

Supplementary Notes on Multiple Imputation.

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Part A: Comparison with FIML in the case of normal data.

Stephen du Toit

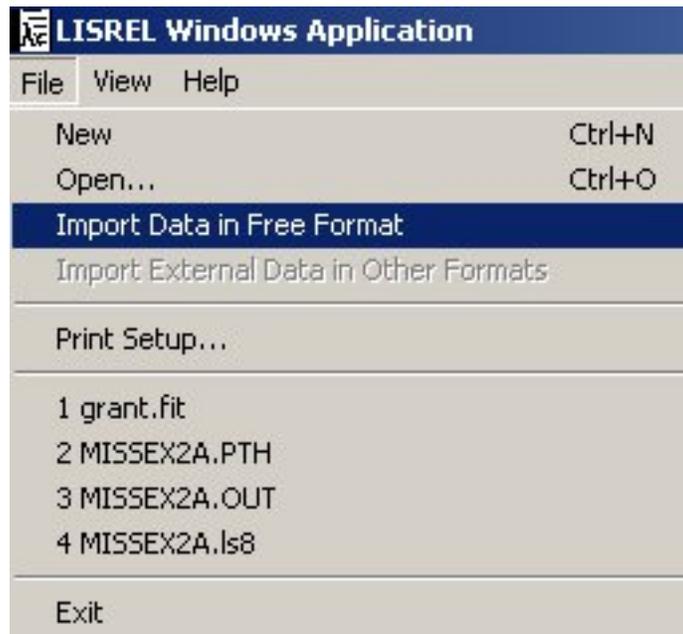
Multivariate data sets, where missing values occur on more than one variable, are often encountered in practice. Listwise deletion may result in discarding a large proportion of the data, which in turn, tends to introduce bias.

Researchers frequently use *ad hoc* methods of imputation to obtain a complete data set. The multiple imputation procedure implemented in LISREL 8.7 is described in detail in Schafer (1997) and uses the EM algorithm and the method of generating random draws from probability distributions via Markov chains (MCMC algorithm). Technical details of these methods are given in the *Interactive LISREL: User's Guide*, pages 387-388. Also see pages 165-170 of the same guide for an example.

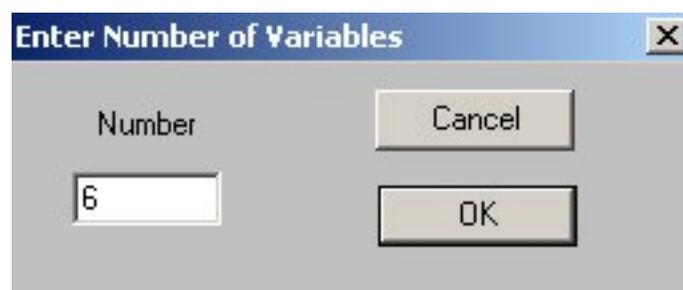
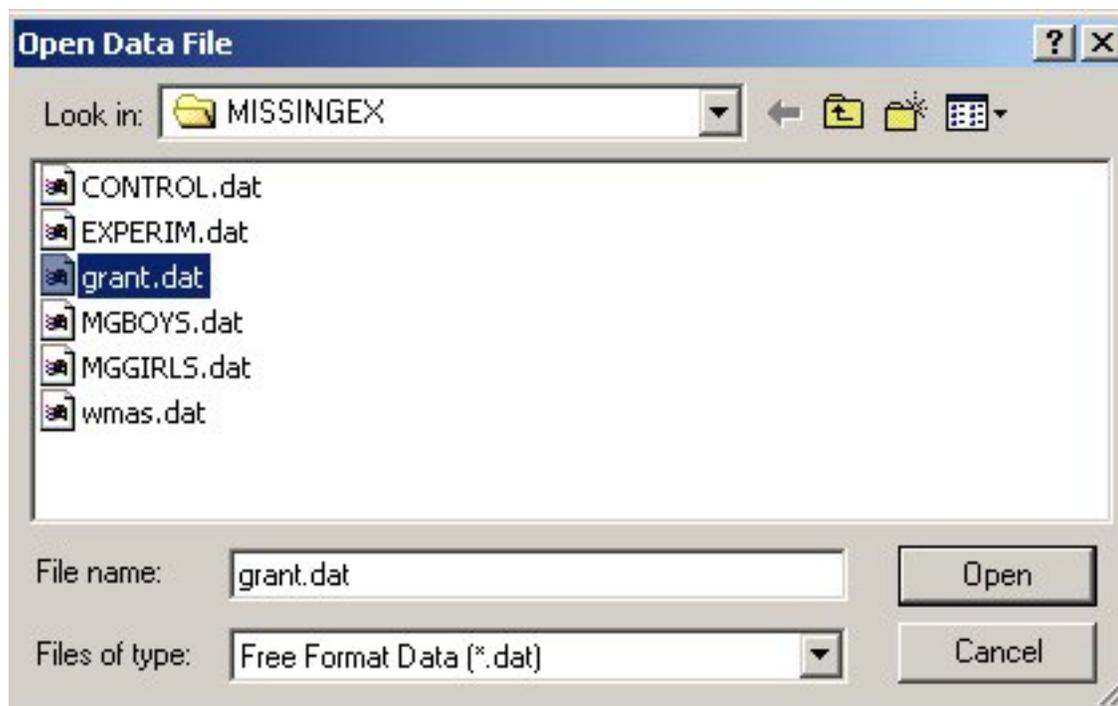
For approximately normally distributed data, with values missing at random, the optimal strategy for fitting structural equation models is to use a full information normal maximum likelihood (FIML) procedure such as the one implemented in LISREL8.7. FIML is illustrated with the set of examples in the **missingex** folder of the LISREL8.7 installation. Part A illustrates this point by showing how one can fit a series of SEM models based on imputed datasets. The means of the estimated parameters thus obtained are subsequently compared with the estimated parameters obtained using FIML.

In Part B, Gerhard Mels investigates the non-normal case and compares robust maximum likelihood (RML) with FIML.

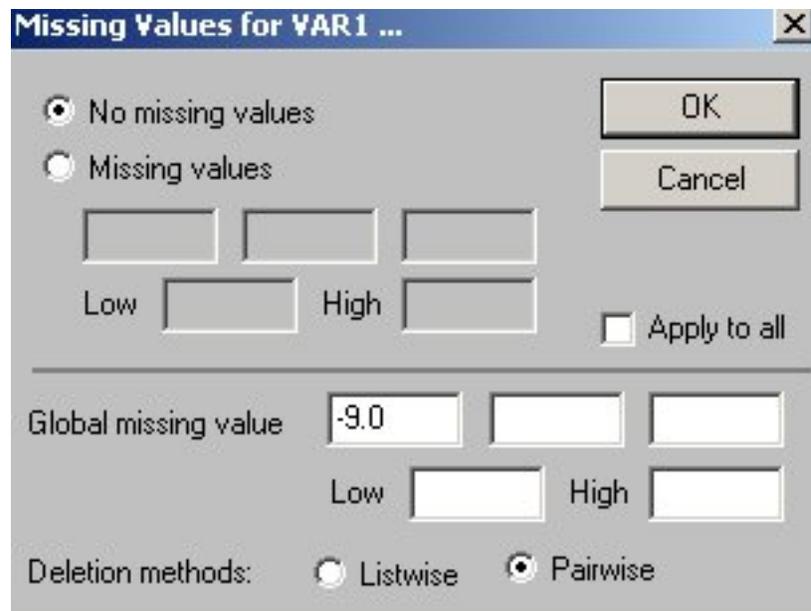
The data set **grant.dat** (simulated data) is based on a real data set containing nine psychological tests administered to seventh- and eighth-grade students (see page 140 of the *LISREL User's Guide*). Only the first 6 variables VISPERC, CUBES, LOZENGES, PARAGRAF, SENTENC and WORDMEAN are considered here. The first three variables are assumed to measure spatial perception and variables four to six verbal perception. From the main menu bar, select the **File, Import Data in Free Format** option.



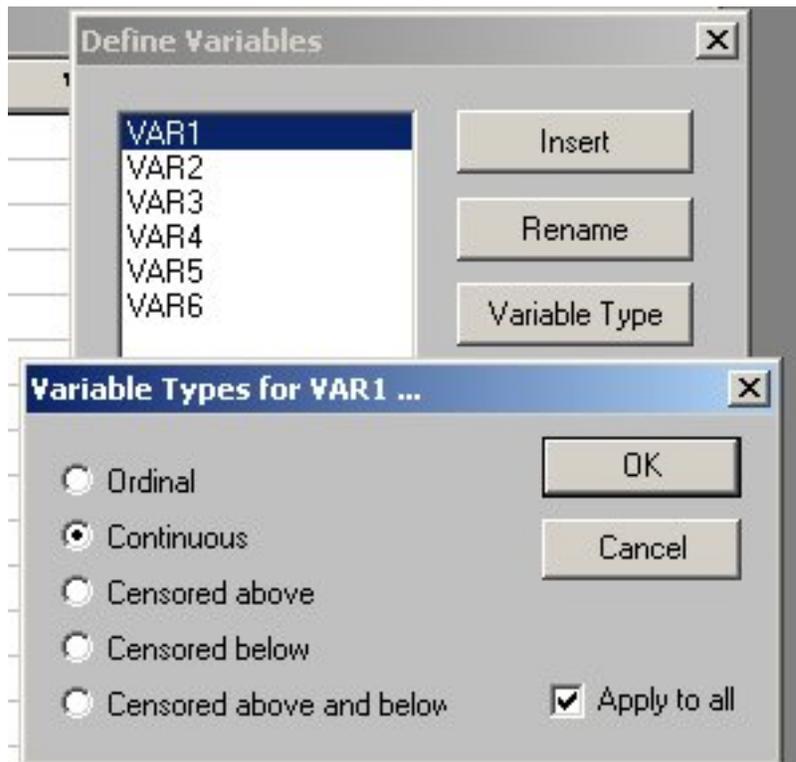
Select the file **grant.dat** from the **missingex** folder. Once selected, click **Open** to activate the **Enter Number of Variables** dialog box. Enter 6 in the **Number** string field.



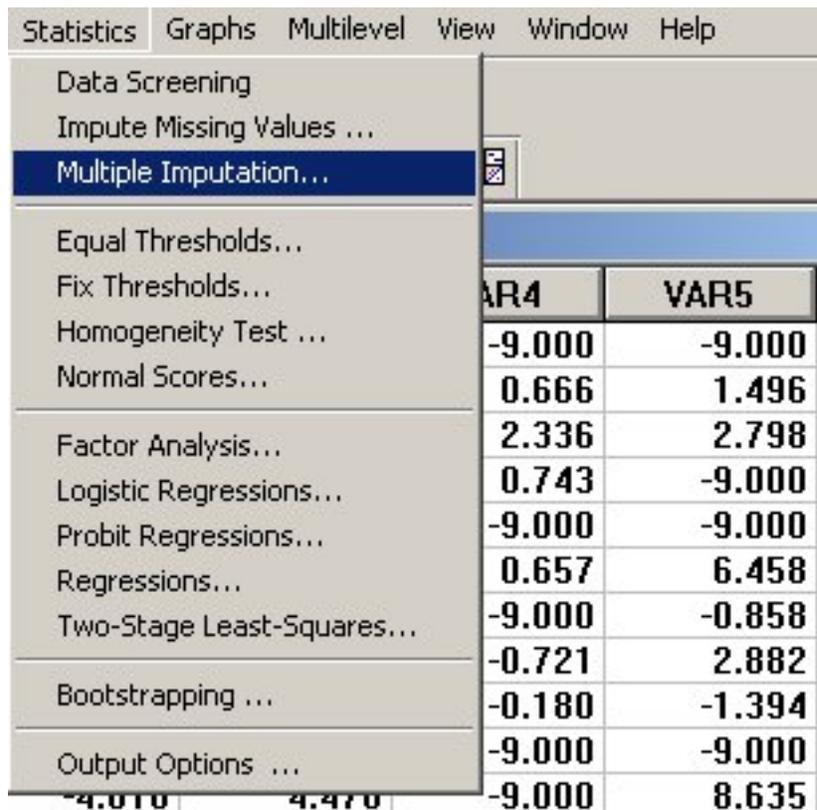
Click **OK** to obtain the PRELIS system file **grant.psf**. Note that default variable names, VAR1, VAR2, ..., VAR6 are assigned. To assign the value -9.0 as the global missing value code, select **Define Variables** from the **Data** menu. Click on any variable to highlight it and then on the **Missing Values** button (see pages 147-148 of the *Interactive Guide* for a detailed description). Enter -9.0, change the method of deletion to **Pairwise** and click **OK** when done.



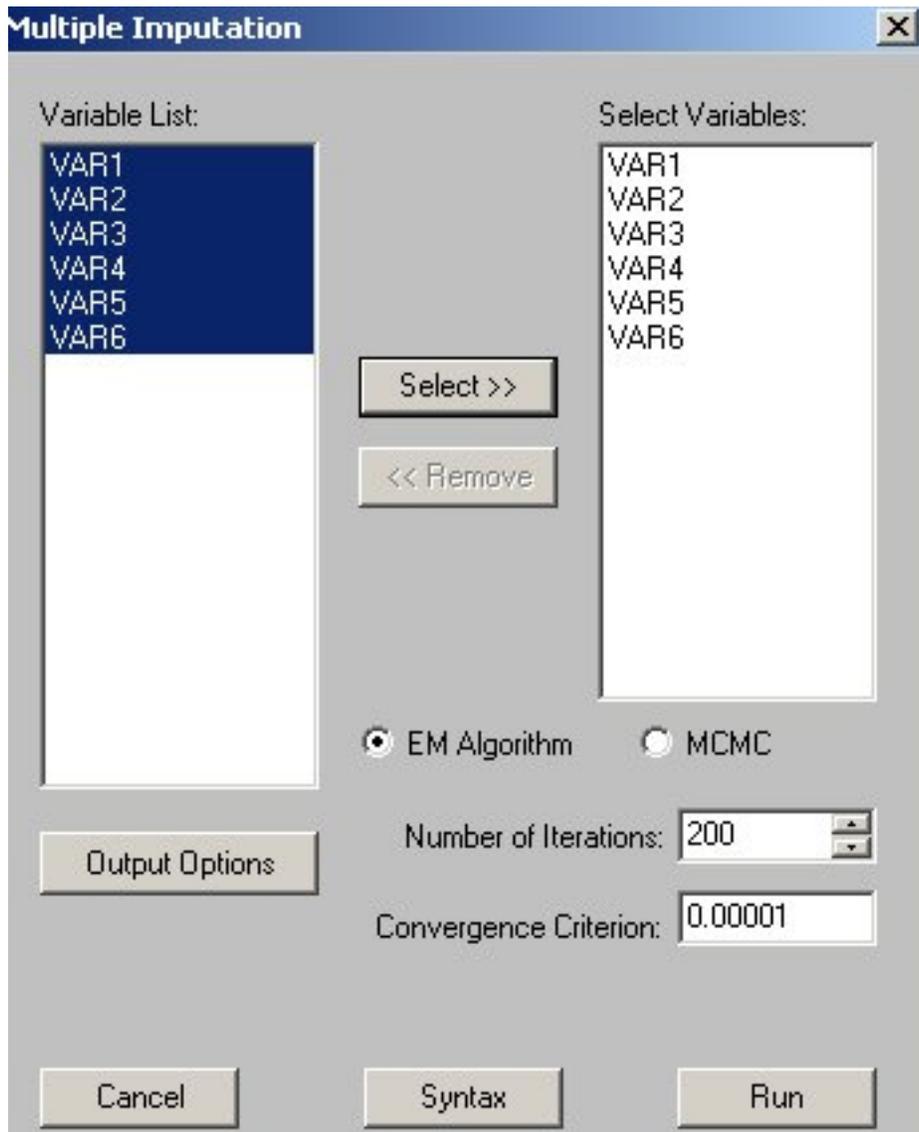
To change the variable type from the default of ordinal to continuous, select the variable VAR1 and click on **Variable Type** on the **Define Variables** dialog box to go to the **Variable Types** dialog box. Check the **Continuous** radio button and the **Apply to all** check box. Then click **OK** to return to the **Define Variables** dialog box. On this dialog box, also click **OK**. Use the **File, Save** option to ensure that the changes made are saved to **grant.psf**.



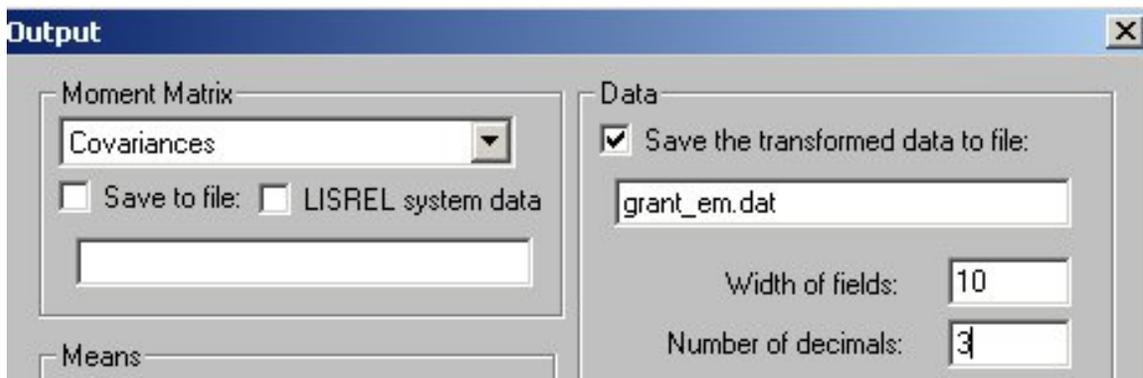
From the **Statistics** menu, select the **Multiple Imputation** option.



Select all the variables from the **Variable List**:. Note that if no variables are selected, PRELIS assumes that all the variables in the data set are to be used.

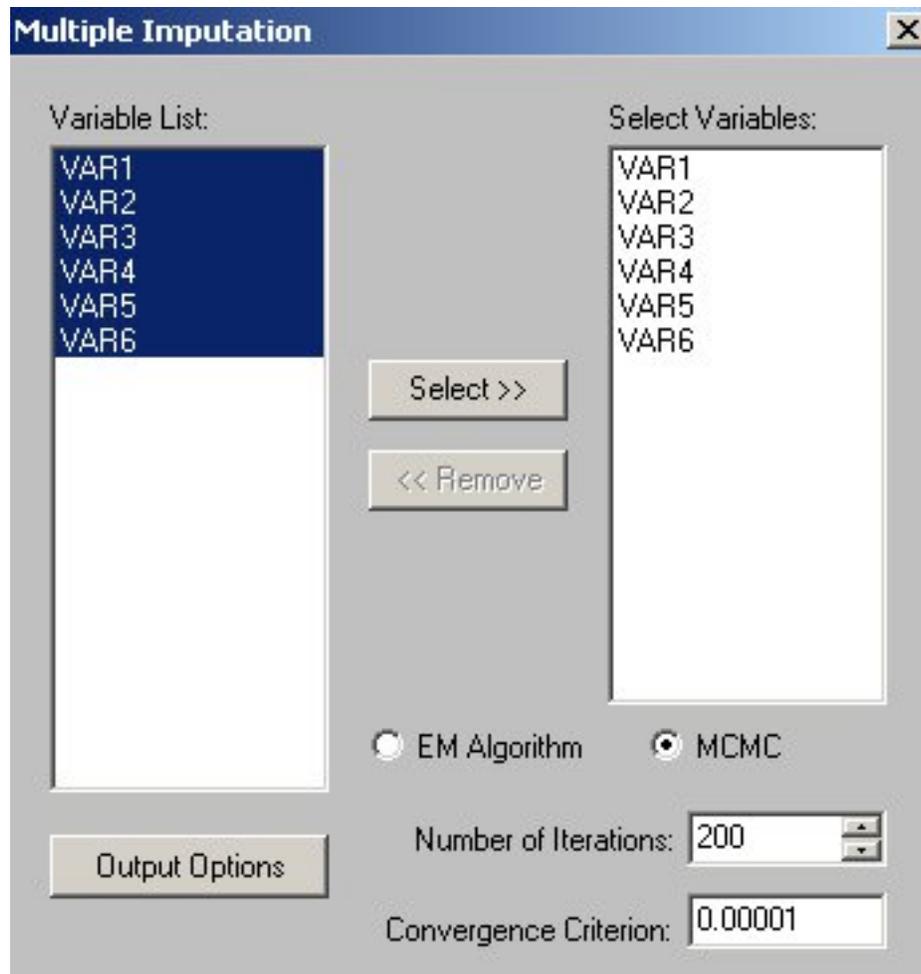


To impute data using the EM algorithm, click the **EM Algorithm** radio button. To save the imputed data to an external file, click the **Output Options** button to open the **Output** dialog box. Enter the values as shown below and click **OK** when done to return to the **Multiple Imputation** dialog box.



Click the **Run** button to do the multiple imputations and to obtain the data set **grant_em.dat**. Note from the PRELIS output that this file contains 4996 observations, as four of the original 5000 observations contained missing values on all 6 variables.

Next, we would like to impute 10 data sets based on **grant.psf** using the MCMC option. To do so, select the **Multiple Imputation** option from the **Statistics** menu.



Check the **MCMC** radio button and click **Output Options** to activate the **Output** dialog box. Enter values as shown below. Note that for this example, the number of repetitions equals 10. Also note that the data set **grant_mcmc.dat** will contain $10 \times 4996 = 49960$ observations. To use an alternative random seed, activate the **Set seed to** radio button and enter a number, for example, 76381.

Output

Moment Matrix
 Covariances
 Save to file: LISREL system data

Means
 Save to file:

Standard Deviations
 Save to file:

Asymptotic Covariance Matrix
 Save to file: Print in output

Asymptotic Variances
 Save to file: Print in output

Data
 Save the transformed data to file:
 grant_mcmc.dat
 Width of fields: 10
 Number of decimals: 3
 Number of repetitions: 10
 Rewind data after each repetition
 Print bivariate frequency tables
 Print tests of underlying bivariate normality
 Perform tests of multivariate normality
 Wide print
 Random seed
 Set seed to 123456

OK Cancel

Click **OK** to return to the **Multiple Imputation** dialog box. If the **Syntax** button is clicked, the PRELIS syntax file shown below is generated.

```
grant.PR2
|PRELIS SYNTAX: Can be edited
SY='C:\lisrel852_student\MISSINGEX\grant.PSF'

SE 1 2 3 4 5 6
MC CC = 0.00001 IT = 200
OU MA=CM RA=grant_mcmc.dat WI=10 ND=3 RP=10 XM XB XT
*
```

Two parts of the output file are shown below. We see that the percentage of missing values equals 31.97%.

grant.OUT

Percentage missing values= 31.97

Estimated Means

VAR1	0.1751
VAR2	0.0624
VAR3	0.1563
VAR4	0.1202
VAR5	0.0170
VAR6	0.2852

Estimated Covariances

	VAR1	VAR2	VAR3	VAR4	VAR5	VAR6
VAR1	46.8254					
VAR2	10.0131	20.0271				
VAR3	25.9298	14.5431	68.8212			
VAR4	7.2859	4.0342	9.7960	11.5139		
VAR5	9.5229	4.4492	12.8710	11.1992	21.0343	
VAR6	15.2964	9.1738	22.4602	19.3301	24.7144	63.3399

Note that the PRELIS analyses are based on all the observations in the imputed data set. The sample means are relatively close to the estimated means.

Total Sample Size = 49960

Univariate Summary Statistics for Continuous Variables

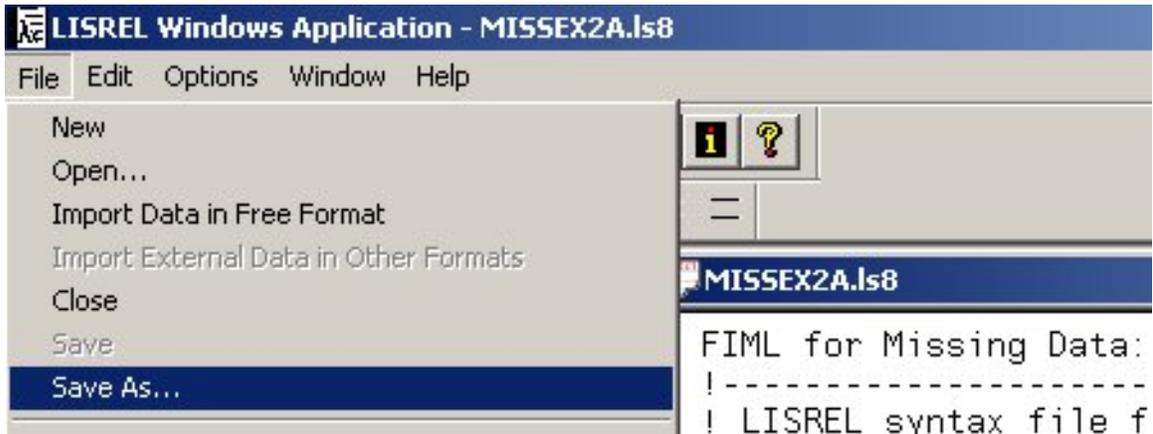
Variable	Mean	St. Dev.	T-Value	Skewness	Kurtosis
VAR1	0.180	6.341	6.355	0.017	0.261
VAR2	0.066	4.142	3.582	0.005	0.330
VAR3	0.190	7.765	5.477	0.043	0.399
VAR4	0.123	3.254	8.466	0.057	0.056
VAR5	0.019	4.391	0.980	0.041	0.132
VAR6	0.262	7.603	7.690	-0.005	0.118

To obtain summary statistics for each individual dataset, one can use the following PRELIS syntax file.

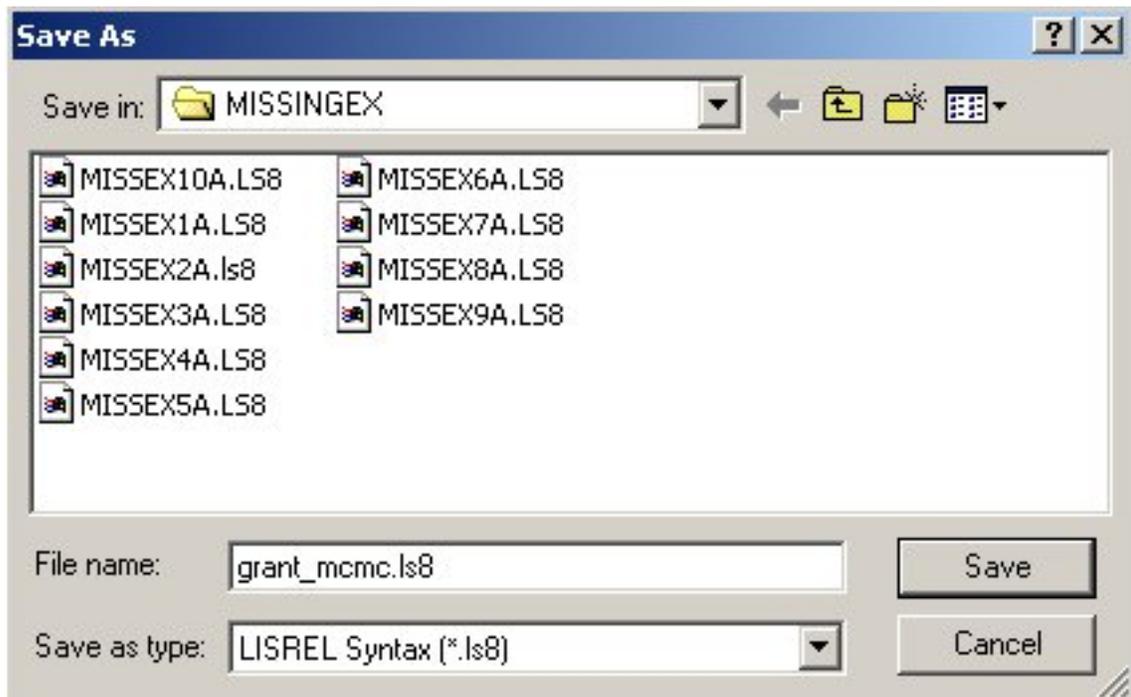
```
GRANT_RP.PR2
TITLE: Means and standard deviations for 10 multiple-imputed datasets
DA NI = 6 NO = 4996 RP=10
RA = GRANT_MCMC.DAT
LA
VISPERC CUBES LOZENGES PARAGRAF SENTENC WORDMEAN
CO ALL
OU MA = CM ME=GRANT.MEA SD= GRANT.STD XM XO=2
**
```

Note that it is also possible to save any of the summary statistics, for example the means and standard deviations, to external files. The keyword **XO=n** on the OU line restricts the output to the first *n* datasets. The files **grant.mea** and **grant.std**, however, contains the means and standard deviations of all the datasets.

Next, we wish to copy the file **missex2a.ls8** to **grant_mcmc.ls8**. Open the file **missex2a.ls8** located in the **missingex** folder. Then use the **File, Save As..** option to invoke the **Save As** dialog box.



Save as **grant_mcmc.ls8** as shown below. Click the **Save** button when done.



Modify **grant_mcmc.ls8** as shown below. Note that **RP = 10** is used on the DA line (MI = - 9 is deleted). We have also added **PV = grant_mcmc.fit** and **SV = grant_mcmc.std** to the OU line. Note that the sample size (**NO = 4996**) must be specified when the RP keyword is used. Click the LISREL **Run** button to fit 10 successive models to the data. The first model reads lines 1 to 4996 from the data file, the next model reads lines 4997 to 9992 and so on.

```

grant_mcmc.ls8
!-----
! LISREL syntax file for Example 2 to illustrate the MCMC method.
! Simulated Data are used.
! Confirmatory Factor Analysis Model.
DA NI=6 NO=4996 NG=1 MA=CM RP=10
LA
visperc cubes lozenges paragraf sentenc wordmean
RA FI=GRANT_MCMC.DAT
MO NX=6 NK=2 LX=FU,FI PH=SY,FR TD=DI,FR
LK
spatial verbal
FR LX(1,1) LX(2,1) LX(3,1) LX(4,2) LX(5,2) LX(6,2)
VA 1.00 PH(1,1) PH(2,2)
PD
OU ME=ML ND=3 SC PV=grant_mcmc.fit SV=grant_mcmc.std

```

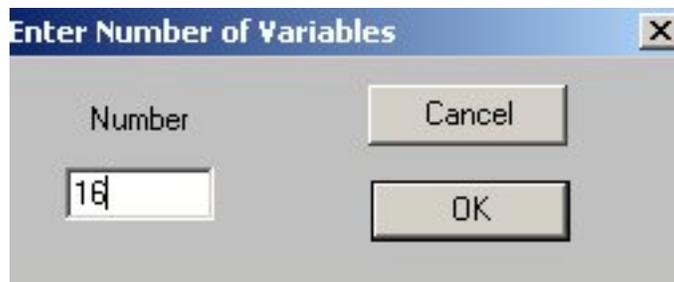
Contents of **grant_mcmc.fit** are shown below. The first line contains the repetition number followed by two zeros indicating no convergence problems were encountered. The values are followed by the 13 estimated free parameters.

```

grant_mcmc.fit
  1 0 0
0.413358D+01 0.230905D+01 0.596160D+01 0.287248D+01 0.371683D+01 0.640235D+01
0.587017D+00 0.189488D+02 0.997660D+01 0.190618D+02 0.163607D+01 0.423855D+01
0.132228D+02
  2 0 0
0.412742D+01 0.231515D+01 0.603073D+01 0.294003D+01 0.373399D+01 0.644898D+01
0.571518D+00 0.232665D+02 0.119290D+02 0.245576D+02 0.216417D+01 0.543774D+01
0.162227D+02
  3 0 0
0.423312D+01 0.243663D+01 0.581795D+01 0.293557D+01 0.373392D+01 0.650547D+01
0.569637D+00 0.229298D+02 0.115789D+02 0.265899D+02 0.212620D+01 0.541832D+01
0.161519D+02

```

To obtain the means of the estimates, select the **Import Data in Free Format** option from the **File** menu, locate **grant_mcmc.fit**, and enter the number of variables as shown below.



Delete the first three variables from the PSF file as shown below.

	VAR1	VAR2	VAR3	VAR4	VAR5	VAR6
1	1.000	0.000	0.000	4.134	2.309	5.962
2	2.000	0.000	0.000	4.127	2.315	6.031
3	3.000	0.000	0.000	4.233	2.437	5.818
4	4.000	0.000	0.000	4.277	2.371	6.058
5	5.000	0.000	0.000	4.335	2.321	5.890
6	6.000	0.000	0.000	4.254	2.343	6.027

Use the **Data, Define Variables** option to change the variable type from ordinal to continuous. Save the modified PSF file and then select the **Data Screening** option from the **Statistics** menu to obtain the following PRELIS output.

Variable	Mean	St. Dev.	T-Value
-----	----	-----	-----
VAR4	4.196	0.075	177.849
VAR5	2.324	0.049	150.449
VAR6	5.976	0.090	209.885
VAR7	2.920	0.020	459.769
VAR8	3.747	0.021	573.285
VAR9	6.458	0.037	556.005
VAR10	0.571	0.006	278.072
VAR11	22.599	1.399	51.088
VAR12	11.756	0.649	57.283
VAR13	24.582	2.117	36.728
VAR14	2.064	0.159	41.017
VAR15	5.244	0.359	46.153
VAR16	16.110	1.043	48.850

The means reported above are in the same order as in the printout of the estimated parameters. One can obtain the so-called FIML estimates of the free parameters by running the example **missex2a.ls8**. These values can subsequently be compared to the means listed above.

References

Du Toit, M. & Du Toit, S.H.C. (2001).

Interactive LISREL User's Guide. Lincolnwood, IL: Scientific Software International, Inc.

Schafer, J.L. (1997).

Analysis of Incomplete Multivariate Data.

Monographs on Statistics and Applied Probability 72, Chapman and Hall/CRC.

Part B: Comparison with FIML in the case of arbitrary data.

Gerhard Mels

1. Introduction

Many of the statistical methods, which are available within LISREL 8.7 for Windows (Jöreskog & Sörbom 2002), assume that the data follow a multivariate Normal distribution. These methods include, amongst others, Multiple Imputation and Full Information Maximum Likelihood (FIML) estimation for missing data. Very little is known about the robustness (sensitivity) of these two methods to violations of the assumption of multivariate Normal data.

In this note, a Confirmatory Factor Analysis (CFA) model and a non-Normal data set are used to illustrate how LISREL 8.7 for Windows may be used to investigate the robustness of Full Information Maximum Likelihood estimation for missing data. In particular, the FIML results are compared with the average Robust Maximum Likelihood (RML) results obtained for 100 imputed data sets.

The data set is described in the next section. Thereafter, the CFA model to be used is described. Section 4 illustrates the use of FIML estimation for missing data to fit the CFA model to the non-Normal data set. In Section 5, the generation of the 100 imputed data sets is illustrated first after which the CFA model is fitted to the 100 imputed data sets. The FIML and robust RML results are compared in Section 6.

2. The Data

The data set to be used is one of 1000 random samples that were generated from a multivariate non-Normal distribution with a specific population correlation matrix. This non-Normal distribution is a multivariate distribution for which the skewnesses and kurtoses of the marginal distributions are all equal to 1.95 and 30 respectively. In the case of the multivariate Normal distribution, these marginal skewnesses and kurtoses are all equal to zero. More details on the simulation study are available in Mels (2000). The Prelis system file **ARDATA0.PSF** contains the original data set. Missing values were inserted at random to enable the application of Multiple Imputation and FIML estimation for missing data. The resulting data set has 15.35% missing values. A value of -9.000 is used to indicate the missing values. A small section of the resulting data set is shown in the PSF window in Figure 1.

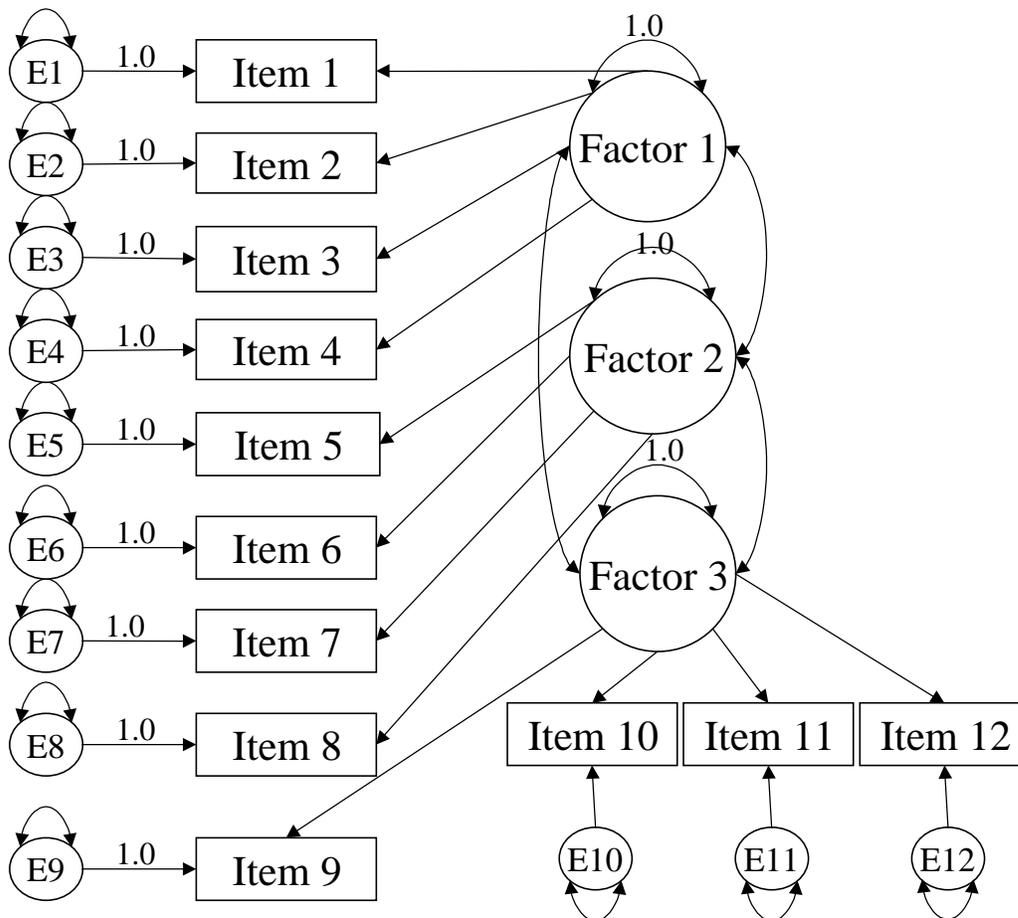
3. The CFA Model

The model, from which multivariate non-Normal data were simulated, is a Confirmatory Factor Analysis (CFA) model that specifies 12 indicators for 3 correlated factors (latent variables). A path diagram of the CFA model is shown in Figure 2. The model, depicted in Figure 2, has 27 unknown parameters (12 factor loadings, 3 factor correlations and 12 measurement error variances).

Figure 1: The PSF Window for Non-Normal Data with Missing Values

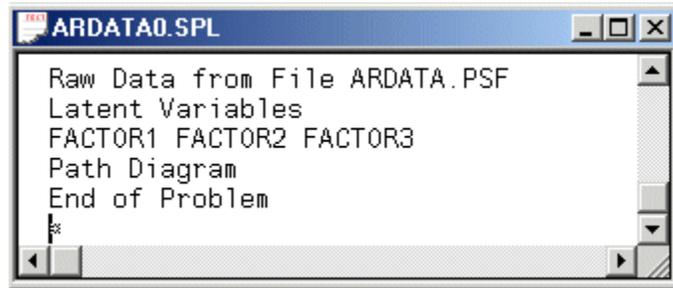
	ITEM1	ITEM2	ITEM3	ITEM4	ITEM5	ITEM
1	0.875	-9.000	1.250	1.226	0.582	
2	-0.836	-9.000	-9.000	-0.840	-0.538	
3	0.661	-9.000	-9.000	1.083	1.167	
4	0.011	0.594	0.450	-0.373	0.902	
5	-0.096	-0.421	-0.928	-0.643	-0.174	
6	1.191	0.853	1.104	1.342	0.561	
7	-0.970	-0.934	-0.795	-1.067	-0.502	
8	-0.068	-9.000	-0.871	-1.098	-9.000	
9	0.186	-0.394	-0.356	-0.308	-0.957	
10	1.155	0.892	1.110	1.279	1.112	
11	1.200	1.207	1.045	1.203	-0.884	
12	-0.547	-0.542	-0.911	0.008	-0.957	
13	-0.465	-0.348	0.007	-0.869	0.998	
14	-0.814	2.687	0.309	1.952	-0.403	
15	1.042	-9.000	-0.225	0.457	1.012	
16	-0.382	-0.458	0.621	-9.000	-0.091	

Figure 2: The CFA model for the FIML and RML Comparison



4. FIML Estimation for Missing Data

We will use a path diagram (PTH file) to fit the model in Figure 2 to the Non-Normal data in Figure 1 by means of FIML estimation. We start out by creating an empty path diagram that only contains the variables of the model. This is achieved by using the SIMPLIS syntax file **ARDATA0.SPL** that is shown in the following text editor window.



```
Raw Data from File ARDATA.PSF
Latent Variables
FACTOR1 FACTOR2 FACTOR3
Path Diagram
End of Problem
```

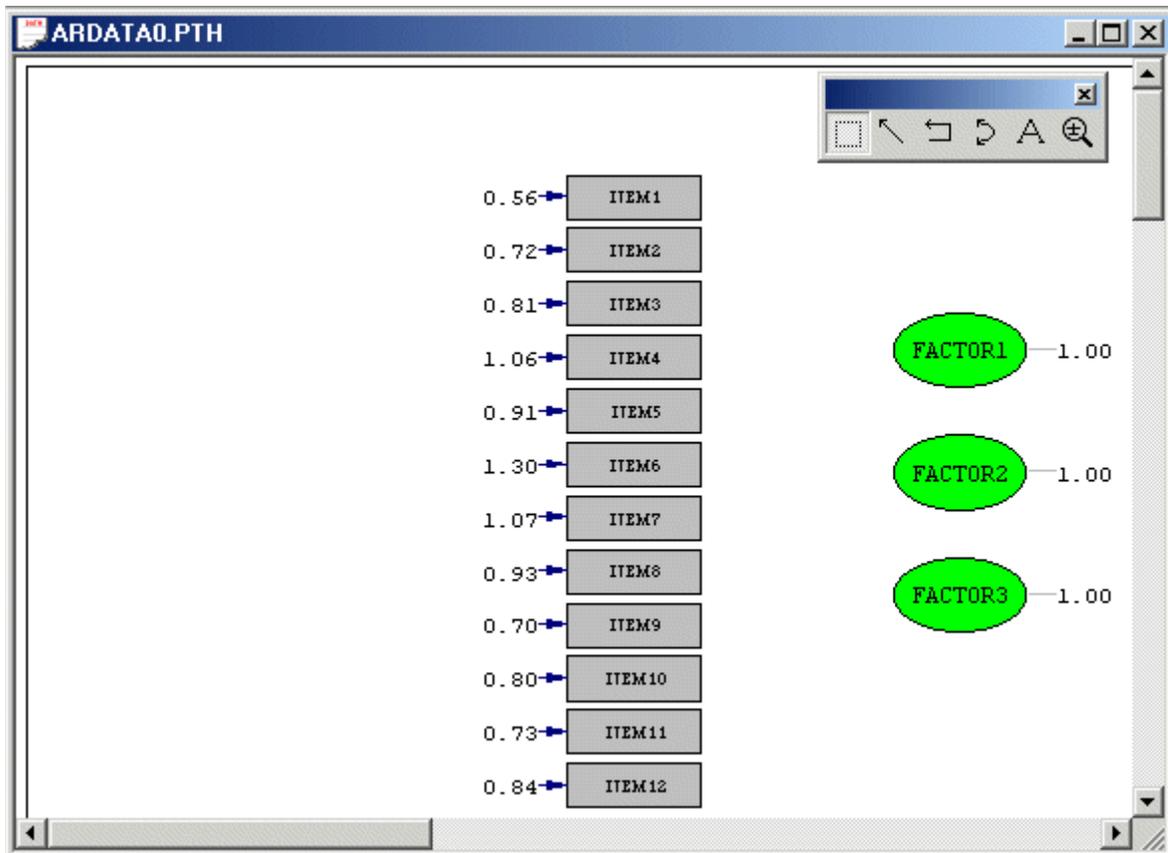
The first line of the syntax file above specifies the data source to be used.

Lines 2-3 specify labels for the latent variables of the CFA model.

Line 4 requests a path diagram (PTH file).

The final line indicates the end of the commands to be processed.

Click on the **Run LISREL** toolbar icon  to produce the following path diagram window.



Activate the **Arrow** icon on the **Draw** toolbar.

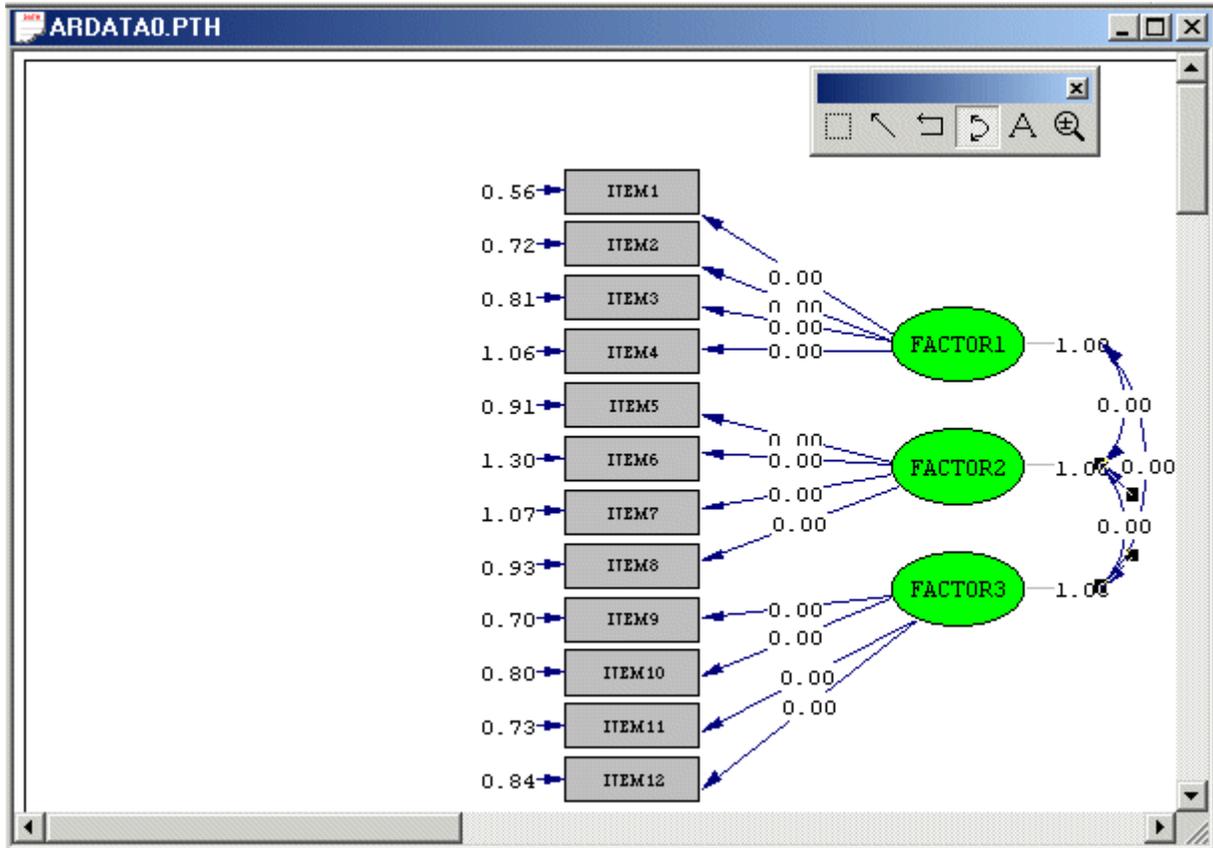
Use your mouse to click and drag 4 indicator paths from the latent variable **FACTOR1** to ITEM1 to ITEM4.

Use your mouse to click and drag 4 indicator paths from the latent variable **FACTOR2** to ITEM5 to ITEM8.

Use your mouse to click and drag 4 indicator paths from the latent variable **FACTOR3** to ITEM9 to ITEM12.

Activate the **Double-headed Arrow** icon on the **Draw** toolbar.

Use your mouse to click and drag 3 covariance paths between the three latent variables **FACTOR1**, **FACTOR2** and **FACTOR3** to produce the following path diagram window.



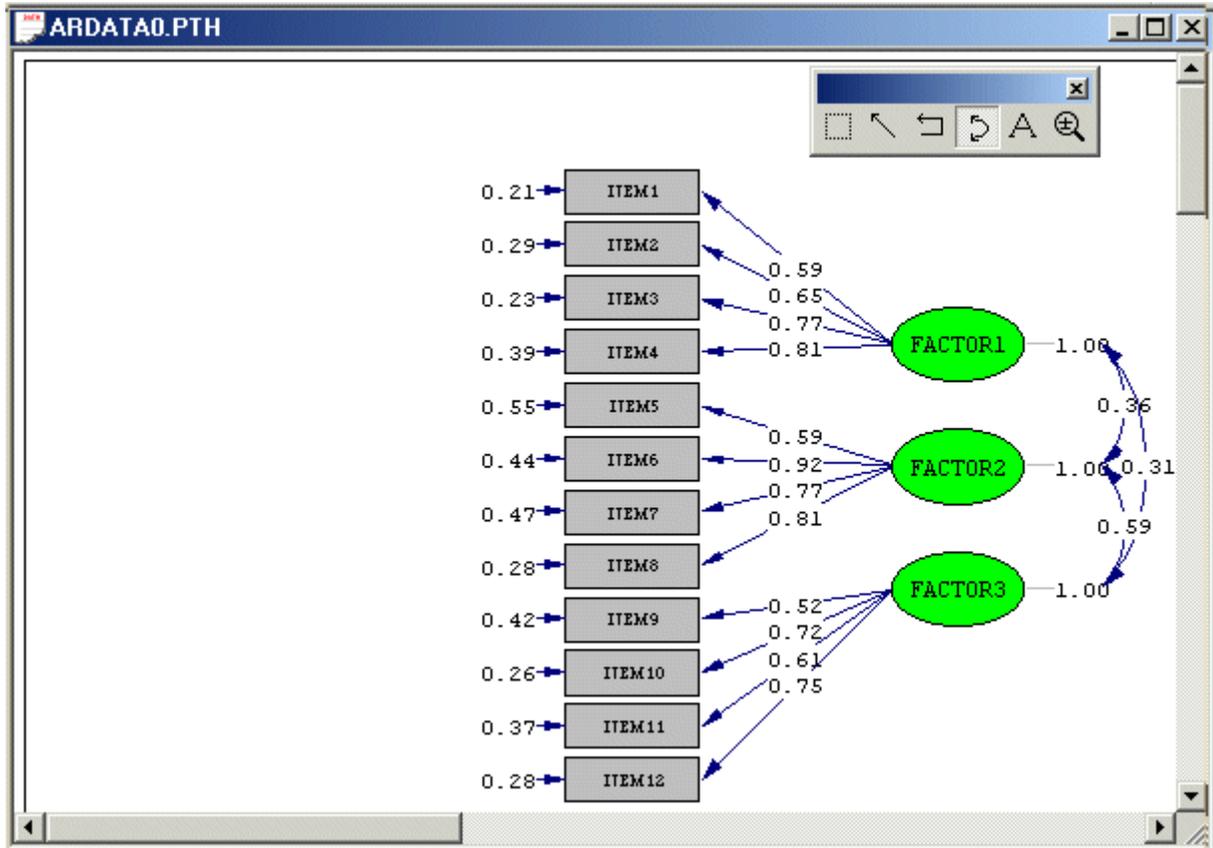
Select the **Build LISREL Syntax** option from the **Setup** menu to generate the following Lisrel Project (LPJ) window.

```

ARDATA0.LPJ
TI
DA NI=12 NO=500 NG=1 MA=CM
RA FI='C:\lisrel1852\Workshop_August_02\ARDDATA.PSF'
SE
1 2 3 4 5 6 7 8 9 10 11 12 /
MO NX=12 NK=3 LX=FU,FI PH=SY,FR TD=DI,FR
LK
FACTOR1 FACTOR2 FACTOR3
FI PH(1,1) PH(2,2) PH(3,3)
FR LX(1,1) LX(2,1) LX(3,1) LX(4,1) LX(5,2) LX(6,2) LX(7,2) LX(8,2) LX(9,3)
FR LX(10,3) LX(11,3) LX(12,3)
VA 1.00 PH(1,1) PH(2,2) PH(3,3)
PD
OU ME=ML |

```

Click on the **Run LISREL** toolbar icon  to produce the following path diagram window.



The results above are the FIML estimates of the parameters of the CFA model in Figure 2. The FIML standard error estimates and measures of fit are provided in the output file **ARDATA0.OUT**.

5. RML Estimation for Imputed Data Sets

The following actions may be used to generate 100 Markov Chain Monte Carlo (MCMC) imputed data sets from the raw data in **ARDATA.PSF**.

Use the **Open** option on the **File** menu of the root window to open **ARDATA.PSF**.

Select the **Multiple Imputation** option on the **Statistics** menu of the PSF window to load the **Multiple Imputation** dialog box.

Highlight all the labels in the **Variable List:** list box.

Click on the **Select** push button to transfer the selected labels to the **Select Variables:** list box.

Activate the **MCMC** radio button.

Click on the **Output Options** push button to load the **Output** dialog box.

Check the **Save to file:** checkbox in the **Save transformed data to file:** section.

Enter the name **ARDATA_MCMC.DAT** in the string field in the **Save transformed data to file:** section.

Enter **100** in the **Number of Repetitions** string field.

Click on the **OK** push button to return to the **Multiple Imputation** dialog box.

Click on the **Run** push button to produce the following output file window.

```

-----
EM Algorithm for missing Data:
-----

Number of different missing-value patterns=      193
Convergence of EM-algorithm in      12 iterations
-2 Ln(L) =      11303.05534

Percentage missing values=   15.35

Estimated Means

```

To fit the CFA model in Figure 2 to the 100 MCMC imputed data sets in **ARDATA_MCMC.DAT** by means of RML, the 100 corresponding sample covariance matrices and estimated asymptotic covariance matrices of the sample variances and covariances are required. These matrices may be obtained by using the PRELIS syntax file **ARDATA2.PR2** that is shown in the following text editor window.

```

ARDATA2.PR2
DA NI=12 NO=500 RP=100
LA
ITEM1 ITEM2 ITEM3 ITEM4 ITEM5 ITEM6
ITEM7 ITEM8 ITEM9 ITEM10 ITEM11 ITEM12
RA = ARDATA_MCMC.DAT
CO ALL
OU MA=CM CM=ARDATA_MCMC.COV AC=ARDATA_MCMC.ACM
*

```

The DA command line specifies that each one of the 100 MCMC data sets (RP=100) contains 500 cases (NO=500) of 12 variables (NI=12). Lines 2-4 specify labels for the 12 observed variables in each MCMC imputed data set. The RA command line specifies the raw data source. Line 6 specifies that all 12 variables are continuous. The OU command line specifies that the sample covariance matrices should be computed (MA=CM) and saved to the file ARDATA_MCMC.COV (CM=ARDATA_MCMC.COV). It also specifies that the 100 estimated asymptotic covariance matrices should be computed and saved to the file ARDATA_MCMC.ACM (CM=ARDATA_MCMC.ACM).

Click on the **Run Prelis** toolbar icon to generate the output file window for **ARDATA2.OUT**. Use the **Open** option on the **File** menu to open the LPJ file **ARDATA0.LPJ**. Use the **Save As** option on the **File** menu to save the file as **ARDATA1.LS8**. Add the option RP=100 to the DA command line. Replace the command line

RA FI='C:\lisrel852\Workshop_August_02\ARDATA.PSF'

with the following command lines

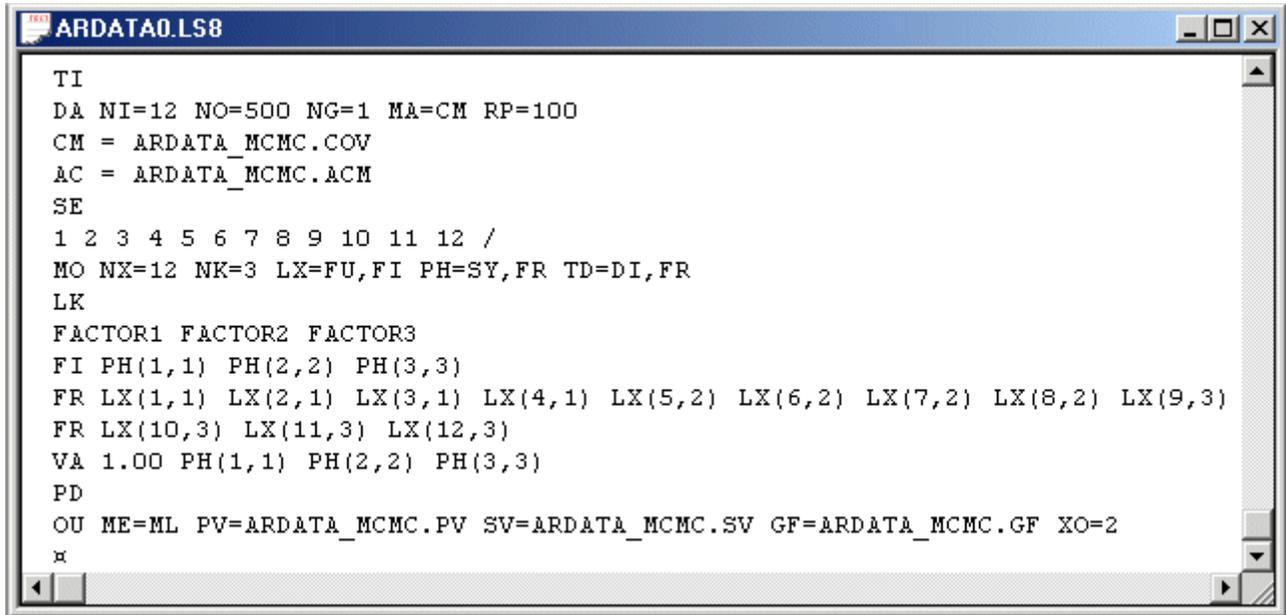
CM=ARDATA_MCMC.COV

AC=ARDATA_MCMC.ACM

Add the options PV=ARDATA_MCMC.PV (saving all the parameter estimates to the file ARDATA_MCMC.PV), SV=ARDATA_MCMC.SV (saving all the standard error estimates to the file ARDATA_MCMC.SV) and GF=ARDATA_MCMC.GF (saving all the measures of fit to the file ARDATA_MCMC.GF) to the OU command line.

Add the option XO=2 to the OU command line to restrict the output file to the results for the first two data sets only.

The resulting LISREL syntax file is shown in the following text editor window.



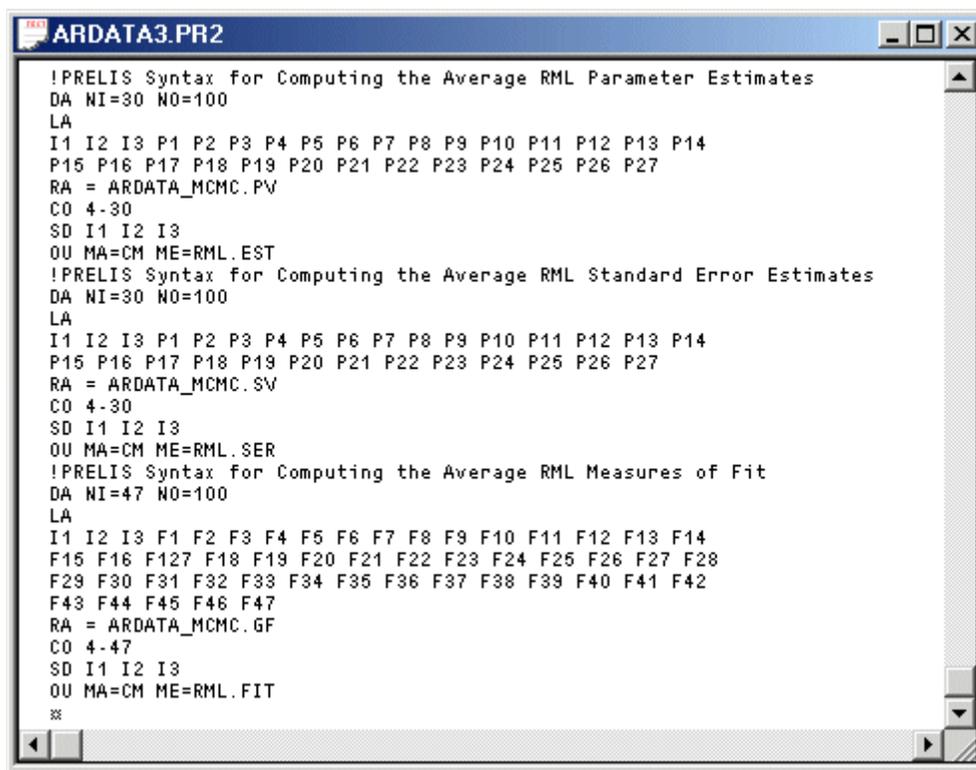
```
ARDATA0.LS8
TI
DA NI=12 NO=500 NG=1 MA=CM RP=100
CM = ARDATA_MCMC.COV
AC = ARDATA_MCMC.ACM
SE
1 2 3 4 5 6 7 8 9 10 11 12 /
MO NX=12 NK=3 LX=FU,FI PH=SY,FR TD=DI,FR
LK
FACTOR1 FACTOR2 FACTOR3
FI PH(1,1) PH(2,2) PH(3,3)
FR LX(1,1) LX(2,1) LX(3,1) LX(4,1) LX(5,2) LX(6,2) LX(7,2) LX(8,2) LX(9,3)
FR LX(10,3) LX(11,3) LX(12,3)
VA 1.00 PH(1,1) PH(2,2) PH(3,3)
PD
OU ME=ML PV=ARDATA_MCMC.PV SV=ARDATA_MCMC.SV GF=ARDATA_MCMC.GF XO=2
*
```

Click on the **Run LISREL** toolbar icon  to produce the output file window for ARDATA0.OUT.

6. Comparison of FIML and RML Results

The PRELIS syntax file **ARDATA3.PR2**, which is shown in Figure 3, may be used to obtain the average RML parameter and standard error estimates as well as mean RML measures of fit for the parameters of the CFA model in Figure 2 for the 100 MCMC imputed data sets.

Figure 3: A Prelis Syntax File to obtain Mean RML Results



```
!PRELIS Syntax for Computing the Average RML Parameter Estimates
DA NI=30 NO=100
LA
I1 I2 I3 P1 P2 P3 P4 P5 P6 P7 P8 P9 P10 P11 P12 P13 P14
P15 P16 P17 P18 P19 P20 P21 P22 P23 P24 P25 P26 P27
RA = ARDATA_MCMC.PV
CO 4-30
SD I1 I2 I3
OU MA=CM ME=RML.EST
!PRELIS Syntax for Computing the Average RML Standard Error Estimates
DA NI=30 NO=100
LA
I1 I2 I3 P1 P2 P3 P4 P5 P6 P7 P8 P9 P10 P11 P12 P13 P14
P15 P16 P17 P18 P19 P20 P21 P22 P23 P24 P25 P26 P27
RA = ARDATA_MCMC.SV
CO 4-30
SD I1 I2 I3
OU MA=CM ME=RML.SER
!PRELIS Syntax for Computing the Average RML Measures of Fit
DA NI=47 NO=100
LA
I1 I2 I3 F1 F2 F3 F4 F5 F6 F7 F8 F9 F10 F11 F12 F13 F14
F15 F16 F17 F18 F19 F20 F21 F22 F23 F24 F25 F26 F27 F28
F29 F30 F31 F32 F33 F34 F35 F36 F37 F38 F39 F40 F41 F42
F43 F44 F45 F46 F47
RA = ARDATA_MCMC.GF
CO 4-47
SD I1 I2 I3
OU MA=CM ME=RML.FIT
**
```

Click on the **Run Prelis** toolbar icon to generate the output file window for **ARDATA3.OUT**.

The FIML and the mean RML parameter and standard error estimates are summarized in Table 1, while selected FIML and mean RML measures of fit are summarized in Table 2.

The results in Tables 1 and 2 indicate that there are discrepancies between the FIML and RML results. However, there are very few substantial differences. Furthermore, there is no clear pattern in these discrepancies. An extensive Monte Carlo study is required to assess the performances of these two statistical methods.

Table 1: FIML and Mean RML Parameter and Standard Error Estimates

Parameter	FIML Estimate	Mean RML Estimate	FIML Std. Error Estimate	Mean RML Std. Error Estimate
LX (1,1)	0.586	0.591	0.032	0.028
LX (2,1)	0.654	0.655	0.036	0.040
LX (3,1)	0.765	0.760	0.037	0.027
LX (4,1)	0.810	0.812	0.044	0.046
LX (5,2)	0.593	0.596	0.045	0.058
LX (6,2)	0.922	0.910	0.048	0.118
LX (7,2)	0.774	0.787	0.045	0.069
LX (8,2)	0.812	0.781	0.041	0.055
LX (9,3)	0.525	0.525	0.039	0.037
LX (10,3)	0.717	0.728	0.038	0.041
LX (11,3)	0.609	0.586	0.039	0.037
LX (11,3)	0.747	0.748	0.039	0.040
PH (1,2)	0.360	0.369	0.047	0.058
PH (1,3)	0.305	0.312	0.049	0.051
PH (2,3)	0.589	0.625	0.039	0.054
TD (1,1)	0.209	0.190	0.020	0.021
TD (2,2)	0.289	0.265	0.026	0.032
TD (3,3)	0.229	0.209	0.027	0.031
TD (4,4)	0.393	0.355	0.038	0.087
TD (5,5)	0.553	0.506	0.043	0.095
TD (6,6)	0.444	0.432	0.047	0.093
TD (7,7)	0.474	0.422	0.042	0.063
TD (8,8)	0.281	0.284	0.033	0.036
TD (9,9)	0.423	0.392	0.033	0.060
TD (10,10)	0.263	0.255	0.029	0.070
TD (11,11)	0.372	0.354	0.032	0.037
TD (12,12)	0.280	0.255	0.032	0.060

Table 2: Selected FIML and Mean RML Measures of Fit

Measure	FIML Value	Mean RML Value
Chi-Square Test Statistic Value	120.899	138.970
RMSEA Point Estimate	0.052	0.059
Lower Limit of 90% CI for RMSEA	0.040	0.047
Upper Limit of 90% CI for RMSEA	0.065	0.071

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