Structural Equation Models (Confirmatory Factor Analysis)

Statistics 407, ISU

Definition

A model is specified, describing the expected associations between variables. For example,

X_1 causes X_2 causes X_3, X_4 cause X_5 which causes X_2 but nothing else is related.

This forms a hypothesis, that is tested by fitting a model, based on the associations between variables.

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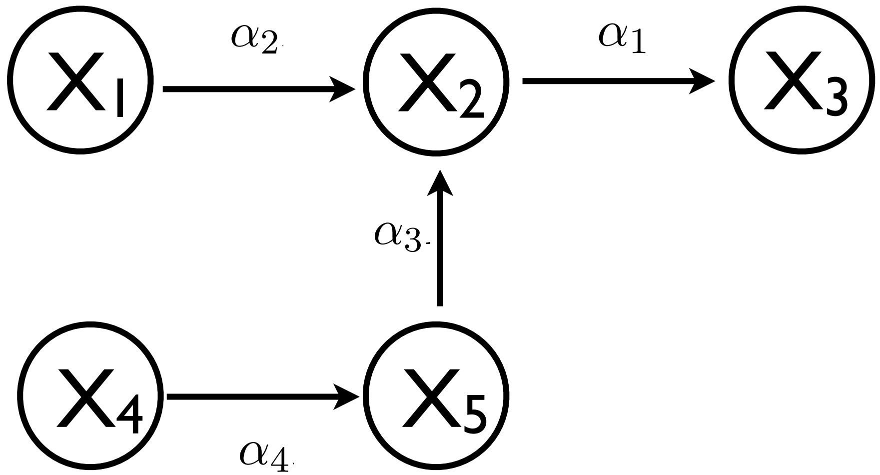
Endogenous variables, depend on others

Path diagram



$$X_3 = \alpha_1 X_2, X_2 = \alpha_2 X_1 + \alpha_3 X_5, X_5 = \alpha_4 X_4$$

Association

$$\begin{array}{c|c} & \begin{matrix} x_1 & x_2 & x_3 & x_4 & x_5 \end{matrix} \\ \begin{matrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{matrix} & \left[\begin{matrix} & + & + & 0 & 0 \\ 0 & & + & 0 & 0 \\ 0 & 0 & & 0 & 0 \\ 0 & + & + & & + \\ 0 & + & + & 0 & \end{matrix}\right] \end{array}$$

Model specification corresponds to expecting these relationships between the variables

Modeling

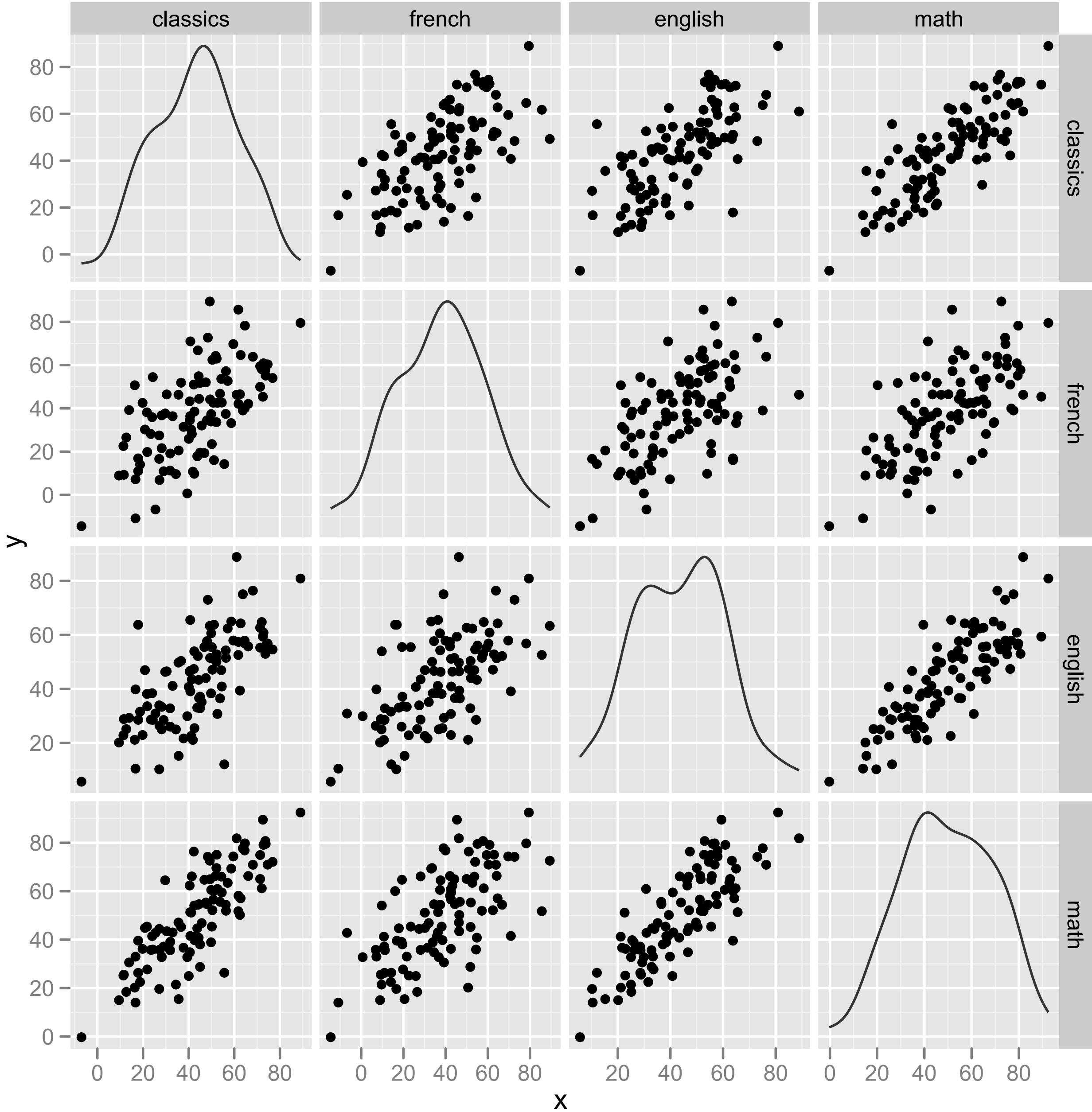
- Begins with the covariance or correlation matrix or similarity matrix.
- Fitting is done using Maximum Likelihood (like factor analysis) needing a distribution assumption on the exogenous variables - usually normality.
- Models are compared using chisquare difference tests, information criteria, or mean square of residuals.

Example

- One factor, synthetic data (used in factor analysis notes)
- Replicating Spearman's example, students tested on classics, french, english, math.

$$classics = 0.80f + \varepsilon_{classics}, \varepsilon_{classics} \sim N(0, 10)$$
$$french = 0.70f + \varepsilon_{french}, \varepsilon_{classics} \sim N(0, 15)$$
$$english = 0.76f + \varepsilon_{english}, \varepsilon_{classics} \sim N(0, 9)$$
$$math = 0.9f + \varepsilon_{math}, \varepsilon_{classics} \sim N(0, 5)$$

- f is simulated from standard normal and scaled to be between 0-100



All variables strongly related

Means

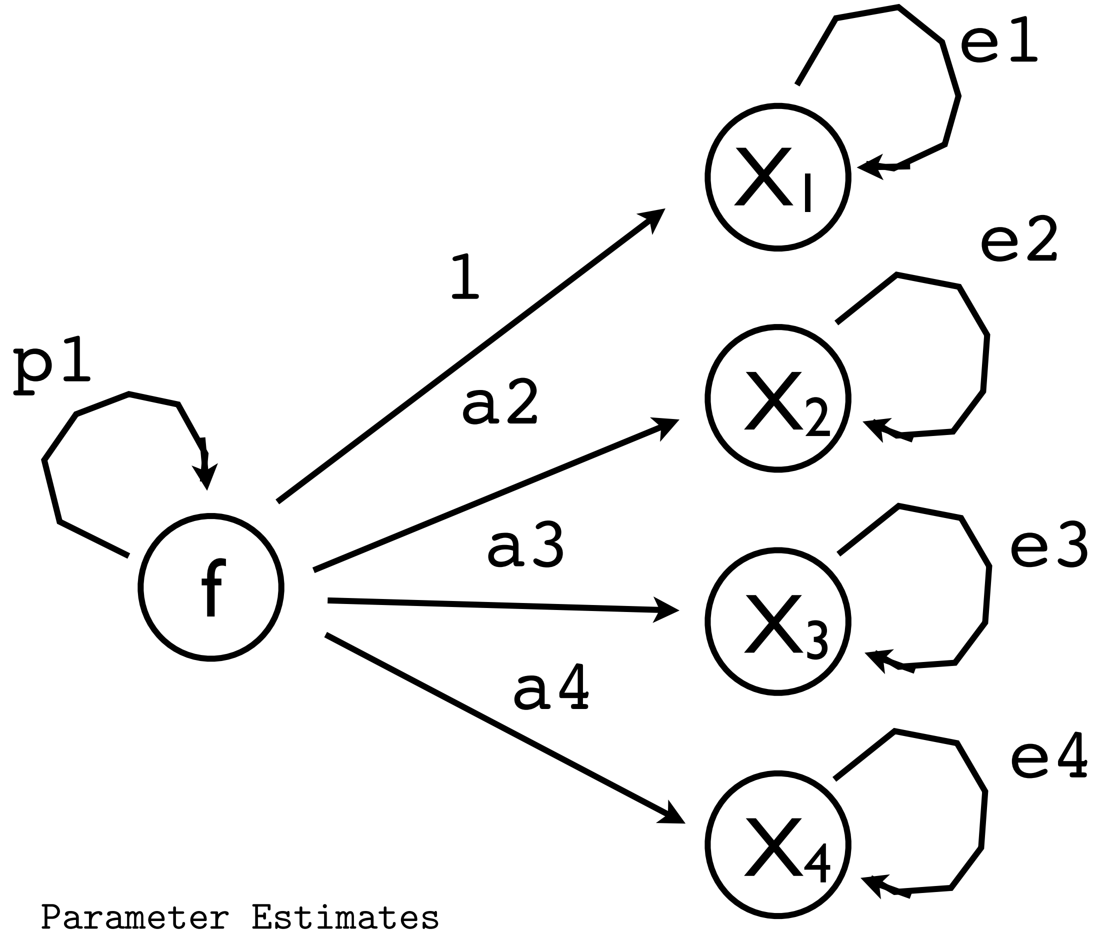
classics	french	english	math
43.39	37.89	43.63	49.88

Correlation

	classics	french	english	math
classics	1.00	0.63	0.70	0.82
french	0.63	1.00	0.60	0.66
english	0.70	0.60	1.00	0.82
math	0.82	0.66	0.82	1.00

Covariance

	classics	french	english	math
classics	345.08	247.92	217.56	295.84
french	247.92	448.60	211.97	270.07
english	217.56	211.97	279.70	266.74
math	295.84	270.07	266.74	375.49




```
 Parameter Estimates
   Estimate  Std Error z value Pr(>|z|)
a2   0.92917  0.115989   8.0108 1.1102e-15 french <--- intell
a3   0.89840  0.082237 10.9245 0.0000e+00 english <--- intell
a4   1.18318  0.089522 13.2168 0.0000e+00 math <--- intell
e1  95.32458 16.605810   5.7404 9.4434e-09 classics <--> classics
e2 232.97400 35.518036   6.5593 5.4055e-11 french <--> french
e3  78.11326 13.301687   5.8724 4.2945e-09 english <--> english
e4  25.85219 13.235897   1.9532 5.0797e-02 math <--> math
p1 249.75715 48.125783   5.1897 2.1066e-07 intell <--> intell
```

All relationships are significant

Model Fit Diagnostics

```
Model Chisquare =  2.3108   Df =  2 Pr(>Chisq) = 0.31494
Chisquare (null model) =  285.98   Df =  6
Goodness-of-fit index =  0.9889
Adjusted goodness-of-fit index =  0.94452
RMSEA index =  0.039616   90% CI: (NA, 0.20758)
Bentler-Bonnett NFI =  0.99192
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Residuals

	classics	french	english	math
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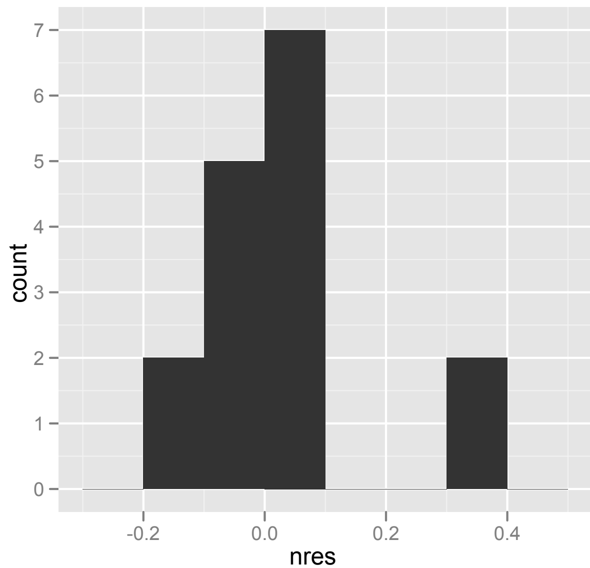

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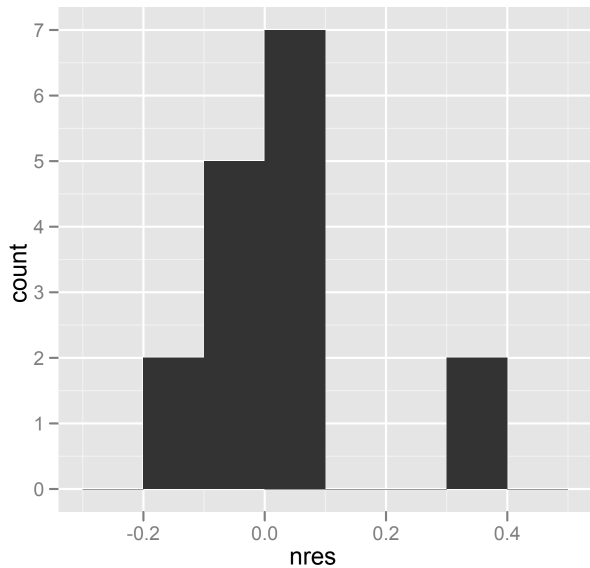

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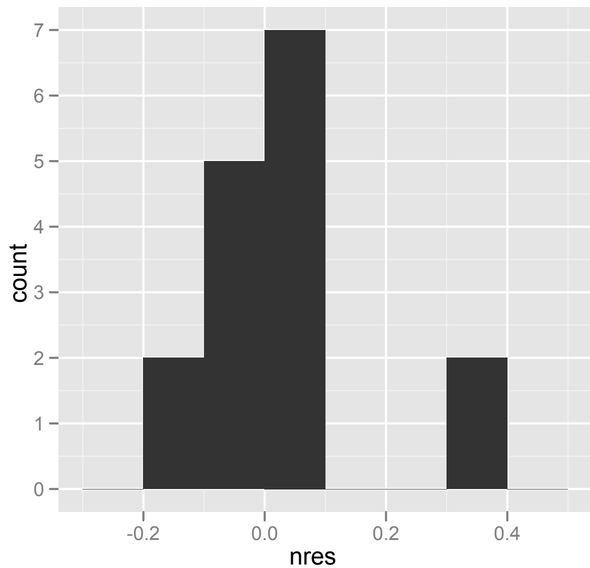

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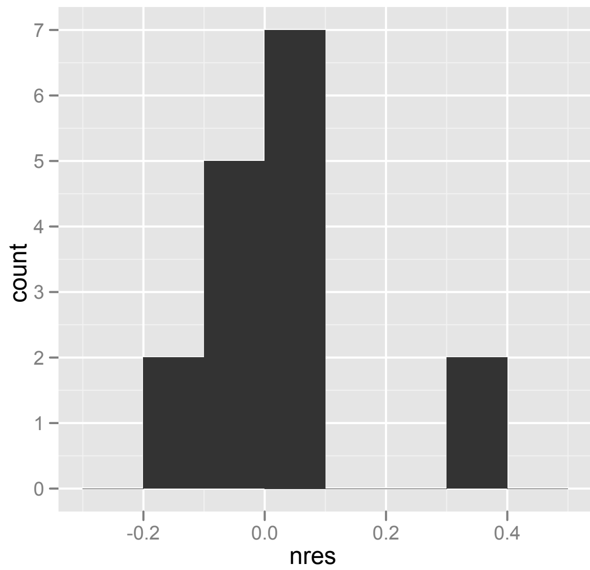

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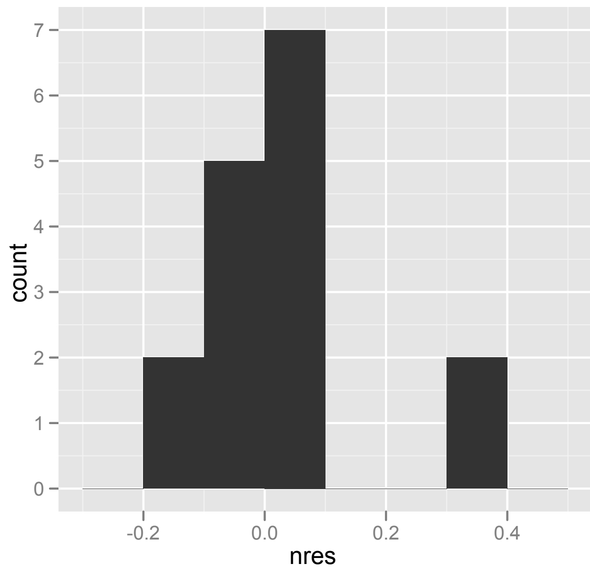
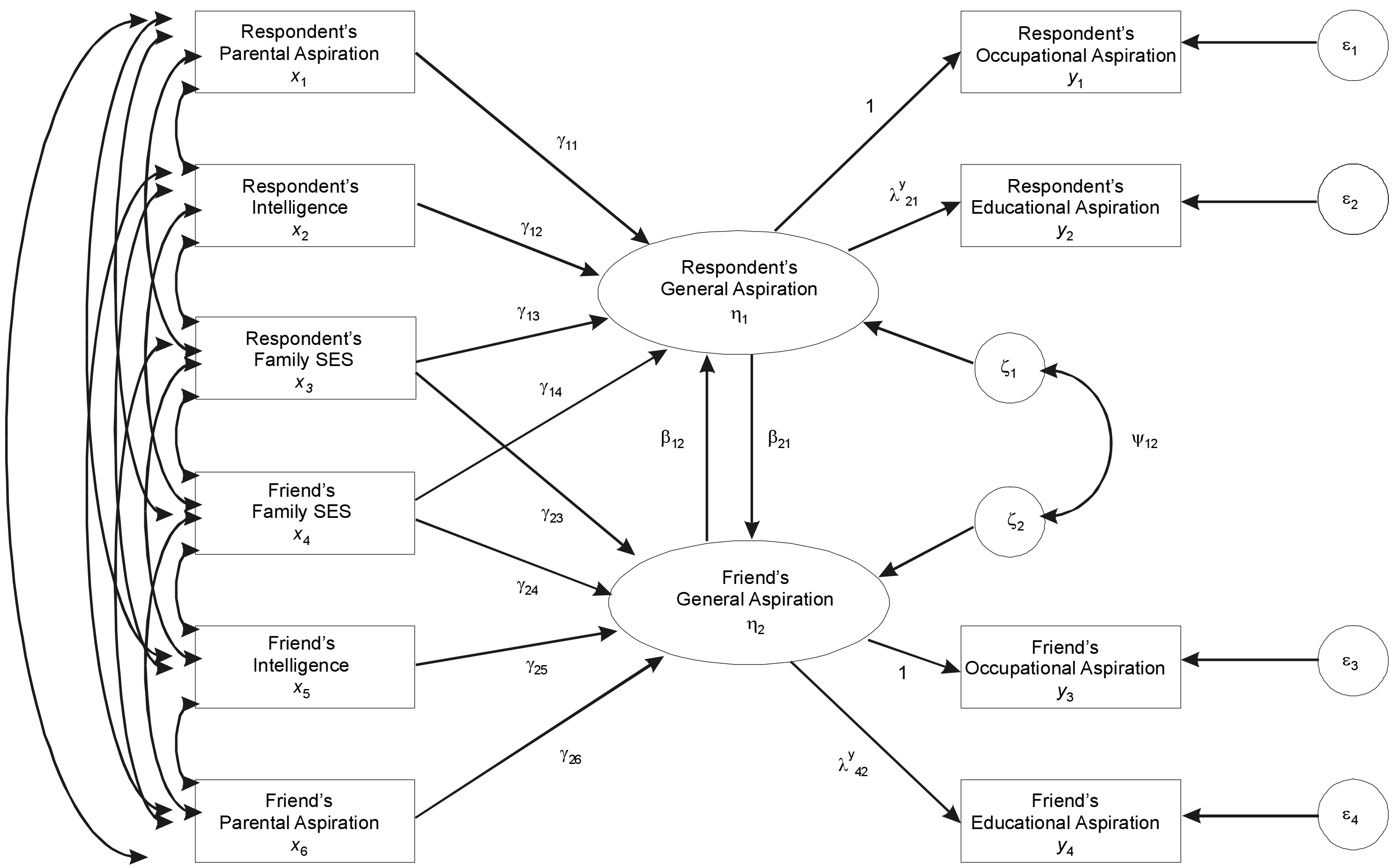


Observations

- Strict distributional assumptions need to be checked - but most people start with correlation or covariance matrix.
- The raw data should be investigated for problems such as outliers, clustering, that invalidate the use of correlation/covariance as the summary of the relationship.

Example

Duncan, Haller, and Portes's general structural equation model for peer influences on aspirations.



Correlation Matrix - Input

	y_1	y_2	y_3	y_4	x_1	x_2	x_3	x_4	x_5	x_6
	ROccAsp	REdAsp	FOccAsp	FEdAsp	RParAsp	RIQ	RSES	FSES	FIQ	FParAsp
ROccAsp	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
REdAsp	0.62	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FOccAsp	0.33	0.37	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
FEdAsp	0.42	0.33	0.64	1.00	0.00	0.00	0.00	0.00	0.00	0.00
RParAsp	0.21	0.27	0.11	0.08	1.00	0.00	0.00	0.00	0.00	0.00
RIQ	0.41	0.40	0.29	0.26	0.18	1.00	0.00	0.00	0.00	0.00
RSES	0.32	0.40	0.31	0.28	0.05	0.22	1.00	0.00	0.00	0.00
FSES	0.29	0.24	0.41	0.36	0.02	0.19	0.27	1.00	0.00	0.00
FIQ	0.30	0.29	0.52	0.50	0.08	0.34	0.23	0.29	1.00	0.00
FParAsp	0.08	0.07	0.28	0.20	0.11	0.10	0.09	-0.04	0.21	1.00

Estimates

	Estimate	Std Error	z value	Pr(>|z|)	
gam11	0.16	0.04	4.19	0.00	RGenAsp <— RParAsp
gam12	0.25	0.04	5.60	0.00	RGenAsp <— RIQ
gam13	0.22	0.04	5.02	0.00	RGenAsp <— RSES
gam14	0.07	0.05	1.43	0.15	RGenAsp <— FSES
gam23	0.06	0.05	1.20	0.23	FGenAsp <— RSES
gam24	0.23	0.04	5.14	0.00	FGenAsp <— FSES
gam25	0.35	0.04	7.83	0.00	FGenAsp <— FIQ
gam26	0.16	0.04	3.98	0.00	FGenAsp <— FParAsp
beta12	0.18	0.10	1.91	0.06	RGenAsp <— FGenAsp
beta21	0.24	0.12	1.97	0.05	FGenAsp <— RGenAsp
lam21	1.06	0.09	11.55	0.00	REdAsp <— RGenAsp
lam42	0.93	0.07	13.07	0.00	FEdAsp <— FGenAsp
ps11	0.28	0.05	6.07	0.00	RGenAsp <–> RGenAsp
ps22	0.26	0.04	5.88	0.00	FGenAsp <–> FGenAsp
ps12	-0.02	0.05	-0.44	0.66	FGenAsp <–> RGenAsp
theta1	0.41	0.05	7.89	0.00	ROccAsp <–> ROccAsp
theta2	0.34	0.05	6.30	0.00	REdAsp <–> REdAsp
theta3	0.31	0.05	6.67	0.00	FOccAsp <–> FOccAsp
theta4	0.40	0.05	8.66	0.00	FEdAsp <–> FEdAsp

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gam14	0.07	0.05	1.43	0.15	RGenAsp <— FSES
gam23	0.06	0.05	1.20	0.23	FGenAsp <— RSES
gam24	0.23	0.04	5.14	0.00	FGenAsp <— FSES
gam25	0.35	0.04	7.83	0.00	FGenAsp <— FIQ
gam26	0.16	0.04	3.98	0.00	FGenAsp <— FParAsp
beta12	0.18	0.10	1.91	0.06	RGenAsp <— FGenAsp
beta21	0.24	0.12	1.97	0.05	FGenAsp <— RGenAsp
lam21	1.06	0.09	11.55	0.00	REdAsp <— RGenAsp
lam42	0.93	0.07	13.07	0.00	FEdAsp <— FGenAsp
ps11	0.28	0.05	6.07	0.00	RGenAsp <–> RGenAsp
ps22	0.26	0.04	5.88	0.00	FGenAsp <–> FGenAsp
ps12	-0.02	0.05	-0.44	0.66	FGenAsp <–> RGenAsp
theta1	0.41	0.05	7.89	0.00	ROccAsp <–> ROccAsp
theta2	0.34	0.05	6.30	0.00	REdAsp <–> REdAsp
theta3	0.31	0.05	6.67	0.00	FOccAsp <–> FOccAsp
theta4	0.40	0.05	8.66	0.00	FEdAsp <–> FEdAsp

Estimates

	Estimate	Std Error	z value	Pr(>|z|)	
gam11	0.16	0.04	4.19	0.00	RGenAsp <— RParAsp
gam12	0.25	0.04	5.60	0.00	RGenAsp <— RIQ
gam13	0.22	0.04	5.02	0.00	RGenAsp <— RSES
gam14	0.07	0.05	1.43	0.15	RGenAsp <— FSES
gam23	0.06	0.05	1.20	0.23	FGenAsp <— RSES
gam24	0.23	0.04	5.14	0.00	FGenAsp <— FSES
gam25	0.35	0.04	7.83	0.00	FGenAsp <— FIQ
gam26	0.16	0.04	3.98	0.00	FGenAsp <— FParAsp
beta12	0.18	0.10	1.91	0.06	RGenAsp <— FGenAsp
beta21	0.24	0.12	1.97	0.05	FGenAsp <— RGenAsp
lam21	1.06	0.09	11.55	0.00	REdAsp <— RGenAsp
lam42	0.93	0.07	13.07	0.00	FEdAsp <— FGenAsp
ps11	0.28	0.05	6.07	0.00	RGenAsp <–> RGenAsp
ps22	0.26	0.04	5.88	0.00	FGenAsp <–> FGenAsp
ps12	-0.02	0.05	-0.44	0.66	FGenAsp <–> RGenAsp
theta1	0.41	0.05	7.89	0.00	ROccAsp <–> ROccAsp
theta2	0.34	0.05	6.30	0.00	REdAsp <–> REdAsp
theta3	0.31	0.05	6.67	0.00	FOccAsp <–> FOccAsp
theta4	0.40	0.05	8.66	0.00	FEdAsp <–> FEdAsp

Estimates

	Estimate	Std Error	z value	Pr(>|z|)	
gam11	0.16	0.04	4.19	0.00	RGenAsp <— RParAsp
gam12	0.25	0.04	5.60	0.00	RGenAsp <— RIQ
gam13	0.22	0.04	5.02	0.00	RGenAsp <— RSES
gam14	0.07	0.05	1.43	0.15	RGenAsp <— FSES
gam23	0.06	0.05	1.20	0.23	FGenAsp <— RSES
gam24	0.23	0.04	5.14	0.00	FGenAsp <— FSES
gam25	0.35	0.04	7.83	0.00	FGenAsp <— FIQ
gam26	0.16	0.04	3.98	0.00	FGenAsp <— FParAsp
beta12	0.18	0.10	1.91	0.06	RGenAsp <— FGenAsp
beta21	0.24	0.12	1.97	0.05	FGenAsp <— RGenAsp
lam21	1.06	0.09	11.55	0.00	REdAsp <— RGenAsp
lam42	0.93	0.07	13.07	0.00	FEdAsp <— FGenAsp
ps11	0.28	0.05	6.07	0.00	RGenAsp <–> RGenAsp
ps22	0.26	0.04	5.88	0.00	FGenAsp <–> FGenAsp
ps12	-0.02	0.05	-0.44	0.66	FGenAsp <–> RGenAsp
theta1	0.41	0.05	7.89	0.00	ROccAsp <–> ROccAsp
theta2	0.34	0.05	6.30	0.00	REdAsp <–> REdAsp
theta3	0.31	0.05	6.67	0.00	FOccAsp <–> FOccAsp
theta4	0.40	0.05	8.66	0.00	FEdAsp <–> FEdAsp

Model Fit

```
Model Chisquare =  26.697   Df =  15 Pr(>Chisq) = 0.031302
 Chisquare (null model) =  872   Df =  45
 Goodness-of-fit index =  0.98439
 Adjusted goodness-of-fit index =  0.94275
 RMSEA index =  0.048759   90% CI: (0.014517, 0.07831)
 Bentler-Bonnett NFI =  0.96938
 Tucker-Lewis NNFI =  0.95757
 Bentler CFI =  0.98586
 SRMR =  0.020204
 BIC =  -60.244
```

All looks good

Residuals

	ROccAsp	REdAsp	FOccAsp	FEdAsp	RParAsp	RIQ	RSES	FSES	FIQ	FParAsp
ROccAsp	-0.00	0.00	-0.03	0.09	-0.03	0.02	-0.03	0.04	0.03	-0.03
REdAsp	0.00	0.00	-0.01	-0.02	0.02	-0.01	0.03	-0.03	0.00	-0.04
FOccAsp	-0.03	-0.01	0.00	0.00	0.00	0.01	0.00	0.01	-0.01	0.02
FEdAsp	0.09	-0.02	0.00	-0.00	-0.02	-0.00	-0.00	-0.01	0.01	-0.04
RParAsp	-0.03	0.02	0.00	-0.02	0.00	0.00	0.00	0.00	0.00	0.00
RIQ	0.02	-0.01	0.01	-0.00	0.00	0.00	0.00	0.00	0.00	0.00
RSES	-0.03	0.03	0.00	-0.00	0.00	0.00	0.00	0.00	0.00	0.00
FSES	0.04	-0.03	0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00
FIQ	0.03	0.00	-0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
FParAsp	-0.03	-0.04	0.02	-0.04	0.00	0.00	0.00	0.00	0.00	0.00

Must be magic!