simsem: SIMulated Structural Equation Modeling in R

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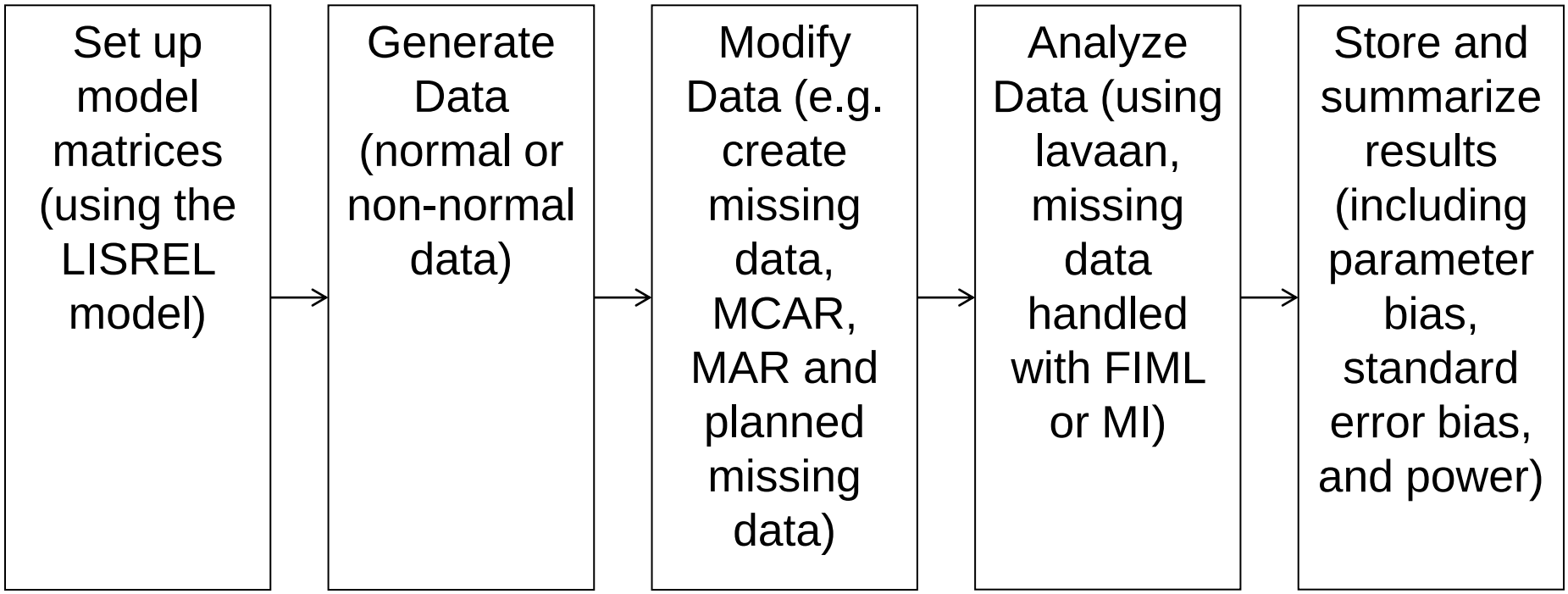
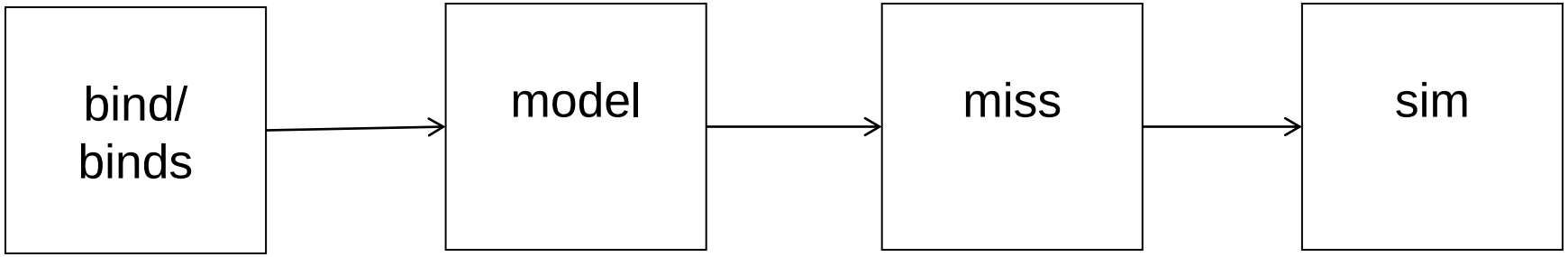
simsem

- An R package designed to automate Monte Carlo Simulations using SEM
- *simsem* can:
  - Generate data
  - Modify generated data
  - Analyze data
  - Summarize results

simsem


Set up model matrices (using the LISREL model)
Generate Data (normal or non-normal data)
Modify Data (e.g. create missing data, MCAR, MAR and planned missing data)
Analyze Data (using lavaan, missing data handled with FIML or MI)
Store and summarize results (including parameter bias, standard error bias, and power)

simsem: Main Functions



Some Future Plans

- Categorical indicators
- Multilevel SEM
- Non-linear constraints
- Additional analysis (e.g., OpenMx) and imputation packages (e.g, mi)
- Latent interactions
- Syntax entry

Thank you. Questions?

- Thanks to
  - Paul Johnson
  - Yves Rosseel

simsem: simsem.org

example code available at: simsem.org

email: schoemann@ku.edu

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Also…

- Another R package that may interest R users familiar with SEM
- semTools
  - Useful tools for conducting SEM in R
    - e.g., runMI, imputes missing data, runs each imputed data set, and combines results
  - An open source, community supported package
    - Have an idea for a function? Or a way to improve an existing function? Let us know!

Example 1: Power Analysis

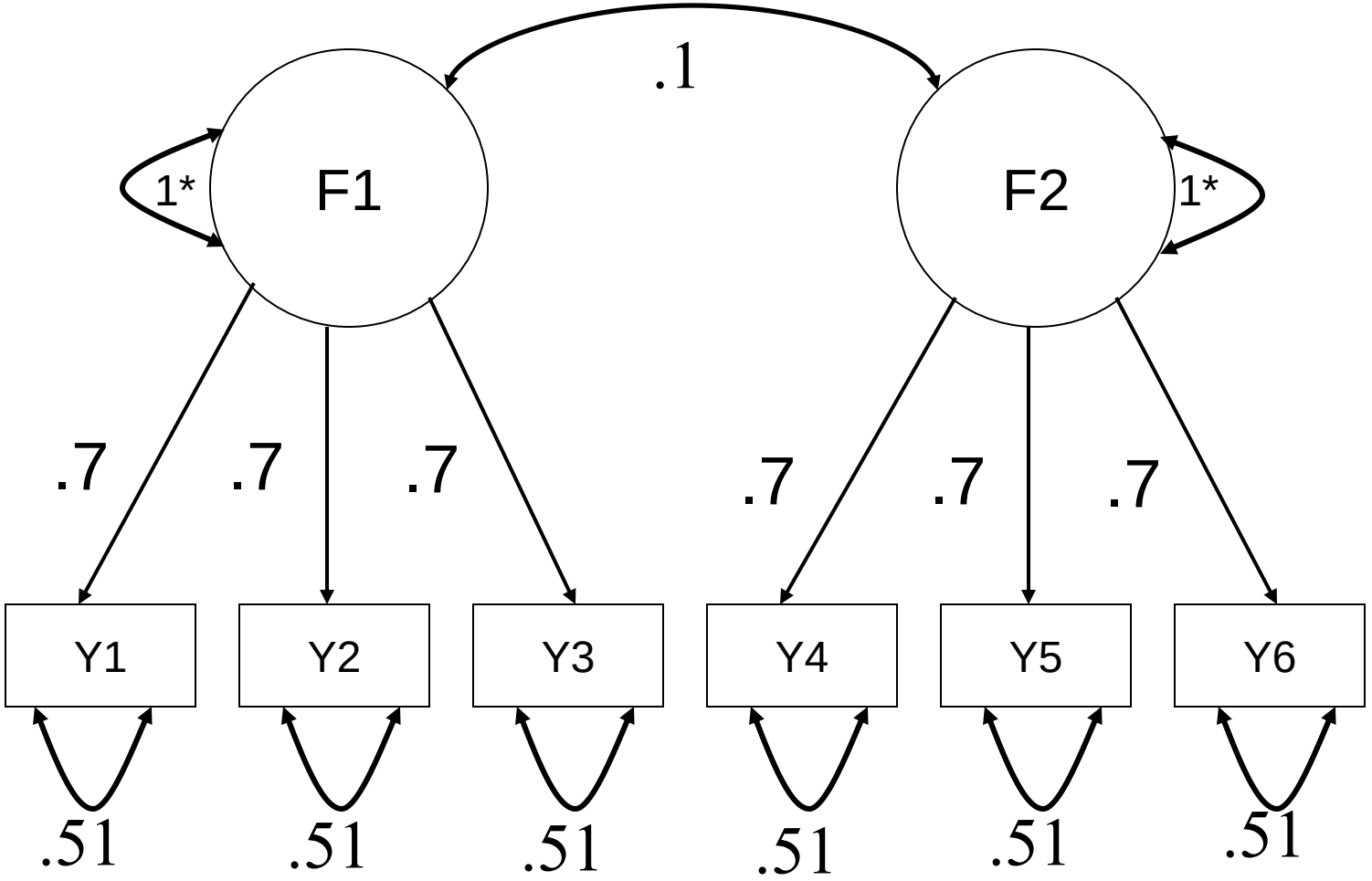
- Given population parameters, what sample size will result in a given level of power (e.g., .80)?
  - Continuously varying sample size approach
    - Specify model and a range of sample sizes
    - Generate 2000+ replications varying sample size across replications
    - Record each parameter's significance for each replication (0 not sig., 1 sig.)

Example 1: Power Analysis

- Given population parameters, what sample size will results in a given level of power (e.g., .80)?
  - Use logistic regression to predict a parameter's significance (across all replications) from the sample size of each replication.
  - The predicted probability from the logistic regression at a given N is power for that parameter at that N

$$p = \frac{e^{B_0 + B_1 N}}{1 + e^{B_0 + B_1 N}}$$

Example 1: Power Analysis



Example 1: Power Analysis

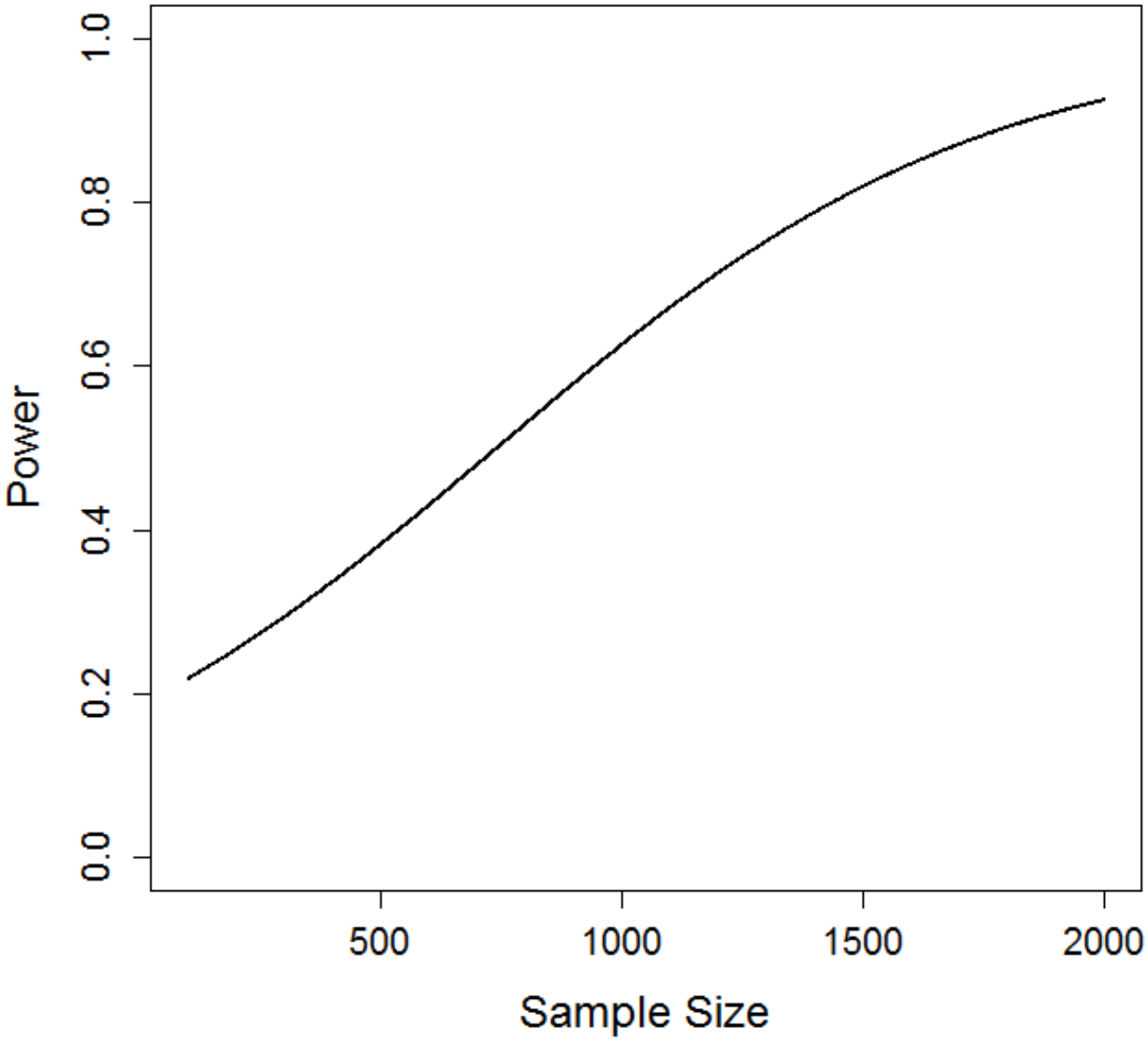
$$LY = \begin{matrix} 0.7 & 0 \\ 0.7 & 0 \\ 0.7 & 0 \\ 0 & 0.7 \\ 0 & 0.7 \\ 0 & 0.7 \end{matrix}$$

$$PS = \begin{matrix} 1 & 0.1 \\ 0.1 & 1 \end{matrix}$$

$$TE = \begin{matrix} 0.51 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.51 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0.51 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.51 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.51 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0.51 \end{matrix}$$

Example 1: Power Analysis

- Results: What sample size results in power for the latent correlation of .80?
  - 3000 replications, randomly varying N between 100-2000
  - logit(power) = $\beta_0 + \beta_1 N$
  - Power = .80 when N = 1436

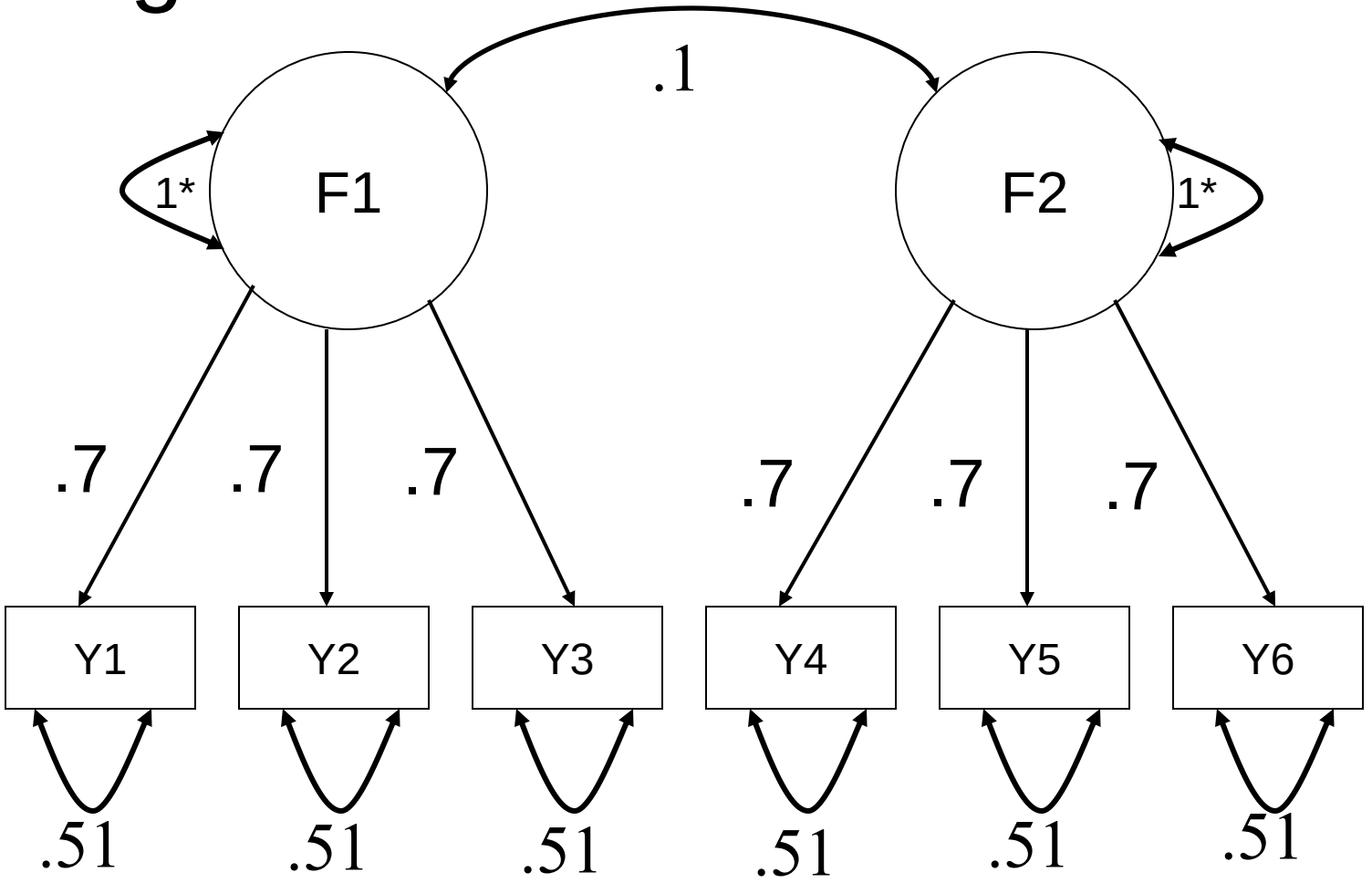

Power
0.0
0.2
0.4
0.6
0.8
1.0
500
1000
1500
2000
Sample Size

Example 2: Planned Missing Data Design

- Investigate power and bias in a 3 form planned missing data design

Form	Common Set X	Variable Set A	Variable Set B	Variable Set C
1	¼ of items	¼ of items	¼ of items	Missing
2	¼ of items	¼ of items	Missing	¼ of items
3	¼ of items	Missing	¼ of items	¼ of items

Example 2: Planned Missing Data Design



Example 2: Planned Missing Data Design

- Planned missing design:
  - X block:Y1 and Y4
  - A block: Y2 and Y5
  - B block: Y3
  - C Block: Y4
- Missing data is handled thought 5 imputations in Amelia
- N = 500
- 1000 replications

Example 2: Results

========== Fit Indices Cutoffs ============

	0.1	0.05	0.01	0.001	Mean
Chi	14.793	18.995	27.851	43.315	5.420
AIC	7962.256	7986.963	8049.541	8076.073	7846.052
BIC	8042.333	8067.041	8129.618	8156.151	7926.130
RMSEA	0.041	0.052	0.070	0.094	0.010
CFI	0.984	0.974	0.949	0.881	0.996
TLI	0.970	0.951	0.905	0.776	1.014
SRMR	0.041	0.044	0.050	0.056	0.032

Example 2: Results

========== Parameter Estimates and Standard Errors ============

	Estimate.Average	Estimate.SD	Average.SE	Power..Not.equal.0.	Std.Est	Std.Est.SD
LY1_1	0.699	0.063	0.060	1.000	0.700	0.055
LY2_1	0.703	0.066	0.067	1.000	0.704	0.055
LY3_1	0.701	0.068	0.067	1.000	0.702	0.056
LY4_2	0.699	0.060	0.061	1.000	0.700	0.052
LY5_2	0.701	0.069	0.067	1.000	0.704	0.057
LY6_2	0.704	0.068	0.067	1.000	0.703	0.055
PS2_1	0.098	0.068	0.067	0.317	0.098	0.068
TE1_1	0.503	0.077	0.073	0.994	0.506	0.078
TE2_2	0.499	0.078	0.076	1.000	0.502	0.077
TE3_3	0.502	0.080	0.076	0.999	0.504	0.079
TE4_4	0.505	0.075	0.073	0.995	0.507	0.074
TE5_5	0.496	0.078	0.076	1.000	0.501	0.079
TE6_6	0.501	0.076	0.077	0.999	0.502	0.077
TY1	0.000	0.045	0.045	0.052	0.000	0.045
TY2	0.001	0.055	0.053	0.061	0.001	0.055
TY3	0.000	0.052	0.053	0.052	0.000	0.052
TY4	0.000	0.044	0.045	0.051	0.000	0.044
TY5	0.000	0.055	0.053	0.061	0.000	0.055
TY6	0.001	0.052	0.053	0.049	0.001	0.052

Example 2: Results

	Average.Param	Average.Bias	Coverage	Average.FMI1	SD.FMI1	Average.FMI2	SD.FMI2
LY1_1	0.70	-0.001	0.939	0.325	0.160	0.356	0.177
LY2_1	0.70	0.003	0.936	0.443	0.168	0.485	0.182
LY3_1	0.70	0.001	0.928	0.446	0.175	0.487	0.190
LY4_2	0.70	-0.001	0.949	0.327	0.163	0.358	0.180
LY5_2	0.70	0.001	0.927	0.447	0.174	0.489	0.188
LY6_2	0.70	0.004	0.936	0.445	0.174	0.487	0.188
PS2_1	0.10	-0.002	0.944	0.218	0.117	0.237	0.131
TE1_1	0.51	-0.007	0.945	0.432	0.181	0.472	0.195
TE2_2	0.51	-0.011	0.941	0.496	0.175	0.541	0.186
TE3_3	0.51	-0.008	0.928	0.498	0.179	0.543	0.191
TE4_4	0.51	-0.005	0.947	0.434	0.185	0.474	0.200
TE5_5	0.51	-0.014	0.918	0.491	0.178	0.535	0.190
TE6_6	0.51	-0.009	0.943	0.499	0.179	0.544	0.191
TY1	0.00	0.000	0.948	0.000	0.000	0.000	0.000
TY2	0.00	0.001	0.939	0.265	0.135	0.290	0.151
TY3	0.00	0.000	0.948	0.267	0.132	0.292	0.148
TY4	0.00	0.000	0.949	0.000	0.000	0.000	0.000
TY5	0.00	0.000	0.939	0.273	0.133	0.299	0.149
TY6	0.00	0.001	0.951	0.271	0.131	0.296	0.147