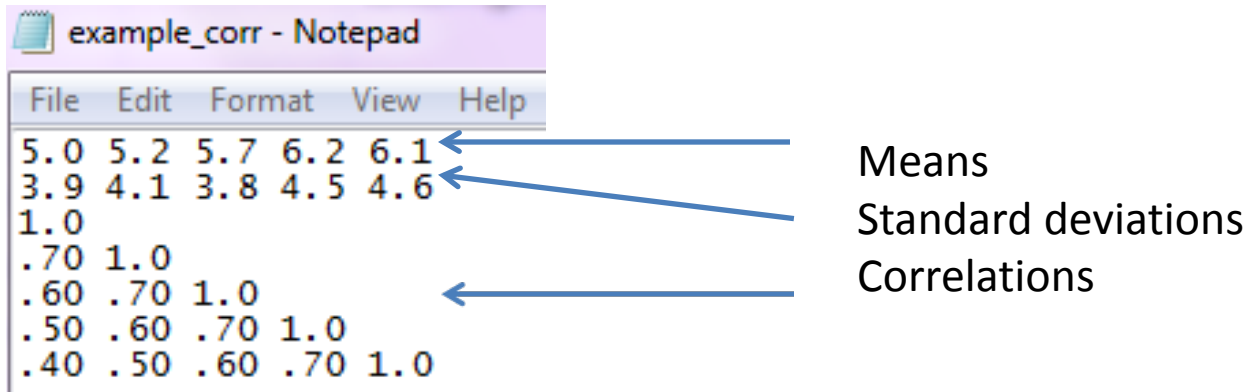


PSY 9556B (Jan8) Design Issues and Missing Data Continued

Examples of Simulations for Projects

- Let's create a data for a variable measured repeatedly over five occasions
- We could create raw data (for each subject) or summary data for the sample
- Here's an example of summary data



File	Edit	Format	View	Help
5.0	5.2	5.7	6.2	6.1
3.9	4.1	3.8	4.5	4.6
1.0				
.70	1.0			
.60	.70	1.0		
.50	.60	.70	1.0	
.40	.50	.60	.70	1.0

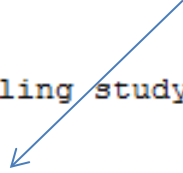
Means
Standard deviations
Correlations

- Notice that I have simulated a growth pattern
- with increasing variation over time
- and fairly substantial stability in rank ordering (correlations) across time
- But with higher correlations for time points in closer proximity

Simulated Data Example: Syntax (Mplus) of a Latent Growth Model

I can analyze a LGM model with summary data

```
Title: Example of a latent-growth-modeling study with summary data;
data:
file is example_corr.txt;
nobservations = 200;
type=correlation means stdeviations;
variable:
names are x1 x2 x3 x4 x5;
usevariables are x1 x2 x3 x4 x5;
analysis:
estimator = ml; !note summary data such as correlation matrix cannot use mlr
model:
I S | x1@0 x2@1 x3@2 x4@3 x5@4;
plot:
type is plot3; !note this function does not work with summary data
series = x1(0) x2(1) x3(2) x4(3) x5(4);
output: sampstat residual stdyx tech4 modindices;
!to make your own plot of the linear trend use the mean intercept as the
!starting point (on the y axis) and add the amount of the mean slope at
!each time unit.
```



Simulated Data Example: LGM Model and Results

Chi-Square Test of Model Fit

Value	14.650
Degrees of Freedom	10
P-Value	0.1454

RMSEA (Root Mean Square Error Of Approximation)

Estimate	0.048	
90 Percent C.I.	0.000	0.098
Probability RMSEA <= .05	0.469	

CFI/TLI

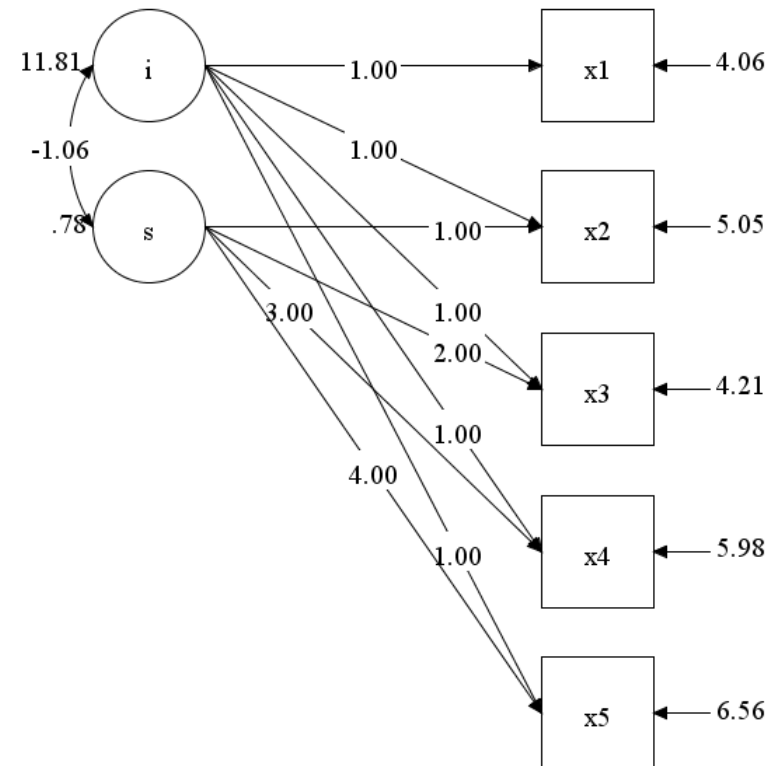
CFI	0.992
TLI	0.992

Chi-Square Test of Model Fit for the Baseline Model

Value	568.088
Degrees of Freedom	10
P-Value	0.0000

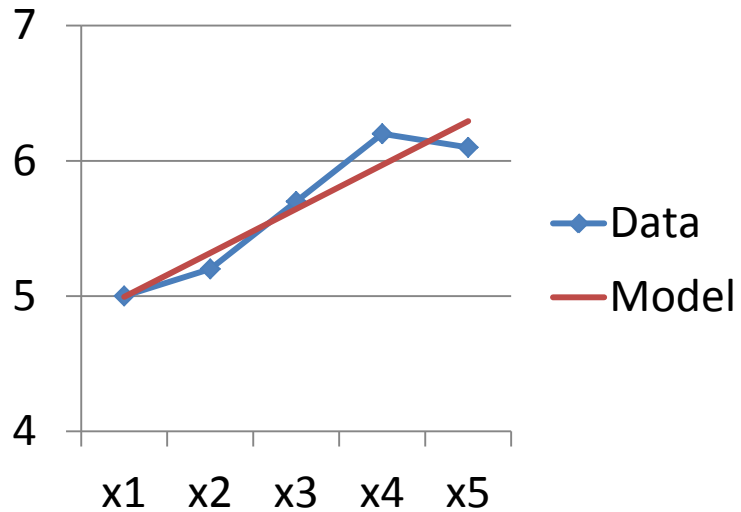
SRMR (Standardized Root Mean Square Residual)

Value	0.047
-------	-------



Simulated Data Example: Results

S	WITH				
I		-1.057	0.362	-2.923	0.003
Means					
I		4.994	0.269	18.569	0.000
S		0.325	0.081	4.021	0.000
Intercepts					
X1		0.000	0.000	999.000	999.000
X2		0.000	0.000	999.000	999.000
X3		0.000	0.000	999.000	999.000
X4		0.000	0.000	999.000	999.000
X5		0.000	0.000	999.000	999.000
Variances					
I		11.810	1.488	7.937	0.000
S		0.784	0.143	5.504	0.000
Residual Variances					
X1		4.056	0.823	4.926	0.000
X2		5.046	0.657	7.685	0.000
X3		4.213	0.547	7.704	0.000
X4		5.979	0.795	7.518	0.000
X5		6.558	1.119	5.861	0.000



Simulated Data Example: Adding a Quadratic Component

model:

I S Q| x1@0 x2@1 x3@2 x4@3 x5@4;

Chi-Square Test of Model Fit

Value	6.228
Degrees of Freedom	6
P-Value	0.3982

RMSEA (Root Mean Square Error Of Approximation)

Estimate	0.014
90 Percent C.I.	0.000 0.094
Probability RMSEA <= .05	0.674

CFI/TLI

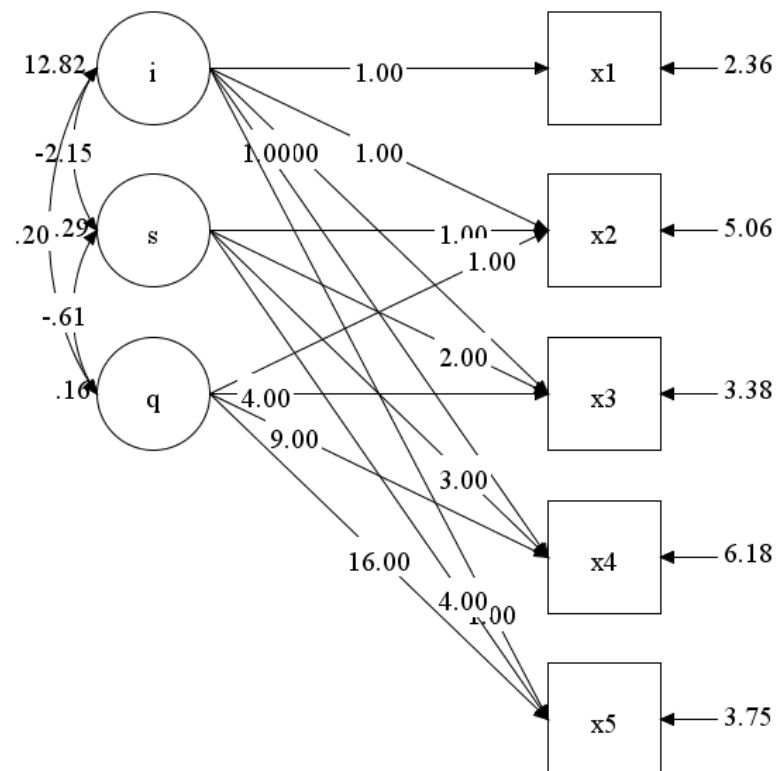
CFI	1.000
TLI	0.999

Chi-Square Test of Model Fit for the Baseline Model

Value	568.088
Degrees of Freedom	10
P-Value	0.0000

SRMR (Standardized Root Mean Square Residual)

Value	0.030
-------	-------

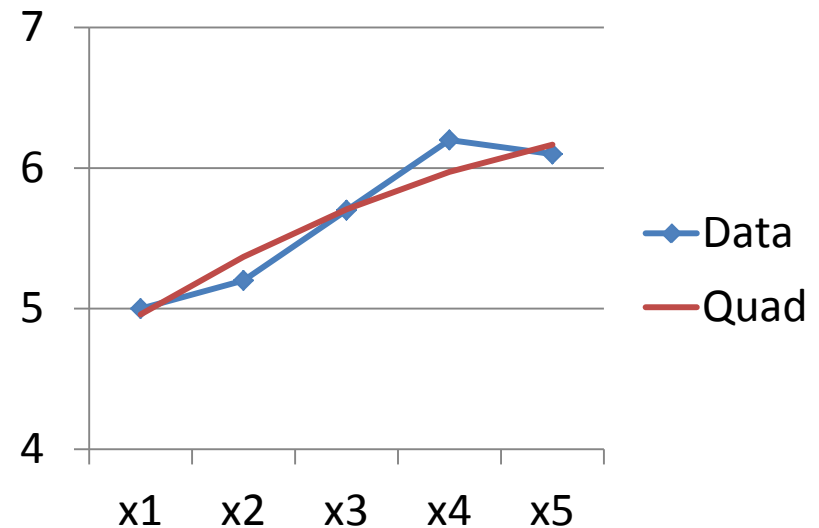


Simulated Data Example: Adding a Quadratic Component

S	WITH				
I		-2.152	1.345	-1.600	0.110
Q	WITH				
I		0.196	0.268	0.731	0.465
S		-0.614	0.262	-2.349	0.019
Means					
I		4.959	0.274	18.085	0.000
S		0.446	0.190	2.347	0.019
Q		-0.036	0.045	-0.801	0.423
Intercepts					
X1		0.000	0.000	999.000	999.000
X2		0.000	0.000	999.000	999.000
X3		0.000	0.000	999.000	999.000
X4		0.000	0.000	999.000	999.000
X5		0.000	0.000	999.000	999.000
Variances					
I		12.815	1.961	6.536	0.000
S		3.294	1.243	2.651	0.008
Q		0.162	0.064	2.539	0.011
Residual Variances					
X1		2.362	1.420	1.663	0.096
X2		5.062	0.696	7.278	0.000
X3		3.380	0.594	5.693	0.000
X4		6.180	0.826	7.484	0.000
X5		3.754	1.759	2.134	0.033

Quadratic not significant

Chisquare diff test (4 df) =
 $14.650 - 6.228 = 8.422$ n.s.
 (crit value at .05 = 9.488)



*Tested a cubic component; n.s.

Simulated Data Example: SPSS MANOVA (matrix data)

```
matrix data variables = rowtype_ d1 d2 d3 d4 d5.  
begin data  
mean 5.0 5.2 5.7 6.2 6.1  
stddev 3.9 4.1 3.8 4.5 4.6  
n 200 200 200 200 200  
corr 1  
corr .7 1  
corr .6 .7 1  
corr .5 .6 .7 1  
corr .4 .5 .6 .7 1  
end data.  
manova d1 to d5  
/transform (d1 d2 d3 d4 d5) = polynomial  
/print= cellinfo (all) error transform param(all) signif (efsize) signif (multiv univ)  
/ matrix=in(*)  
/ design.
```

Note that to get equivalent results in LGM residuals are set to 0 and you
Would need some codes for polynomials instead of the 0, 1, 2, 3, 4

Simulated Data Example: Using Montecarlo in Mplus

- In my previous example, the simulated data was a sample
- It would be possible to create a population instead with the same parameters
- Once we have a population, we can obtain random samples and study properties such as sample size and power.
- Let's try an example using the Montecarlo procedure in Mplus
- Using the previous LGM analysis syntax, I add a line at the end "savedata:" to save the parameters describing the model for further analysis with Montecarlo.

```
Title: Example of a latent-growth-modeling study with summary data;
data:
file is example_corr.txt;
nobservations = 200;
type=correlation means stdeviations;
variable:
names are x1 x2 x3 x4 x5;
usevariables are x1 x2 x3 x4 x5;
analysis:
estimator = ml; !note summary data such as correlation matrix cannot use mlr
model:
I S Q| x1@0 x2@1 x3@2 x4@3 x5@4;
plot:
series = x1(0) x2(1) x3(2) x4(3) x5(4);
output: sampstat residual stdyx tech4 modindices;
savedata: estimates = lgmestimates.dat;
```


Simulated Data Example: Using Montecarlo in Mplus

```
montecarlo:
names are x1 x2 x3 x4 x5;
nobservations = 200;
nreps = 1000;
seed = 45335;
save = repl.dat;
population = lgmestimates.dat;
coverage = lgmestimates.dat;
model population:
I S Q| x1@0 x2@1 x3@2 x4@3 x5@4;
model:
I S Q| x1@0 x2@1 x3@2 x4@3 x5@4;
output: tech9;
```

MODEL RESULTS

	Population	ESTIMATES Average	Std. Dev.	S. E. Average	M. S. E.	95% Cover	% Sig Coeff
WITH							
S							
I	-2.152	-2.1136	1.2862	1.3420	1.6541	0.952	0.325
WITH							
Q							
I	0.196	0.1882	0.2584	0.2670	0.0668	0.951	0.082
S	-0.614	-0.6059	0.2686	0.2614	0.0722	0.945	0.659
Means							
I	4.959	4.9385	0.2677	0.2732	0.0720	0.956	1.000
S	0.446	0.4485	0.2013	0.1894	0.0405	0.933	0.643
Q	-0.036	-0.0367	0.0481	0.0449	0.0023	0.933	0.161
Intercepts							
X1	0.000	0.0000	0.0000	0.0000	0.0000	1.000	0.000
X2	0.000	0.0000	0.0000	0.0000	0.0000	1.000	0.000
X3	0.000	0.0000	0.0000	0.0000	0.0000	1.000	0.000
X4	0.000	0.0000	0.0000	0.0000	0.0000	1.000	0.000
X5	0.000	0.0000	0.0000	0.0000	0.0000	1.000	0.000
Variances							
I	12.815	12.7244	1.9484	1.9555	3.8007	0.947	1.000
S	3.294	3.2574	1.2526	1.2424	1.5688	0.940	0.758
Q	0.162	0.1595	0.0662	0.0638	0.0044	0.941	0.715
Residual Variances							
X1	2.362	2.3705	1.3434	1.4213	1.8029	0.964	0.380
X2	5.062	5.0790	0.6574	0.6967	0.4320	0.965	1.000
X3	3.380	3.3683	0.6097	0.5931	0.3715	0.941	1.000
X4	6.180	6.1958	0.8643	0.8268	0.7465	0.935	1.000
X5	3.754	3.7529	1.8003	1.7551	3.2379	0.945	0.574

Simulated Data Example: Using Montecarlo in Mplus

```
TITLE: growth1.inp normal, no covariate, no missing
MONTECARLO:
NAMES ARE x1-x5;
NOOBSERVATIONS = 200;
NREPS = 1000;
SEED = 53487;
SAVE = growth1.sav;
ANALYSIS:
MODEL POPULATION:
i s q | x1@0 x2@1 x3@2 x4@3 x5@4;
[x1-x5@0];
[i*4.959 s*0.446 q*-0.036];
i*12.815;
s*3.294;
q*0.162;
i WITH s*-2.152;
i WITH q*0.196;
s WITH q*-.614;
x1*2.362;
x2*5.062;
x3*3.380;
x4*6.180;
x5*3.754;
MODEL:
i s q | x1@0 x2@1 x3@2 x4@3 x5@4;
[x1-x5@0];
[i*4.959 s*0.446 q*-0.036];
i*12.815;
s*3.294;
q*0.162;
i WITH s*-2.152;
i WITH q*0.196;
s WITH q*-.614;
x1*2.362;
x2*5.062;
x3*3.380;
x4*6.180;
x5*3.754;
OUTPUT: TECH9;
```

Alternatively, you could specify the parameters yourself. In this example, you would specify the mean intercept and slope, the variance of the intercepts and slopes, the correlation between the slopes and intercepts, and the residuals.

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TEACHER'S CORNER

How to Use a Monte Carlo Study to Decide on Sample Size and Determine Power

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Understanding the Three Mechanisms of Missing Data

RISK	Reading Score	MCAR	MAR	NMAR
Disadv	174	174	174	.
Disadv	179	.	.	.
Disadv	194	194	194	.
Disadv	194	194	194	.
Disadv	203	203	.	.
Disadv	206	.	.	206
Disadv	209	209	.	209
Disadv	213	213	213	213
Disadv	233	233	233	233
Disadv	248	.	.	248
Adv	208	208	208	208
Adv	217	217	217	217
Adv	219	219	219	219
Adv	221	221	221	221
Adv	225	.	225	225
Adv	228	.	228	228
Adv	234	234	234	234
Adv	236	236	236	236
Adv	236	236	236	236
Adv	243	243	243	243

From Long, J. D. (2012). *Longitudinal data analysis for the behavioral sciences using R*. Thousand Oaks Sage, California: Sage. (p. 91)

Simulation Example of Missing Data

	x1	x2	x3	x4	x5	new1	new2
1	4.664270	.532908	1.093350	-.088013	-7.890250	-7.89	999.00
2	.077985	.220060	.817038	-3.586656	-4.809571	-4.81	999.00
3	1.620843	.985304	4.112497	1.413266	-4.304725	-4.30	999.00
4	4.204337	4.618360	2.314004	-.964795	-3.037667	-3.04	999.00
5	7.918704	.731640	1.249133	-.493786	-2.953642	-2.95	999.00
6	-2.666700	-2.295355	-4.158282	-2.220752	-2.916542	-2.92	999.00
7	.535243	1.373632	-4.169932	1.833149	-2.684271	-2.68	999.00
8	-.277904	-1.049819	-.643203	-.503458	-2.381333	-2.38	999.00
9	1.082189	6.667872	7.732547	-.349096	-2.357714	-2.36	999.00
10	1.089092	4.720787	.029987	-.325337	-2.190490	-2.19	999.00
11	2.028279	4.427999	5.199293	4.125208	-1.365259	-1.37	-1.37
12	.590648	-.149356	5.137088	3.811625	-1.160693	-1.16	-1.16
13	-4.613561	-.443791	.751505	-3.472063	-1.019762	-1.02	-1.02
14	.546872	-1.053835	1.869084	-1.048805	-1.018047	-1.02	-1.02
15	-1.328994	2.811242	2.084779	2.368853	-.990130	-.99	-.99
16	1.538687	.448791	-1.362049	1.386721	-.969791	-.97	-.97
17	1.195198	-1.130505	.936015	-2.308565	-.841942	-.84	-.84
18	-.999140	2.314413	2.610304	1.905061	-.807042	-.81	-.81
19	4.491838	3.073584	1.752912	-.049674	-.696999	-.70	-.70
20	5.890434	7.076167	9.228248	6.462100	-.568524	-.57	-.57
21	2.290458	2.489073	5.752497	3.977106	.209326	.21	.21
22	10.049971	9.525242	1.538150	6.319548	.486037	.49	.49
23	5.323121	7.264900	3.657205	9.248732	.538043	.54	.54
24	-1.097981	.489432	.088079	3.808075	.651980	.65	.65
25	-2.076057	-2.582060	3.244246	.974815	.749493	.75	.75
26	2.052521	6.715822	4.975799	3.186590	.778931	.78	.78
27	7.790298	3.480114	10.860715	10.358933	.849868	.85	.85
28	6.572593	4.117977	3.012412	6.617684	1.231090	999.00	1.23
29	3.800202	3.017381	3.473497	-3.425224	1.307617	1.31	1.31

Data derived from previous LGM model with 200 cases

New1 is a duplicate of X5 with 10 cases MCAR

New2 is a duplicate of X5 with 10 cases MNAR

Simulation Example of Missing Data

Lets see what happens to the descriptive statistics when we use a listwise deletion.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
x5	200	-7.890250	18.340545	5.92731016	4.438446019
new1	190	-7.89	18.34	5.9426	4.47728
new2	190	-1.37	18.34	6.4263	3.94866
Valid N (listwise)	180				

Correlations

		x5	new1	new2
x1	Pearson Correlation	.492	.505	.476
	Sig. (2-tailed)	.000	.000	.000
	N	200	190	190
x2	Pearson Correlation	.556	.555	.525
	Sig. (2-tailed)	.000	.000	.000
	N	200	190	190
x3	Pearson Correlation	.687	.691	.666
	Sig. (2-tailed)	.000	.000	.000
	N	200	190	190
x4	Pearson Correlation	.708	.713	.663
	Sig. (2-tailed)	.000	.000	.000
	N	200	190	190

- The true mean value is 5.927 (variable x5)
- New1 has a similar mean of 5.943 because it was MCAR
- New2 has a biased mean of 6.426 because it was MNAR
- See also standard deviation and correlation differences

Multiple Imputation of new2

The screenshot displays the IBM SPSS Statistics Data Editor window with the 'rep1-missing.sav' dataset. The 'Analyze' menu is open, and the 'Multiple Imputation' option is selected. The 'Impute Missing Data Values...' dialog box is open, showing the 'Variables' tab. The 'Variables' list contains 'x5' and 'new1'. The 'Variables in Model' list contains 'new2', 'x1', 'x2', 'x3', and 'x4'. The 'Imputations' field is set to 5. The 'Location of Imputed Data' section has 'Create a new dataset' selected, with the 'Dataset name' field containing 'imputeddata'. The 'Analysis Weight' field is empty. The 'OK' button is highlighted.

rep1-missing.sav [DataSet1] - IBM SPSS Statistics Data Editor

File Edit View Data Transform Analyze Direct Marketing Graphs Utilities Add-ons Window Help

Visible: 7 of 7 Variables

	x1	x4	x5	new1	new2	var	var	var	var	var	var
1	4.664270		-0.88013	-7.890250	-7.89	999.00					
2	.077985		-3.586656	-4.809571	-4.81	999.00					
3	1.620843		1.413266	-4.304725	-4.30	999.00					
4	4.204337		-.964795	-3.037667	-3.04	999.00					
5	7.918704		-.493786	-2.953642	-2.95	999.00					
6	-2.666700		-2.220752	-2.916542	-2.92	999.00					
7	.535243		1.833149	-2.684271	-2.68	999.00					
8	-.277904		-.503458	-2.381333	-2.38						
9	1.082189		-.349096	-2.357714	-2.36						
10	1.089092		-.325337	-2.190490	-2.19						
11	2.028279		4.125208	-1.365259	-1.37						
12	.590648		3.811625	-1.160693	-1.16						
13	-4.613561		-.3472063	-1.019762	-1.02						
14	.546872		-1.048805	-1.018047	-1.02						
15	-1.328994		2.368853	-.990130	-.99						
16	1.538687		1.386721	-.969791	-.97						
17	1.195198				-.84						
18	-.999140				-.81						
19	4.491838				-.70						
20	5.890434				-.57						
21	2.290458				.21						
22	10.049971				.49						
23	5.323121				.54						
24	-1.097981				.65						
25	-2.076057				.75						
26	2.052521				.78						
27	7.790298				.85						
28	6.572593				999.00						
29	3.800202				1.31						

Impute Missing Data Values

Variables Method Constraints Output

Variables: x5, new1

Variables in Model: new2, x1, x2, x3, x4

Analysis Weight:

Imputations: 5

Location of Imputed Data

☒ Create a new dataset

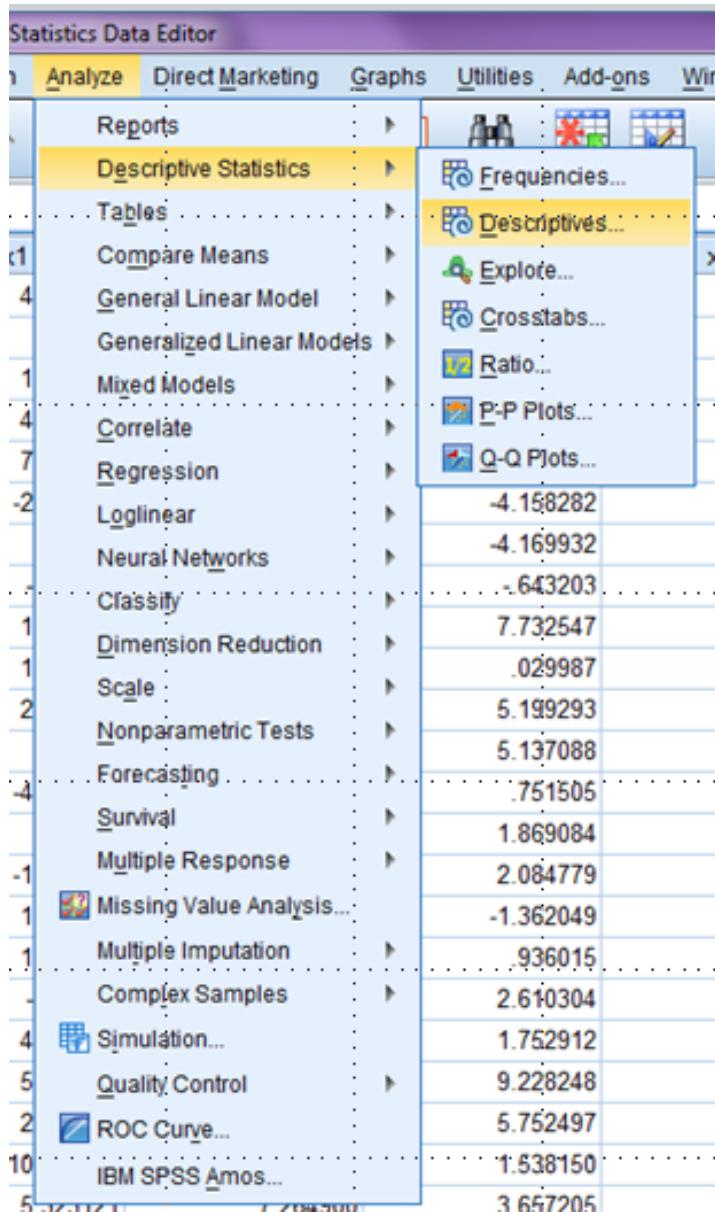
Dataset name: imputeddata

☐ Write to a new data file

After generating a dataset containing the imputed values, you can use ordinary SPSS Statistics analysis procedures marked by the icon to analyze your data. See Help for a complete list of supported analysis procedures.

OK Paste Reset Cancel Help

Multiple Imputation of new2



Descriptive Statistics

Imputation	Imputation Number	N	Minimum	Maximum	Mean	Std. Deviation
Original data	new2	190	-1.37	18.34	6.4263	3.94866
	Valid N (listwise)	190				
1	new2	200	-1.37	18.34	6.2683	3.95366
	Valid N (listwise)	200				
2	new2	200	-3.92	18.34	6.2139	4.04366
	Valid N (listwise)	200				
3	new2	200	-1.40	18.34	6.2341	3.97070
	Valid N (listwise)	200				
4	new2	200	-3.36	18.34	6.1913	4.03663
	Valid N (listwise)	200				
5	new2	200	-5.65	18.34	6.1542	4.11310
	Valid N (listwise)	200				
Pooled	new2	200			6.2123	
	Valid N (listwise)	200				

Note that the pooled mean of 6.21 is better than the listwise value of 6.43 in approximating the correct value of 5.93 but there is still some bias due to the fact that it was missing not at random (MNAR)

Missing Data Estimation with FIML in Mplus

- Continuing with our example, I specify a simple basic analysis in Mplus.
- I start with a LISTWISE deletion.
- As can be seen below, 10 cases are deleted ($200 - 10 = 190$)

```
DATA:
  FILE IS C:\Users\ptrembla\Documents\Longitudinal course\LGM examples\rep1-missing.dat;
LISTWISE=ON;
VARIABLE:
  MISSING ARE ALL (999);
  NAMES ARE x1 x2 x3 x4 x5 new1 new2;
  USEVARIABLES ARE x1 x2 x3 x4 new2;
ANALYSIS:
  type = basic;
OUTPUT: sampstat;
```

SUMMARY OF ANALYSIS

Number of groups	1
Number of observations	190
Number of dependent variables	5
Number of independent variables	0
Number of continuous latent variables	0

Observed dependent variables

Continuous					
X1	X2	X3	X4	NEW2	

Estimator	ML
-----------	----

Missing Data Estimation in Mplus: Listwise Deletion

SAMPLE STATISTICS

Means					
	X1	X2	X3	X4	NEW2
1	5.211	5.798	6.202	6.202	6.426
Covariances					
	X1	X2	X3	X4	NEW2
X1	13.320				
X2	9.709	14.095			
X3	7.256	9.392	13.196		
X4	6.727	9.003	9.925	16.521	
NEW2	6.853	7.777	9.549	10.640	15.592
Correlations					
	X1	X2	X3	X4	NEW2
X1	1.000				
X2	0.709	1.000			
X3	0.547	0.689	1.000		
X4	0.453	0.590	0.672	1.000	
NEW2	0.476	0.525	0.666	0.663	1.000

- As can be seen all means are biased (compare to SPSS) but New2 has the same value in both analyses as expected

Descriptive Statistics

	N	Maximum	Mean	Std. Deviation
x1	200	16.505708	5.04160956	3.688753275
x2	200	19.249330	5.59053005	3.816377768
x3	200	14.869597	5.93351681	3.804905237
x4	200	17.939640	5.86592636	4.238476275
new2	190	18.34	6.4263	3.94866
x5	200	18.340545	5.92731016	4.438446019
Valid N (listwise)	190			

From SPSS

Maximum Likelihood Estimation of Missing Data:???

- In this example I use the default ML missing data estimation.
- However, I have only one variable in my model: New2
- There is no other information for estimating missing data
- Therefore the results remain the same (i.e., mean = 6.426)

```
DATA:
  FILE IS C:\Users\ptrembla\Documents\Longitudinal course\LGM examples\rep1-missing.dat;
VARIABLE:
  MISSING ARE ALL (999);
  NAMES ARE x1 x2 x3 x4 x5 new1 new2;
  USEVARIABLES new2;
ANALYSIS:
  type = basic;
OUTPUT: sampstat;
```

SUMMARY OF ANALYSIS		ESTIMATED SAMPLE STATISTICS	
Number of groups	1		
Number of observations	190		
Number of dependent variables	1	Means	
Number of independent variables	0	NEW2	
Number of continuous latent variables	0		
Observed dependent variables		1	6.426
Continuous			
NEW2			
Estimator	ML		

Maximum Likelihood Estimation of Missing Data

- Now we have x1 x2 x3 x4 in the model that will perhaps help in the estimation
- Note that we have 200 cases (not 190)

```
DATA:
  FILE IS C:\Users\ptrembla\Documents\Longitudinal course\LGM examples\repl-missing.dat;
VARIABLE:
  MISSING ARE ALL (999);
  NAMES ARE x1 x2 x3 x4 x5 new1 new2;
  USEVARIABLES x1 x2 x3 x4 new2;
ANALYSIS:
  type = basic;
OUTPUT: sampstat;
```

SUMMARY OF ANALYSIS

Number of groups	1
Number of observations	200
Number of dependent variables	5
Number of independent variables	0
Number of continuous latent variables	0

Observed dependent variables

Continuous					
X1	X2	X3	X4	NEW2	

Estimator

ML

Maximum Likelihood Estimation of Missing Data

SUMMARY OF DATA

Number of missing data patterns

2



SUMMARY OF MISSING DATA PATTERNS

MISSING DATA PATTERNS (x = not missing)

	1	2
X1	x	x
X2	x	x
X3	x	x
X4	x	x
NEW2	x	

MISSING DATA PATTERN FREQUENCIES

Pattern	Frequency	Pattern	Frequency
1	190	2	10

COVARIANCE COVERAGE OF DATA

Minimum covariance coverage value 0.100

PROPORTION OF DATA PRESENT

	Covariance Coverage				
	X1	X2	X3	X4	NEW2
X1	1.000				
X2	1.000	1.000			
X3	1.000	1.000	1.000		
X4	1.000	1.000	1.000	1.000	
NEW2	0.950	0.950	0.950	0.950	0.950

Two patterns of missing data:

1. No values missing
2. Values missing on New2

Maximum Likelihood Estimation of Missing Data

- Note that the mean for New2 is now 6.180. This value is comparable to the multiple imputed value of 6.21 on the SPSS analysis
- Due the MNAR mechanism it was impossible to eliminate all the bias

ESTIMATED SAMPLE STATISTICS

Means					
	X1	X2	X3	X4	NEW2
1	5.042	5.591	5.934	5.866	6.180
Covariances					
	X1	X2	X3	X4	NEW2
X1	13.539				
X2	9.936	14.492			
X3	7.888	10.226	14.405		
X4	7.488	9.878	11.112	17.875	
NEW2	7.410	8.450	10.524	11.685	16.380
Correlations					
	X1	X2	X3	X4	NEW2
X1	1.000				
X2	0.709	1.000			
X3	0.565	0.708	1.000		
X4	0.481	0.614	0.692	1.000	
NEW2	0.498	0.548	0.685	0.683	1.000

$$Sd = \sqrt{16.38} = 4.05$$

Descriptive Statistics

	N	Maximum	Mean	Std. Deviation
x1	200	16.505708	5.04160956	3.688753275
x2	200	19.249330	5.59053005	3.816377768
x3	200	14.869597	5.93351681	3.804905237
x4	200	17.939640	5.86592636	4.238476275
new2	190	18.34	6.4263	3.94866
x5	200	18.340545	5.92731016	4.438446019
Valid N (listwise)	190			

Mplus Examples: Maximum Likelihood Estimation

Auxiliary Variables

The analysis below is similar to the previous one with the exception that x1, x2, x3, x4 are not brought into the model but are used to estimate missing data in New2. (Produces identical estimates)

DATA:

FILE IS C:\Users\ptrembla\Documents\Longitudinal course\LGM examples\repl-missing.dat;

VARIABLE:

MISSING ARE ALL (999);

NAMES ARE x1 x2 x3 x4 x5 new1 new2;

USEVARIABLES new2;

AUXILIARY = (m) x1 x2 x3 x4;

Specification of auxiliary variables in missing analysis (m)

ANALYSIS:

MODEL:

new2;

OUTPUT: sampstat;

ESTIMATED SAMPLE STATISTICS

SUMMARY OF ANALYSIS

Number of groups	1
Number of observations	200
Number of dependent variables	1
Number of independent variables	0
Number of continuous latent variables	0

Observed dependent variables

Continuous
NEW2

Observed auxiliary variables

X1 X2 X3 X4

Estimator

ML

Means	
NEW2	
1	6.180
Covariances	
NEW2	
NEW2	16.380
Correlations	
NEW2	
NEW2	1.000

Imputation in Mplus

EXAMPLE 11.6: MULTIPLE IMPUTATION FOLLOWED BY THE ESTIMATION OF A GROWTH MODEL USING MAXIMUM LIKELIHOOD

```
TITLE:      this is an example of multiple imputation
             followed by the estimation of a growth
             model using maximum likelihood
DATA:       FILE = ex11.6.dat;
VARIABLE:   NAMES = x1 y1-y4 z x2;
             USEVARIABLES = y1-y4 x1 x2;
             MISSING = ALL(999);
DATA IMPUTATION:
             IMPUTE = y1-y4 x1 (c) x2;
             NDATASETS = 10;
ANALYSIS:   ESTIMATOR = ML;
MODEL:      i s | y1@0 y2@1 y3@2 y4@3;
             i s ON x1 x2;
OUTPUT:     TECH1 TECH8;
```

See p. 398-399 Mplus manual Version 7