the	Baseline Model	I_ENJOY	-0.220	0.081	-2.701	0.007
Value	1945.417					
Degrees of Freedom	66					
P-Value	0.0000					
SRMR (Standardized Root Mean Square	Residual)					
Value	0.066					
10200	0.000					

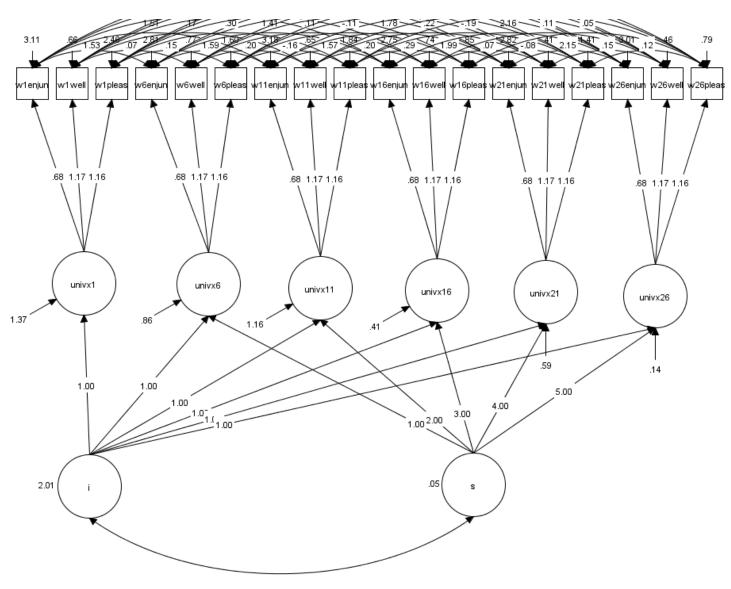
#### **One Trajectory with Time Varying Covariates**

I will investigate the previous trajectory of drinking and add time varying covariates of Enjoyed University. Recall that in the previous example, Enjoyed University was modelled as a separate trajectory. In the present example, I ignore the growth factor of Enjoyed University.

```
model:
I_drink S_drink | week1a@0 week6a@1 week11a@2 week16a@3 week21a@4 week26a@5;
week1a on w1enjun;
week6a on w6enjun;
week11a on w11enjun;
week16a on w16enjun;
week21a on w21enjun;
week26a on w26enjun;
I_drink S_drink with w1enjun w6enjun w11enjun w16enjun w21enjun w26enjun;
output: sampstat residual stdyx tech4 modindices;
```

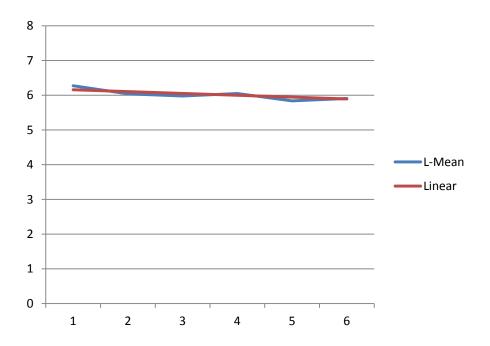
## **One Trajectory with Time Varying Covariates**

Number o	f Free Parameters	56					
Loglikel	ihood		Not	a good m	nodel;		
000000000000000000000000000000000000000	HO Value	-10728.518	COV	ariate do i	not add	much	
000000000000000000000000000000000000000	H1 Value	-10665.836	COV		not ada	mach	
Informat	ion Criteria						
			WEEK1A ON				
	Akaike (AIC)	21569.035	W1ENJUN	0.151	0.225	0.671	0.502
00	Bayesian (BIC)	21794.348					
	Sample-Size Adjusted BIC	21616.648	WEEK6A ON				
000000000000000000000000000000000000000	(n* = (n + 2) / 24)		W6ENJUN	0.228	0.179	1.274	0.203
Chi-Smua	re Test of Model Fit		WEEK11A ON				
oni bquu	re rebo or moder rro		W11ENJUN	0.145	0.159	0.914	0.361
	Value	125.363					
	Degrees of Freedom	34	WEEK16A ON				
	P-Value	0.0000	W16ENJUN	0.265	0.182	1.457	0.145
RMSEA (R	oot Mean Square Error Of App:	roximation)	WEEK21A ON				
1410211 (10	ood nean bquare brior or npp.		W21ENJUN	0.336	0.255	1.320	0.187
	Estimate	0.081					
	90 Percent C.I.	0.066 0.096	WEEK26A ON				
000000000000000000000000000000000000000	Probability RMSEA <= .05	0.000	W26ENJUN	0.285	0.327	0.874	0.382
CFI/TLI			I DRINK WITH				
011,111			W1ENJUN	1.101	1.223	0.900	0.368
	CFI	0.861	W6ENJUN	2.469	1.193	2.069	0.039
	TLI	0.791	W11ENJUN	2.848	1.265	2.251	0.024
		377.22	W16ENJUN	2.331	1.122	2.079	0.038
Chi-Squa	re Test of Model Fit for the	Baseline Model	W21ENJUN	2.411	1.083	2.227	0.026
			W26ENJUN	1.830	1.154	1.587	0.113
	Value	705.935					
	Degrees of Freedom	51	S DRINK WITH				
	P-Value	0.0000	W1ENJUN	-0.282	0.324	-0.872	0.383
			W6ENJUN	-0.540	0.337	-1.602	0.109
SRMR (St	andardized Root Mean Square I	Residual)	W11ENJUN	-0.541	0.333	-1.624	0.104
•		•	W16ENJUN	-0.599	0.364		0.099
S0000000000000000000000000000000000000	Value	0.045	W21ENJUN	-0.654	0.358	-1.829	0.067
V0000000000000000000000000000000000000			W26ENJUN	-0.666	0.412	-1.619	0.106
V0			I DRINK	-3.332	1.000	-3.332	0.001
5				2.002		2.002	2.001



#### Steps:

- Allow residuals of indicators to correlate across time
- Test for strong invariance (loadings and intercepts across time points)
- Constrain loadings and intercepts to equality across time points
- Fix intercepts of the level-1 factors (i.e., univx1 univx2...in this example) at 0
- In Mplus, the intercept growth factor is fixed at 0; free this parameter

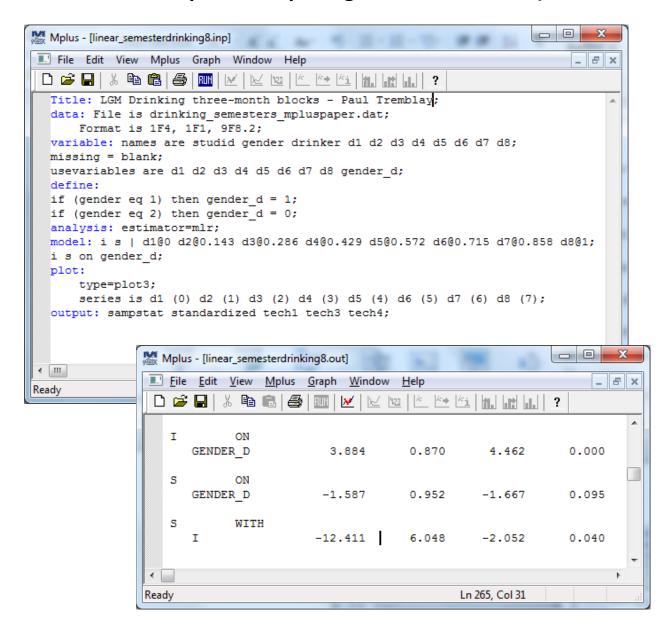


```
MODEL:
univx1 by wlenjun* (L1)
w1well (L2)
w1pleas (L3);
univx6 by w6enjun* (L1)
w6well (L2)
w6pleas (L3);
univx11 by w11enjun* (L1)
w11well (L2)
w11pleas (L3);
univx16 by w16enjun* (L1)
w16well (L2)
w16pleas (L3);
univx21 by w21enjun* (L1)
w21well (L2)
w21pleas (L3);
univx26 by w26enjun* (L1)
w26well (L2)
w26pleas (L3);
[w1enjun] (T1);
[w1well] (T2);
[w1pleas] (T3);
[w6enjun] (T1);
[w6well] (T2);
[w6pleas] (T3);
[w11enjun] (T1);
[w11well] (T2);
[w11pleas] (T3);
[w16enjun] (T1);
[w16well] (T2);
[w16pleas] (T3);
[w21enjun] (T1);
[w21well] (T2);
[w21pleas] (T3);
[w26enjun] (T1);
[w26well] (T2);
[w26pleas] (T3);
```

```
w1pleas with w6pleas w11pleas w16pleas w21pleas w26pleas;
w6pleas with w11pleas w16pleas w21pleas w26pleas;
w11pleas with w16pleas w21pleas w26pleas;
w16pleas with w21pleas w26pleas;
w21pleas with w26pleas;
w1well with w6well w11well w16well w21well w26well;
w6well with w11well w16well w21well w26well:
w11well with w16well w21well w26well;
w16well with w21well w26well;
w21well with w26well;
wlenjun with w6enjun w11enjun w16enjun w21enjun w26enjun;
w6enjun with w11enjun w16enjun w21enjun w26enjun;
w11enjun with w16enjun w21enjun w26enjun;
w16enjun with w21enjun w26enjun;
w21enjun with w26enjun;
![univx1 univx6 univx11 univx16 univx21 univx26];
I S | univx100 univx601 univx1102 univx1603 univx2104 univx2605;
[I];
MODEL CONSTRAINT: L1 = 3 - L2 - L3;
T1 = 0 - T2 - T3;
output: sampstat residual stdyx tech4 modindices (5);
```

Loglikelihood  H0 Value -10821.321 H1 Value -10686.827
H1 Value -10686.827
Information Criteria S WITH
I -0.003 0.033 -0.077 0.93
Akaike (AIC) 21798.643
Bayesian (BIC) 22112.472 Means
Sample-Size Adjusted BIC 21864.960 I 6.158 0.087 71.160 0.00
(n* = (n + 2) / 24) S $-0.053$ 0.018 $-2.998$ 0.003
Chi-Square Test of Model Fit
Variances
Value 268.989 I 1.986 0.210 9.454 0.00
Degrees of Freedom 111 S 0.053 0.010 5.249 0.00
P-Value 0.0000
RMSEA (Root Mean Square Error Of Approximation) Residual Variances
***************************************
Estimate 0.059 UNIVX1 1.444 0.183 7.909 0.000
90 Percent C.I. 0.050 0.068 UNIVX6 0.878 0.120 7.297 0.000
Probability RMSEA <= .05 0.054 UNIVX11 1.171 0.138 8.512 0.000
UNIVX16 0.421 0.070 5.994 0.000
CFI/TLI UNIVX21 0.644 0.089 7.209 0.000
UNIVX26 0.148 0.080 1.846 0.065
CFI 0.970
TLI 0.959
Chi-Square Test of Model Fit for the Baseline Model
Value 5487.539
Degrees of Freedom 153
P-Value 0.0000
SRMR (Standardized Root Mean Square Residual)
Value 0.076

### LGM with Intercept and Slope Regressed on Gender (Time Invariant Covariate)



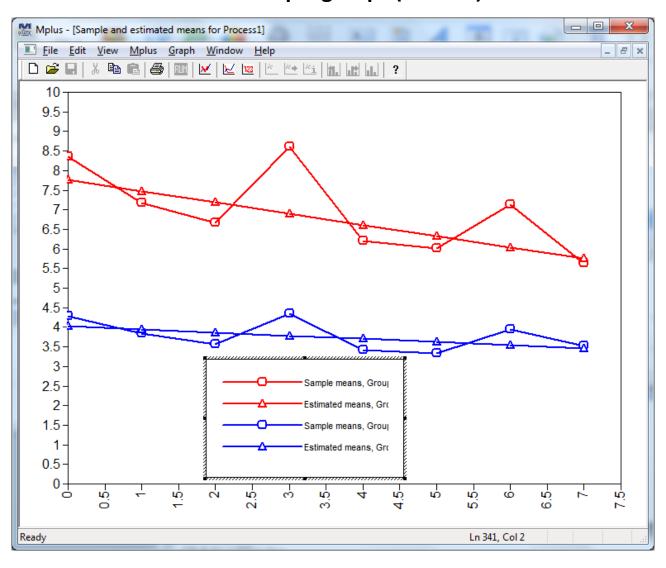
### **LGM Multiple groups (Gender)**

```
Mplus - [linear_semesterdrinking6.inp]
File Edit View Mplus Graph Window Help
                                                                             8 X
 Title: Drinking three-month blocks Paul Tremblay;
  data: File is c:\paul\mplus\may10\drinking semesters mpluspaper.dat;
      Format is 1F4, 1F1, 9F8.2;
  variable: names are studid gender drinker d1 d2 d3 d4 d5 d6 d7 d8;
  missing = blank;
  usevariables are d1 d2 d3 d4 d5 d6 d7 d8;
  grouping is gender (1=male 2=female);
  analysis:
  estimator = mlr;
  model: i s | d1@0 d2@0.143 d3@0.286 d4@0.429 d5@0.572 d6@0.715 d7@0.858 d8@1;
  plot:
      type=plot3;
      series is d1 (0) d2 (1) d3 (2) d4 (3) d5 (4) d6 (5) d7 (6) d8 (7);
  output: sampstat stdyx tech1 tech3 tech4 modindices;
.III.
                                                       Ln 4, Col 57
Ready
```

# **LGM Multiple groups (Gender)**

Mplus - [linear_semester	drinking6.out]			_ D X
<u>File Edit View Mp</u>	us <u>G</u> raph <u>W</u> indow	<u>H</u> elp		_ & ×
	<b>∌</b>   <b>™</b>   <b>⊻</b>   <b>⊵</b>	123   1/4   1/4 →		?
MODEL RESULTS				^
				Two-Tailed
	Estimate	S.E.	Est./S.E.	
Group MALE				
Means				
I	7.764	0.805	9.647	0.000
S	-2.011	0.888	-2.265	0.024
Variances				
I	61.958	16.424	3.772	0.000
S	52.528	19.285	2.724	0.006
Group FEMALE				
Means				
I	4.029	0.312	12.909	0.000
5	-0.569	0.290	-1.961	0.050
Variances				
I	18.580	2.549		0.000
5	10.387	2.640	3.935	0.000
<b>▼</b>				<b>+</b>
Ready			Ln 341, Col 2	

## LGM Multiple groups (Gender)



#### **Measures within Persons**

```
Title: PSY9555 Regression examples;
!note that two outliers of 0 were removed in average;
data: File is sem mplus2.dat;
    Format is 1F4, 1F1, 1F2, 23F8.2, 1F11.3, 72F8.2;
data widetolong: <
wide = drink1 drink2 drink3 drink4:
long = drink:
idvariable = person;
repetition = time;
variable: names are studid gender age
bppa bpv bpa bph bptot
sq1 sq2 sq3 sq4 sq5 sq6 sq7 sq8 sq9 sq10 sq11 sq12 sq13 sq14 sq15
es es pt es fin grade
drink1 drink2 drink3 drink4 epis1 epis2 epis3 epis4
stress1 stress2 stress3 stress4 pleased1 pleased2 pleased3 pleased4
enjoyc1 enjoyc2 enjoyc3 enjoyc4 enjoyu1 enjoyu2 enjoyu3 enjoyu4
effort1 effort2 effort3 effort4 harm1 harm2 harm3 harm4 dep1 dep2 dep3 dep4
drink1b drink2b drink3b drink4b epis1b epis2b epis3b epis4b
stress1b stress2b stress3b stress4b please1b please2b please3b please4b
enjoyc1b enjoyc2b enjoyc3b enjoyc4b enjoyu1b enjoyu2b enjoyu3b enjoyu4b
effort1b effort2b effort3b effort4b harm1b harm2b harm3b harm4b
dep1b dep2b dep3b dep4b;
missing = blank;
usevariables are drink person time;
cluster = person;
within = time:
analysis:
type = twolevel random;
model:
%within%
s | drink on time;
%between%
s with drink:
output: sampstat tech1;
```

When your data file is structured in the conventional one line per subject with repeated measures on the same line

## **Measures within Persons**

Loglikelihood						
HO Value HO Scalin for MLR	g Correction		-4756.126 3.5791		Time 10.076	
Information Criteri	a				(linear) Slope	
			9524.253 9556.568 9537.507		Drink	
MODEL RESULTS	Estimate	S.E.	Est./S.E.	Two-Tailed P-Value	WITHIN	
Within Level					BETWEEN	
Residual Variances DRINK Between Level		1.428	7.056	0.000	Mean = 5.236 Var = 31.765 Drink (intercept)	1
S WITH DRINK	-0.139	1.168	-0.119	0.905	-0.1	.39
Means DRINK S		0.306 0.085	17.090 -1.396	0.000 0.163	Mean =118	
Variances DRINK S	31.765 0.782	4.088 0.478	7.769 1.636	0.000 0.102	Var = .782 Slope	

### Measures within Persons (Previous Model specified as LGM)

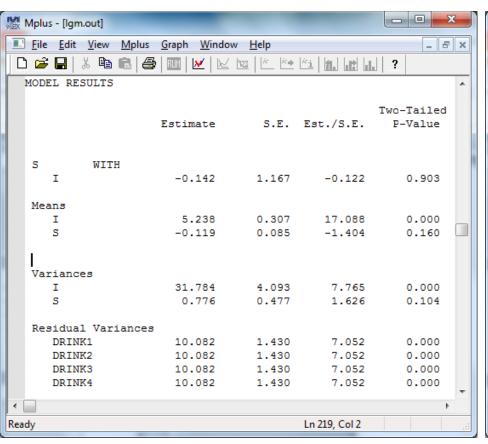
```
Title: PSY9555 Regression examples;
!note that two outliers of 0 were removed in average;
data: File is sem mplus2.dat;
    Format is 1F4, 1F1, 1F2, 23F8.2, 1F11.3, 72F8.2;
!LISTWISE = ON:
variable: names are studid gender age
bppa bpv bpa bph bptot
sq1 sq2 sq3 sq4 sq5 sq6 sq7 sq8 sq9 sq10 sq11 sq12 sq13 sq14 <del>sq1</del>5
es es pt es fin grade
drink1 drink2 drink3 drink4 epis1 epis2 epis3 epis4
stress1 stress2 stress3 stress4 pleased1 pleased2 pleased3 pleased4
enjoyc1 enjoyc2 enjoyc3 enjoyc4 enjoyu1 enjoyu2 enjoyu3 enjoyu4
effort1 effort2 effort3 effort4 harm1 harm2 harm3 harm4 dep1 dep2 dep3 dep4
drink1b drink2b drink3b drink4b epis1b epis2b epis3b epis4b
stress1b stress2b stress3b stress4b please1b please2b please3b please4b
enjoyc1b enjoyc2b enjoyc3b enjoyc4b enjoyu1b enjoyu2b enjoyu3b enjoyu4b
effort1b effort2b effort3b effort4b harm1b harm2b harm3b harm4b
dep1b dep2b dep3b dep4b;
missing = blank;
usevariables are drink1 drink2 drink3 drink4;
analysis:
type = general;
estimator = mlr;
I S | drink1@0 drink2@1 drink3@2 drink4@3;
drink1-drink4 (1); \leftarrow
plot:
type is plot3;
series = drink1 (0) drink2 (1) drink3 (2) drink4 (3);
output: sampstat residual stdyx tech4 modindices;
```

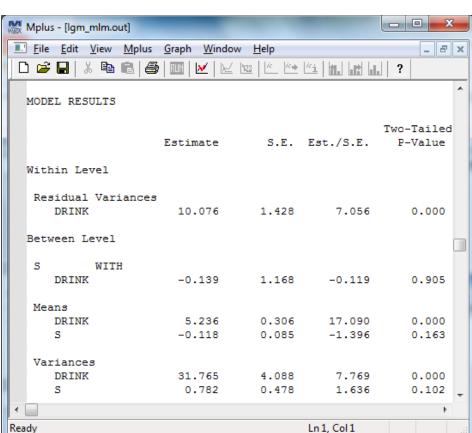
Back to the conventional data structure specification

IN LGM these residuals are usually not constrained to equality but they are in MLM. I constrained them here.

#### **Example: Measures within Persons (LGM and MLM)**

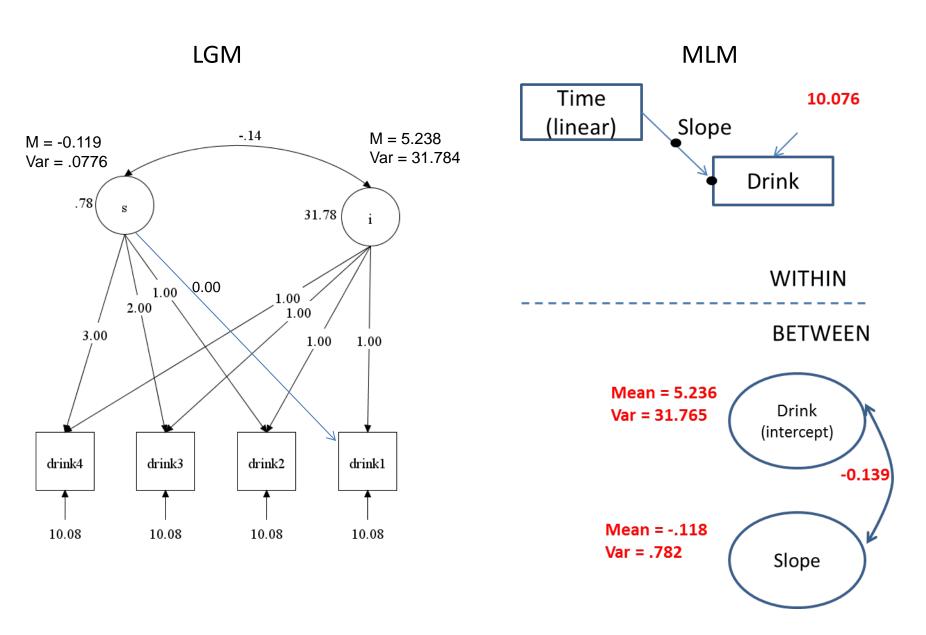
LGM MLM





Same as in slide 13

## **Example: Measures within Persons (LGM and MLM)**



## **Example: Measures within Persons (LGM and MLM)**

LGM MLM

MODEL FIT	INFORMATION		MODEL FIT INFORMATION	
Number of	Free Parameters	6	Number of Free Parameters	6
Loglikeli	hood		Loglikelihood	
	HO Value	-4756.126	HO Value	-4756.126
	HO Scaling Correction Factor for MLR	3.5794	HO Scaling Correction Factor for MLR	3.5791
	H1 Value	-4731.180		
	H1 Scaling Correction Factor for MLR	3.6974	Information Criteria	
			Akaike (AIC)	9524.253
Informati	on Criteria		Bayesian (BIC)	9556.568
			Sample-Size Adjusted BIC	9537.507
	Akaike (AIC)	9524.252	(n* = (n + 2) / 24)	
	Bayesian (BIC)	9548.407		
	Sample-Size Adjusted BIC	9529.368		
	(n* = (n + 2) / 24)			
Chi-Squar	e Test of Model Fit			

13.178\*

0.1059

3.7860

8

Value

P-Value

for MLR

Degrees of Freedom

Scaling Correction Factor