

Analysis 2011

Contents

Preparations	2
Analysis	8
H1 and H2	8
Define the model	8
Fit the model	8
Respecify the model by introducing the preregistered residual correlation	10
Fit the respecified model	10
Exploratory analysis for H1 and H2: Seek misspecification to improve the overall model fit	15
Exploratory respecification	16
Seek for additional misspecifications	18
Exploratory factor analysis for CS-data	27
H1 and H2 with a subset of CS-items	33
Fit the respecified model	33
H3 and H4	42
Define the model	42
Fit the configural model	43
Fit the respecified model	43
Model for KD	58
Model for KESK	59
Model for KOK	60
Model for PS	61
Model for RKP	62
Model for SDP	68
Model for VAS	69
Model for VIHR	70
Summary of H3-H4 with MG-CFA approach	71
H3 and H4 with group-mean centered variables and no grouping structure	72
Define the model	74
Fit the model	74
Fit the respecified model	75
Exploratory for H3 and H4: Seek misspecification to improve the overall model fit	76
Exploratory respecification	77
Examine how self-placement on	78

Preparations

Load packages

```
library(here)
library(dplyr)
library(labelled)
library(ggplot2)
library(tidyr)
library(stringr)
library(psych)
library(lavaan)
library(semTools)
library(semPlot)
library(haven)
library(sjlabelled)
#library(robumeta)
```

Read data file

```
df2011 <- readRDS("data/final/candsurvey_vaa_2011.rds")
```

Select variables used in the analysis

```
VAA_LR_items<-c("y22","y23","y26","y27","y9","y19")
VAA_LR_items %in% names(df2011)
```

```
## [1] TRUE TRUE TRUE TRUE TRUE TRUE
```

```
VAA_GT_items<-c("y4","y5","y1","y21")
VAA_GT_items %in% names(df2011)
```

```
## [1] TRUE TRUE TRUE TRUE
```

```
CS_LR_items<-c("C1_2","C1_7","C1_8")
CS_LR_items %in% names(df2011)
```

```
## [1] TRUE TRUE TRUE
```

```
CS_GT_items<-c("C1_1","C1_3","C1_4","C1_5","C1_6","C1_10","C1_11")
CS_GT_items %in% names(df2011)
```

```
## [1] TRUE TRUE TRUE TRUE TRUE TRUE TRUE
```

```
Party_item<-c("puolue")
Party_item %in% names(df2011)
```

```
## [1] TRUE
```

```
#vector for all item names
```

```
all_items<-c(Party_item,
             VAA_LR_items,
             VAA_GT_items,
             CS_LR_items,
             CS_GT_items)
```

```
#vector for observed variables in CFA (and party)
```

```
obs_items<-c(Party_item,
             VAA_LR_items,
             VAA_GT_items,
             CS_LR_items,
             CS_GT_items)
```

Print the responses to the observed items

```
for (i in 1:length(obs_items)){
  print(obs_items[i])
  print(table(df2011[,obs_items[i]],useNA="always"))
}
```

```
## [1] "puolue"
##
##      IP   KD KESK  KOK  KTP  M11 Muut  PIR   PS  RKP  SDP  SKP  SSP  STP  VAS VIHR
##      69 192 233  232  46   66  34  127  239  83  238  144  44  47  237  228
##      VP <NA>
##      60   0
## [1] "y22"
##
##      1   2   3   4   5 <NA>
## 574 515   22 573 216 419
## [1] "y23"
##
##      1   2   3   4   5 <NA>
## 744 654   22 360 120 419
## [1] "y26"
##
##      1   2   3   4   5 <NA>
##   73 204   2 618 1002 420
## [1] "y27"
##
##      1   2   3   4   5 <NA>
## 145 398   3 805 550 418
## [1] "y9"
##
##      1   2   3   4   5 <NA>
## 186 463  13 747 496 414
## [1] "y19"
##
##      1   2   3   4   5 <NA>
##   87 426   6 530 854 416
## [1] "y4"
##
##      1   2   3   4   5 <NA>
## 341 294  20 407 849 408
## [1] "y5"
##
##      1   2   3   4   5 <NA>
## 370 538  12 548 441 410
## [1] "y1"
##
##      1   2   3   4   5 <NA>
## 628 611   4 591 81 404
```

```
## [1] "y21"
##
##      1      2      3      4      5 <NA>
## 190  505   80  607  518  419
## [1] "C1_2"
##
##      1      2      3      4      5   99 <NA>
## 424  309   42  100   26   14 1404
## [1] "C1_7"
##
##      1      2      3      4      5   99 <NA>
##   11   66   56  449  320   13 1404
## [1] "C1_8"
##
##      1      2      3      4      5   99 <NA>
##   16   89   66  306  424   14 1404
## [1] "C1_1"
##
##      1      2      3      4      5   99 <NA>
##   15   82   69  440  296   13 1404
## [1] "C1_3"
##
##      1      2      3      4      5   99 <NA>
##   27   86   83  322  387   10 1404
## [1] "C1_4"
##
##      1      2      3      4      5   99 <NA>
## 469  111   83   69  166   17 1404
## [1] "C1_5"
##
##      1      2      3      4      5   99 <NA>
## 208  209  268  161   53   16 1404
## [1] "C1_6"
##
##      1      2      3      4      5   99 <NA>
##   37  162  136  366  200   14 1404
## [1] "C1_10"
##
##      1      2      3      4      5   99 <NA>
##   76  136  114  388  191   10 1404
## [1] "C1_11"
##
##      1      2      3      4      5   99 <NA>
##   28   54   55  190  571   17 1404
```

Recode middle-responses (3) from yle items to NA, and 99 responses from CS to NA

```
VAA_items<-c(VAA_LR_items,VAA_GT_items)
CS_items<-c(CS_LR_items,CS_GT_items)

three.to.na<-function(var){
  return(ifelse(var==3,NA,var))
}

df2011[,VAA_items]<-sapply(df2011[,VAA_items],three.to.na)
```

```

ninenine.to.na<-function(var){
  return(ifelse(var==99,NA,var))
}

df2011[,CS_items]<-sapply(df2011[,CS_items],ninenine.to.na)

for (i in 1:length(all_items)){
  print(all_items[i])
  print(table(df2011[,all_items[i]],useNA="always"))
}

## [1] "puolue"
##
##      IP      KD  KESK   KOK   KTP   M11 Muut   PIR    PS   RKP   SDP   SKP   SSP   STP   VAS  VIHR
##      69    192   233   232    46    66    34   127   239    83   238   144    44    47   237   228
##      VP <NA>
##      60      0
## [1] "y22"
##
##      1      2      4      5 <NA>
##    574   515   573   216   441
## [1] "y23"
##
##      1      2      4      5 <NA>
##    744   654   360   120   441
## [1] "y26"
##
##      1      2      4      5 <NA>
##      73   204   618  1002   422
## [1] "y27"
##
##      1      2      4      5 <NA>
##    145   398   805   550   421
## [1] "y9"
##
##      1      2      4      5 <NA>
##    186   463   747   496   427
## [1] "y19"
##
##      1      2      4      5 <NA>
##      87   426   530   854   422
## [1] "y4"
##
##      1      2      4      5 <NA>
##    341   294   407   849   428
## [1] "y5"
##
##      1      2      4      5 <NA>
##    370   538   548   441   422
## [1] "y1"
##

```

```
##      1      2      4      5 <NA>
## 628 611 591 81 408
## [1] "y21"
##
##      1      2      4      5 <NA>
## 190 505 607 518 499
## [1] "C1_2"
##
##      1      2      3      4      5 <NA>
## 424 309 42 100 26 1418
## [1] "C1_7"
##
##      1      2      3      4      5 <NA>
## 11 66 56 449 320 1417
## [1] "C1_8"
##
##      1      2      3      4      5 <NA>
## 16 89 66 306 424 1418
## [1] "C1_1"
##
##      1      2      3      4      5 <NA>
## 15 82 69 440 296 1417
## [1] "C1_3"
##
##      1      2      3      4      5 <NA>
## 27 86 83 322 387 1414
## [1] "C1_4"
##
##      1      2      3      4      5 <NA>
## 469 111 83 69 166 1421
## [1] "C1_5"
##
##      1      2      3      4      5 <NA>
## 208 209 268 161 53 1420
## [1] "C1_6"
##
##      1      2      3      4      5 <NA>
## 37 162 136 366 200 1418
## [1] "C1_10"
##
##      1      2      3      4      5 <NA>
## 76 136 114 388 191 1414
## [1] "C1_11"
##
##      1      2      3      4      5 <NA>
## 28 54 55 190 571 1421
```

Exclude completely missing cases

```
df2011$completely_missing<-
  rowSums(is.na(df2011[,obs_items[2:length(obs_items)]]))==length(obs_items)-1

table(df2011$completely_missing)
```

```
##
```

```
## FALSE TRUE
## 2060 259
```

```
dat2011<-df2011 %>%
  filter(!completely_missing)
```

Transform/Reverse code high scores on observed variable to indicate right and TAN positioning

```
reverse_items<-c("y26","y19",
                 "y4","y1","y21",
                 "C1_7","C1_8",
                 "C1_3","C1_5","C1_10","C1_11")
```

```
reverse_items %in% names(df2011)
```

```
## [1] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
```

```
for (i in 1:length(reverse_items)){
  dat2011[,reverse_items[i]]<-6-dat2011[,reverse_items[i]]
}
```

Analysis

H1 and H2

H1. Left-Right placement as computed from responses to the pre-election public Voting Advice Applications (VAAs) is positively associated with Left-Right placement as computed from responses to the privately administered post-election Candidate Survey (CS). This association is stronger than any associations between the Left-Right and GAL-TAN dimensions.

H2. GAL-TAN placement as computed from responses to the pre-election public Voting Advice Applications (VAAs) is positively associated with GAL-TAN placement as computed from responses to the privately administered post-election Candidate Survey (CS). This association is stronger than any associations between the Left-Right and GAL-TAN dimensions.

Define the model

```
model_H1H2<-"
#loadings
VAA_LR=~y22+y23+y26+y27+y9+y19
VAA_GT=~y4+y5+y1+y21
CS_LR=~C1_2+C1_7+C1_8
CS_GT=~C1_1+C1_3+C1_4+C1_5+C1_6+C1_10+C1_11

#latent correlations

#cross-dimension same-method
VAA_LR~~r.VAA*VAA_GT
CS_LR~~r.CS*CS_GT

#concurrent validity
VAA_LR~~r.LR*CS_LR
VAA_GT~~r.GT*CS_GT

#cross-dimension cross-method correlations
VAA_LR~~r.d1*CS_GT
VAA_GT~~r.d2*CS_LR

#custom parameters
test.H1:=r.LR-max(r.VAA,r.CS,r.d1,r.d2)
test.H2:=r.GT-max(r.VAA,r.CS,r.d1,r.d2)

"
```

Fit the model

```
fit_H1H2<-cfa(model=model_H1H2,
               data=dat2011,
               missing="fiml")

## Warning in lav_object_post_check(object): lavaan WARNING: covariance matrix of latent variables
##               is not positive definite;
##               use lavInspect(fit, "cov.lv") to investigate.
```


Some problems with latent variable covariance structure

```
lavInspect(fit_H1H2, "cov.lv")
```

```
##          VAA_LR VAA_GT CS_LR CS_GT
## VAA_LR  1.022
## VAA_GT  0.551  1.468
## CS_LR   0.211  0.040  0.075
## CS_GT   0.266  0.723  0.022  0.282
```

```
#examine standardized estimates
```

```
std.est_H1H2<-standardizedsolution(fit_H1H2)
std.est_H1H2[std.est_H1H2$op=="~~" &
             std.est_H1H2$lhs!=std.est_H1H2$rhs,]
```

```
##      lhs op   rhs est.std   se      z pvalue ci.lower ci.upper
## 21 VAA_LR ~~ VAA_GT   0.450 0.026 17.135  0.000    0.399    0.502
## 22 CS_LR  ~~ CS_GT   0.149 0.044  3.411  0.001    0.063    0.235
## 23 VAA_LR ~~ CS_LR   0.761 0.037 20.300  0.000    0.687    0.834
## 24 VAA_GT ~~ CS_GT   1.125 0.015 76.454  0.000    1.096    1.153
## 25 VAA_LR ~~ CS_GT   0.496 0.031 15.980  0.000    0.435    0.557
## 26 VAA_GT ~~ CS_LR   0.121 0.042  2.876  0.004    0.038    0.203
```

There is an impossible correlation between GAL-TAN factors (absolute value > 1)

```
model_H1H2.re<-paste0(model_H1H2,
                        "y4~~C1_4\n")
```

Respecify the model by introducing the preregistered residual correlation

```
fit_H1H2.re<-cfa(model=model_H1H2.re,
                  data=dat2011,
                  missing="fiml")
```

Fit the respecified model

```
## Warning in lav_object_post_check(object): lavaan WARNING: covariance matrix of latent variables
##           is not positive definite;
##           use lavInspect(fit, "cov.lv") to investigate.
```

The problem persists, inspect the parameter estimates

```
summary(fit_H1H2.re,fit=T,standardized=T,rsquare=T)
```

```
## lavaan 0.6-5 ended normally after 82 iterations
##
##   Estimator                      ML
##   Optimization method          NLMINB
##   Number of free parameters      67
##
##   Number of observations          2060
##   Number of missing patterns      63
##
## Model Test User Model:
##
##   Test statistic                  1811.451
##   Degrees of freedom              163
##   P-value (Chi-square)            0.000
##
## Model Test Baseline Model:
##
##   Test statistic                  8365.164
##   Degrees of freedom              190
##   P-value                        0.000
##
## User Model versus Baseline Model:
##
##   Comparative Fit Index (CFI)      0.798
##   Tucker-Lewis Index (TLI)        0.765
##
## Loglikelihood and Information Criteria:
##
##   Loglikelihood user model (H0)    -43099.896
##   Loglikelihood unrestricted model (H1) -42194.171
##
##   Akaike (AIC)                    86333.792
##   Bayesian (BIC)                   86711.033
##   Sample-size adjusted Bayesian (BIC) 86498.168
```

```

##
## Root Mean Square Error of Approximation:
##
##   RMSEA                                0.070
##   90 Percent confidence interval - lower    0.067
##   90 Percent confidence interval - upper    0.073
##   P-value RMSEA <= 0.05                    0.000
##
## Standardized Root Mean Square Residual:
##
##   SRMR                                0.096
##
## Parameter Estimates:
##
##   Information                                Observed
##   Observed information based on                Hessian
##   Standard errors                            Standard
##
## Latent Variables:
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
## VAA_LR =~
##   y22              1.000
##   y23              0.782    0.036   21.953   0.000    0.788    0.605
##   y26              0.633    0.031   20.614   0.000    0.639    0.569
##   y27              0.609    0.034   18.009   0.000    0.614    0.473
##   y9               0.902    0.037   24.689   0.000    0.910    0.670
##   y19              0.851    0.035   24.315   0.000    0.858    0.651
## VAA_GT =~
##   y4               1.000
##   y5               1.141    0.050   22.918   0.000    1.204    0.797
##   y1               0.427    0.034   12.675   0.000    0.451    0.338
##   y21              0.770    0.037   20.556   0.000    0.813    0.575
## CS_LR =~
##   C1_2             1.000
##   C1_7             1.600    0.264    6.061   0.000    0.438    0.487
##   C1_8             3.240    0.537    6.031   0.000    0.887    0.854
## CS_GT =~
##   C1_1             1.000
##   C1_3             0.755    0.068   11.030   0.000    0.465    0.432
##   C1_4             1.575    0.100   15.728   0.000    0.970    0.616
##   C1_5             0.414    0.072    5.766   0.000    0.255    0.215
##   C1_6             0.985    0.070   14.086   0.000    0.607    0.535
##   C1_10            1.203    0.080   15.112   0.000    0.741    0.612
##   C1_11            0.619    0.066    9.398   0.000    0.382    0.366
##
## Covariances:
##           Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
## VAA_LR ~~
##   VAA_GT (r.VA)    0.480    0.038   12.519   0.000    0.451    0.451
## CS_LR ~~
##   CS_GT (r.CS)    0.024    0.009    2.723   0.006    0.143    0.143
## VAA_LR ~~
##   CS_LR (r.LR)    0.210    0.037    5.734   0.000    0.762    0.762
## VAA_GT ~~

```

```

##      CS_GT   (r.GT)    0.662    0.041   16.077    0.000    1.019    1.019
##      VAA_LR   ~~
##      CS_GT   (r.d1)    0.296    0.028   10.732    0.000    0.476    0.476
##      VAA_GT   ~~
##      CS_LR   (r.d2)    0.040    0.014    2.787    0.005    0.138    0.138
##      .y4     ~~
##      .C1_4                0.942    0.065   14.528    0.000    0.942    0.632
##
## Intercepts:
##              Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      .y22              2.639   0.033   79.332   0.000    2.639    1.810
##      .y23              2.178   0.030   73.067   0.000    2.178    1.672
##      .y26              1.798   0.026   70.198   0.000    1.798    1.602
##      .y27              3.636   0.030  122.654   0.000    3.636    2.803
##      .y9               3.468   0.031  112.184   0.000    3.468    2.555
##      .y19              2.132   0.030   71.118   0.000    2.132    1.619
##      .y4               2.442   0.036   68.064   0.000    2.442    1.527
##      .y5               3.101   0.034   91.051   0.000    3.101    2.053
##      .y1               3.592   0.030  118.219   0.000    3.592    2.697
##      .y21              2.608   0.033   79.891   0.000    2.608    1.847
##      .C1_2             1.887   0.036   51.940   0.000    1.887    1.717
##      .C1_7             1.896   0.029   65.285   0.000    1.896    2.109
##      .C1_8             1.864   0.031   59.548   0.000    1.864    1.796
##      .C1_1             4.021   0.029  139.603   0.000    4.021    4.209
##      .C1_3             1.947   0.034   56.660   0.000    1.947    1.806
##      .C1_4             2.261   0.043   53.040   0.000    2.261    1.435
##      .C1_5             3.400   0.039   86.610   0.000    3.400    2.860
##      .C1_6             3.593   0.035  101.591   0.000    3.593    3.168
##      .C1_10            2.472   0.037   67.049   0.000    2.472    2.041
##      .C1_11            1.643   0.034   48.693   0.000    1.643    1.577
##      VAA_LR            0.000                0.000    0.000
##      VAA_GT            0.000                0.000    0.000
##      CS_LR             0.000                0.000    0.000
##      CS_GT            0.000                0.000    0.000
##
## Variances:
##              Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      .y22              1.109   0.046   23.949   0.000    1.109    0.522
##      .y23              1.076   0.041   26.186   0.000    1.076    0.634
##      .y26              0.853   0.032   26.911   0.000    0.853    0.676
##      .y27              1.306   0.046   28.646   0.000    1.306    0.776
##      .y9               1.015   0.041   24.566   0.000    1.015    0.551
##      .y19              0.998   0.039   25.406   0.000    0.998    0.576
##      .y4               1.444   0.062   23.128   0.000    1.444    0.565
##      .y5               0.831   0.053   15.631   0.000    0.831    0.364
##      .y1               1.571   0.053   29.720   0.000    1.571    0.885
##      .y21              1.334   0.051   26.063   0.000    1.334    0.669
##      .C1_2             1.133   0.055   20.732   0.000    1.133    0.938
##      .C1_7             0.617   0.032   19.033   0.000    0.617    0.763
##      .C1_8             0.292   0.063    4.647   0.000    0.292    0.271
##      .C1_1             0.533   0.030   17.782   0.000    0.533    0.584
##      .C1_3             0.945   0.047   20.160   0.000    0.945    0.814
##      .C1_4             1.540   0.081   18.976   0.000    1.540    0.621
##      .C1_5             1.348   0.064   20.965   0.000    1.348    0.954

```

```
##      .C1_6      0.918    0.048   19.243    0.000    0.918    0.714
##      .C1_10     0.917    0.050   18.166    0.000    0.917    0.625
##      .C1_11     0.940    0.046   20.362    0.000    0.940    0.866
##      VAA_LR     1.016    0.065   15.607    0.000    1.000    1.000
##      VAA_GT     1.114    0.079   14.129    0.000    1.000    1.000
##      CS_LR      0.075    0.023    3.267    0.001    1.000    1.000
##      CS_GT      0.380    0.037   10.265    0.000    1.000    1.000
##
## R-Square:
##      Estimate
##      y22      0.478
##      y23      0.366
##      y26      0.324
##      y27      0.224
##      y9       0.449
##      y19      0.424
##      y4       0.435
##      y5       0.636
##      y1       0.115
##      y21      0.331
##      C1_2     0.062
##      C1_7     0.237
##      C1_8     0.729
##      C1_1     0.416
##      C1_3     0.186
##      C1_4     0.379
##      C1_5     0.046
##      C1_6     0.286
##      C1_10    0.375
##      C1_11    0.134
##
## Defined Parameters:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      test.H1   -0.269   0.051  -5.336   0.000   0.286   0.286
##      test.H2    0.183   0.044   4.154   0.000   0.543   0.543
```

Inspect fit of the model

```
round(inspect(fit_H1H2,"fit")
      [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

```
##      npar      df      chisq      pvalue      cfi      tli      rmsea      srmr
##      66.000    164.000  2057.729      0.000     0.768     0.732     0.075     0.097
```

```
round(inspect(fit_H1H2.re,"fit")
      [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

```
##      npar      df      chisq      pvalue      cfi      tli      rmsea      srmr
##      67.000    163.000  1811.451      0.000     0.798     0.765     0.070     0.096
```

The fits of the models are poor.

Hypotheses 1 and 2

Print standardized estimates to test the difference between correlations

```
std.est_H1H2<-standardizedsolution(fit_H1H2.re)
std.est_H1H2[std.est_H1H2$op=="!=" |
```

```
std.est_H1H2$op=="~~" &
std.est_H1H2$lhs!=std.est_H1H2$rhs,]
```

```
##      lhs op                rhs est.std   se      z pvalue
## 21  VAA_LR ~~            VAA_GT   0.451 0.026 17.600 0.000
## 22   CS_LR ~~            CS_GT   0.143 0.044  3.272 0.001
## 23  VAA_LR ~~            CS_LR   0.762 0.038 20.291 0.000
## 24  VAA_GT ~~            CS_GT   1.019 0.015 69.261 0.000
## 25  VAA_LR ~~            CS_GT   0.476 0.032 15.000 0.000
## 26  VAA_GT ~~            CS_LR   0.138 0.041  3.350 0.001
## 27      y4 ~~            C1_4   0.632 0.025 25.047 0.000
## 76 test.H1 := r.LR-max(r.VAA,r.CS,r.d1,r.d2) 0.286 0.051  5.656 0.000
## 77 test.H2 := r.GT-max(r.VAA,r.CS,r.d1,r.d2) 0.543 0.035 15.680 0.000
##    ci.lower ci.upper
## 21   0.401   0.501
## 22   0.057   0.228
## 23   0.688   0.836
## 24   0.990   1.048
## 25   0.414   0.538
## 26   0.057   0.219
## 27   0.582   0.681
## 76   0.187   0.385
## 77   0.475   0.610
```

```
mis_H1H2<-miPowerFit(fit_H1H2.re,stdLoad=.40,cor=.20)
```

Exploratory analysis for H1 and H2: Seek misspecification to improve the overall model fit

```
## Warning in lav_start_check_cov(lavpartable = lavpartable, start = START): lavaan WARNING: starting v
##          variables involved are: VAA_GT    CS_GT
```

```
mis_H1H2<-mis_H1H2[mis_H1H2$op=="=~" | mis_H1H2$op=="~~",]
#see summary of the decisions
table(mis_H1H2$decision.pow)
```

```
##
##  EPC:M EPC:NM      M      NM
##      7    111      2     131
```

#there are 9 misspecifications

```
rounded.vars<-c("mi","epc","target.epc",
               "std.epc","se.epc")
```

```
num.round<-function(var){
  var<-as.numeric(var)
  var<-round(var,2)
  return(var)
}
```

```
mis_H1H2[,rounded.vars]<-sapply(mis_H1H2[,rounded.vars],num.round)
```

```
printed.vars<-c("lhs","op","rhs","mi","epc","target.epc",
               "std.epc","std.target.epc","significant.mi",
               "high.power","decision.pow","se.epc")
```

#print the output

```
mis_H1H2 %>%
  filter(mis_H1H2$decision.pow=="M" |
         mis_H1H2$decision.pow=="EPC:M") %>%
  dplyr::select(all_of(printed.vars))
```

```
##      lhs op   rhs      mi    epc target.epc std.epc std.target.epc significant.mi
## 1 VAA_LR =~   y1 401.16 -0.76      0.53   -0.58          0.4          TRUE
## 2 VAA_LR =~  C1_2  50.46  0.58      0.44    0.53          0.4          TRUE
## 3 VAA_LR =~  C1_8  24.27 -0.88      0.41   -0.85          0.4          TRUE
## 4 CS_LR =~   y26 136.95  2.92      1.64    0.71          0.4          TRUE
## 5 CS_LR =~   y9  59.26 -2.22      1.98   -0.45          0.4          TRUE
## 6 CS_LR =~   y1 366.17 -2.72      1.95   -0.56          0.4          TRUE
## 7 CS_GT =~   y1  17.43 -1.06      0.86   -0.49          0.4          TRUE
## 8      y1 ~~ C1_10 76.05  0.41      0.32    0.25          0.2          TRUE
## 9   C1_7 ~~  C1_8   5.52  0.17      0.19    0.18          0.2          TRUE
##  high.power decision.pow se.epc
## 1      TRUE          EPC:M  0.04
## 2      TRUE          EPC:M  0.08
## 3     FALSE           M    0.18
## 4      TRUE          EPC:M  0.25
## 5      TRUE          EPC:M  0.29
```

```
## 6      TRUE      EPC:M    0.14
## 7      TRUE      EPC:M    0.25
## 8      TRUE      EPC:M    0.05
## 9     FALSE      M       0.07
```

Item y1 “Finland should continue to financially assist EU countries that are facing economic hardship (r.)” is proposed to load to all other factors besides loading on its specified factor (VAA_GT). It is also proposed to have residual correlation with C1_10 (“Maahanmuutto on hyvä asia Suomen taloudelle”). Exclude item y1 entirely

```
model_H1H2.exp.re<-"
#loadings
VAA_LR=~y22+y23+y26+y27+y9+y19
VAA_GT=~y4+y5+y21
CS_LR=~C1_2+C1_7+C1_8
CS_GT=~C1_1+C1_3+C1_4+C1_5+C1_6+C1_10+C1_11

#latent correlations

#cross-dimension same-method
VAA_LR~~r.VAA*VAA_GT
CS_LR~~r.CS*CS_GT

#concurrent validity
VAA_LR~~r.LR*CS_LR
VAA_GT~~r.GT*CS_GT

#cross-dimension cross-method correlations
VAA_LR~~r.d1*CS_GT
VAA_GT~~r.d2*CS_LR

#custom parameters
test.H1:=r.LR-max(r.VAA,r.CS,r.d1,r.d2)
test.H2:=r.GT-max(r.VAA,r.CS,r.d1,r.d2)

y4~~C1_4
"
```

```
fit_H1H2.exp.re<-cfa(model=model_H1H2.exp.re,
  data=dat2011,
  missing="fiml")
```

Exploratory respecification

```
## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some cases
## 573

## Warning in lav_object_post_check(object): lavaan WARNING: covariance matrix of latent variables
## is not positive definite;
## use lavInspect(fit, "cov.lv") to investigate.
```

Problems are still there

Inspect fit of the model


```
round(inspect(fit_H1H2.re,"fit")
      [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

```
##      npar      df    chisq    pvalue      cfi      tli    rmsea    srmr
##  67.000  163.000 1811.451     0.000    0.798    0.765    0.070    0.096
```

```
round(inspect(fit_H1H2.exp.re,"fit")
      [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

```
##      npar      df    chisq    pvalue      cfi      tli    rmsea    srmr
##  64.000  145.000 1292.194     0.000    0.847    0.820    0.062    0.084
```

The fit of the model is improved by removal of one item (these are not really comparable, because of non-nested modeling).

Retest Hypotheses 1 and 2

Print standardized estimates to test the difference between correlations

```
std.est_H1H2.exp<-standardizedsolution(fit_H1H2.exp.re)
std.est_H1H2.exp[std.est_H1H2.exp$op=="==" |
                  std.est_H1H2.exp$op=="~" &
                  std.est_H1H2.exp$lhs!=std.est_H1H2.exp$rhs,]
```

```
##      lhs op      rhs est.std    se      z pvalue
## 20 VAA_LR ~ VAA_GT  0.508 0.025 20.740      0
## 21 CS_LR ~ CS_GT   0.154 0.044  3.514      0
## 22 VAA_LR ~ CS_LR   0.763 0.038 20.337      0
## 23 VAA_GT ~ CS_GT   1.024 0.015 66.834      0
## 24 VAA_LR ~ CS_GT   0.490 0.032 15.501      0
## 25 VAA_GT ~ CS_LR   0.187 0.042  4.477      0
## 26      y4 ~ C1_4   0.630 0.025 24.785      0
## 73 test.H1 := r.LR-max(r.VAA,r.CS,r.d1,r.d2) 0.254 0.046  5.563      0
## 74 test.H2 := r.GT-max(r.VAA,r.CS,r.d1,r.d2) 0.515 0.028 18.150      0
##      ci.lower ci.upper
## 20    0.460    0.557
## 21    0.068    0.240
## 22    0.689    0.836
## 23    0.994    1.054
## 24    0.428    0.552
## 25    0.105    0.269
## 26    0.580    0.680
## 73    0.165    0.344
## 74    0.459    0.571
```

```
mis.H1H2<-miPowerFit(fit_H1H2.exp.re,stdLoad=.40,cor=.20)
```

Seek for additional misspecifications

```
## Warning in lav_start_check_cov(lavpartable = lavpartable, start = START): lavaan WARNING: starting v
##          variables involved are:  VAA_GT   CS_GT
```

```
mis.H1H2<-mis.H1H2[mis.H1H2$op=="=~" |
                    (mis.H1H2$op=="~~" &
                     mis.H1H2$lhs!=mis.H1H2$rhs),]
#see summary of the decisions
table(mis.H1H2$decision.pow)
```

```
##
##  EPC:M EPC:NM      M      NM
##      3   102      2   122
```

#there are several misspecifications

```
rounded.vars<-c("mi","epc","target.epc",
                "std.epc","se.epc")
```

```
num.round<-function(var){
  var<-as.numeric(var)
  var<-round(var,2)
  return(var)
}
```

```
mis.H1H2[,rounded.vars]<-sapply(mis.H1H2[,rounded.vars],num.round)
```

```
printed.vars<-c("lhs","op","rhs","mi","epc","target.epc",
                "std.epc","std.target.epc","significant.mi",
                "high.power","decision.pow","se.epc")
```

#print the output

```
mis.H1H2 %>%
  filter(mis.H1H2$decision.pow=="M" |
         mis.H1H2$decision.pow=="EPC:M") %>%
  dplyr::select(all_of(printed.vars))
```

```
##      lhs op  rhs      mi   epc target.epc std.epc std.target.epc significant.mi
## 1 VAA_LR =~ C1_2 50.53 0.58      0.44   0.53          0.4          TRUE
## 2 VAA_LR =~ C1_8 23.69 -0.86      0.41  -0.84          0.4          TRUE
## 3 CS_LR =~ y26 135.63 2.91      1.63   0.71          0.4          TRUE
## 4 CS_LR =~ y9  59.16 -2.22      1.97  -0.45          0.4          TRUE
## 5 C1_7 ~~ C1_8  5.97 0.17      0.19   0.18          0.2          TRUE
##  high.power decision.pow se.epc
## 1      TRUE      EPC:M  0.08
## 2     FALSE          M  0.18
## 3      TRUE      EPC:M  0.25
## 4      TRUE      EPC:M  0.29
## 5     FALSE          M  0.07
```

item y26 is indicated to cross-lead quite strongly, it is removed as well.

```

model_H1H2.exp.re.2<-"
#loadings
VAA_LR=~y22+y23+y27+y9+y19
VAA_GT=~y4+y5+y21
CS_LR=~C1_2+C1_7+C1_8
CS_GT=~C1_1+C1_3+C1_4+C1_5+C1_6+C1_10+C1_11

#latent correlations

#cross-dimension same-method
VAA_LR~~r.VAA*VAA_GT
CS_LR~~r.CS*CS_GT

#concurrent validity
VAA_LR~~r.LR*CS_LR
VAA_GT~~r.GT*CS_GT

#cross-dimension cross-method correlations
VAA_LR~~r.d1*CS_GT
VAA_GT~~r.d2*CS_LR

#custom parameters
test.H1:=r.LR-max(r.VAA,r.CS,r.d1,r.d2)
test.H2:=r.GT-max(r.VAA,r.CS,r.d1,r.d2)

y4~~C1_4
"

```

```

fit_H1H2.exp.re.2<-cfa(model=model_H1H2.exp.re.2,
  data=dat2011,
  missing="fiml")

```

```

## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some cases
## 573

```

```

## Warning in lav_object_post_check(object): lavaan WARNING: covariance matrix of latent variables
## is not positive definite;
## use lavInspect(fit, "cov.lv") to investigate.

```

```

round(inspect(fit_H1H2.exp.re,"fit")
  [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)

```

```

##      npar      df    chisq   pvalue     cfi     tli    rmsea    srmr
## 64.000 145.000 1292.194    0.000    0.847    0.820    0.062    0.084

```

```

round(inspect(fit_H1H2.exp.re.2,"fit")
  [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)

```

```

##      npar      df    chisq   pvalue     cfi     tli    rmsea    srmr
## 61.000 128.000 1017.272    0.000    0.867    0.841    0.058    0.079

```

Repeat the misspecification identification again

```

mis.H1H2<-miPowerFit(fit_H1H2.exp.re.2,stdLoad=.40,cor=.20)

```

```

## Warning in lav_start_check_cov(lavpartable = lavpartable, start = START): lavaan WARNING: starting v

```

```
##          variables involved are:  VAA_GT    CS_GT
```

```
mis.H1H2<-mis.H1H2[mis.H1H2$op=="~" |
                    (mis.H1H2$op=="~~" &
                     mis.H1H2$lhs!=mis.H1H2$rhs),]
#see summary of the decisions
table(mis.H1H2$decision.pow)
```

```
##
##  EPC:M EPC:NM      M      NM
##      4      86      2     116
```

```
#there are several misspecifications
```

```
rounded.vars<-c("mi","epc","target.epc",
                "std.epc","se.epc")
```

```
num.round<-function(var){
  var<-as.numeric(var)
  var<-round(var,2)
  return(var)
}
```

```
mis.H1H2[,rounded.vars]<-sapply(mis.H1H2[,rounded.vars],num.round)
```

```
printed.vars<-c("lhs","op","rhs","mi","epc","target.epc",
                "std.epc","std.target.epc","significant.mi",
                "high.power","decision.pow","se.epc")
```

```
#print the output
```

```
mis.H1H2 %>%
  filter(mis.H1H2$decision.pow=="M" |
         mis.H1H2$decision.pow=="EPC:M") %>%
  dplyr::select(all_of(printed.vars))
```

```
##      lhs op   rhs   mi   epc target.epc std.epc std.target.epc significant.mi
## 1 VAA_LR =~ C1_2 47.97 0.49      0.43   0.46           0.4          TRUE
## 2 VAA_LR =~ C1_8 22.69 -0.70      0.40  -0.70           0.4          TRUE
## 3 VAA_LR =~ C1_10 98.93 -0.49      0.47  -0.42           0.4          TRUE
## 4 CS_LR =~ y23 55.61 2.00      1.89   0.42           0.4          TRUE
## 5      y5 ~~ C1_10 71.52 0.37      0.37   0.20           0.2          TRUE
## 6 C1_7 ~~ C1_8 5.31 0.18      0.19   0.20           0.2          TRUE
##  high.power decision.pow se.epc
## 1      TRUE      EPC:M  0.07
## 2     FALSE      M    0.15
## 3      TRUE      EPC:M  0.05
## 4      TRUE      EPC:M  0.27
## 5      TRUE      EPC:M  0.04
## 6     FALSE      M    0.08
```

cross-loading and residual correlations are suggested for C1_10 (Maahanmuutto on hyvä asia Suomen taloudelle). Add the residual correlation with y5 (Tax funds should not be used in the current extent for taking in immigrants)

```

model_H1H2.exp.re.3<-"
#loadings
VAA_LR=~y22+y23+y27+y9+y19
VAA_GT=~y4+y5+y21
CS_LR=~C1_2+C1_7+C1_8
CS_GT=~C1_1+C1_3+C1_4+C1_5+C1_6+C1_10+C1_11

#latent correlations

#cross-dimension same-method
VAA_LR~~r.VAA*VAA_GT
CS_LR~~r.CS*CS_GT

#concurrent validity
VAA_LR~~r.LR*CS_LR
VAA_GT~~r.GT*CS_GT

#cross-dimension cross-method correlations
VAA_LR~~r.d1*CS_GT
VAA_GT~~r.d2*CS_LR

#custom parameters
test.H1:=r.LR-max(r.VAA,r.CS,r.d1,r.d2)
test.H2:=r.GT-max(r.VAA,r.CS,r.d1,r.d2)

y4~~C1_4
y5~~C1_10
"

```

```

fit_H1H2.exp.re.3<-cfa(model=model_H1H2.exp.re.3,
  data=dat2011,
  missing="fiml")

```

```

## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some cases
## 573

```

```

## Warning in lav_object_post_check(object): lavaan WARNING: covariance matrix of latent variables
## is not positive definite;
## use lavInspect(fit, "cov.lv") to investigate.

```

Problem still persists

```

round(inspect(fit_H1H2.exp.re.2,"fit")
  [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)

```

```

##      npar      df    chisq  pvalue    cfi    tli    rmsea    srmr
##  61.000 128.000 1017.272    0.000   0.867   0.841   0.058   0.079

```

```

round(inspect(fit_H1H2.exp.re.3,"fit")
  [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)

```

```

##      npar      df    chisq  pvalue    cfi    tli    rmsea    srmr
##  62.000 127.000  948.797    0.000   0.877   0.852   0.056   0.076

```

Repeat the misspecification identification again

```

mis.H1H2<-miPowerFit(fit_H1H2.exp.re.3,stdLoad=.40,cor=.20)
mis.H1H2<-mis.H1H2[mis.H1H2$op=="~" |
                    (mis.H1H2$op=="==" &
                     mis.H1H2$lhs!=mis.H1H2$rhs),]
#see summary of the decisions
table(mis.H1H2$decision.pow)

```

```

##
##  EPC:M EPC:NM      I      M      NM
##      2      85      6      6     106

```

#there are several misspecifications

```

rounded.vars<-c("mi","epc","target.epc",
                "std.epc","se.epc")

```

```

num.round<-function(var){
  var<-as.numeric(var)
  var<-round(var,2)
  return(var)
}

```

```

mis.H1H2[,rounded.vars]<-sapply(mis.H1H2[,rounded.vars],num.round)

```

```

printed.vars<-c("lhs","op","rhs","mi","epc","target.epc",
                "std.epc","std.target.epc","significant.mi",
                "high.power","decision.pow","se.epc")

```

#print the output

```

mis.H1H2 %>%
  filter(mis.H1H2$decision.pow=="M" |
         mis.H1H2$decision.pow=="EPC:M") %>%
  dplyr::select(all_of(printed.vars))

```

```

##      lhs op   rhs   mi   epc target.epc std.epc std.target.epc significant.mi
## 1 VAA_LR =~ C1_2 45.80 0.48      0.43    0.45          0.4          TRUE
## 2 VAA_LR =~ C1_8 20.55 -0.66      0.40   -0.66          0.4          TRUE
## 3 VAA_GT =~ C1_3 27.06 3.67      0.40    3.66          0.4          TRUE
## 4 VAA_GT =~ C1_5 58.42 6.24      0.44    5.64          0.4          TRUE
## 5 VAA_GT =~ C1_10 64.63 -5.92      0.45   -5.26          0.4          TRUE
## 6 CS_LR =~ y23 56.23 2.02      1.88    0.43          0.4          TRUE
## 7 CS_GT =~ y5  8.61 -3.84      0.97   -1.58          0.4          TRUE
## 8 C1_7 =~ C1_8 5.37 0.18      0.19    0.19          0.2          TRUE
##  high.power decision.pow se.epc
## 1      TRUE      EPC:M    0.07
## 2     FALSE          M    0.15
## 3     FALSE          M    0.71
## 4     FALSE          M    0.82
## 5     FALSE          M    0.74
## 6      TRUE      EPC:M    0.27
## 7     FALSE          M    1.31
## 8     FALSE          M    0.08

```

```
summary(fit_H1H2.exp.re.3,fit=T,standardized=T)
```

```
## lavaan 0.6-5 ended normally after 84 iterations
##
##      Estimator                      ML
##      Optimization method          NLMINB
##      Number of free parameters      62
##
##                               Used      Total
##      Number of observations          2059      2060
##      Number of missing patterns       57
##
## Model Test User Model:
##
##      Test statistic                948.797
##      Degrees of freedom              127
##      P-value (Chi-square)            0.000
##
## Model Test Baseline Model:
##
##      Test statistic                6849.302
##      Degrees of freedom              153
##      P-value                        0.000
##
## User Model versus Baseline Model:
##
##      Comparative Fit Index (CFI)      0.877
##      Tucker-Lewis Index (TLI)        0.852
##
## Loglikelihood and Information Criteria:
##
##      Loglikelihood user model (H0)    -37252.454
##      Loglikelihood unrestricted model (H1) -36778.055
##
##      Akaike (AIC)                    74628.908
##      Bayesian (BIC)                   74977.966
##      Sample-size adjusted Bayesian (BIC) 74780.987
##
## Root Mean Square Error of Approximation:
##
##      RMSEA                          0.056
##      90 Percent confidence interval - lower 0.053
##      90 Percent confidence interval - upper 0.059
##      P-value RMSEA <= 0.05            0.001
##
## Standardized Root Mean Square Residual:
##
##      SRMR                          0.076
##
## Parameter Estimates:
##
##      Information                      Observed
##      Observed information based on      Hessian
##      Standard errors                    Standard
```

```

##
## Latent Variables:
##      Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
## VAA_LR =~
##   y22          1.000
##   y23          0.705    0.034   20.773   0.000    0.728    0.558
##   y27          0.613    0.034   18.270   0.000    0.633    0.488
##   y9           0.907    0.037   24.726   0.000    0.936    0.690
##   y19          0.824    0.034   24.099   0.000    0.850    0.646
## VAA_GT =~
##   y4           1.000
##   y5           1.063    0.047   22.795   0.000    1.142    0.755
##   y21          0.766    0.038   20.423   0.000    0.823    0.583
## CS_LR =~
##   C1_2          1.000
##   C1_7          1.615    0.268    6.026   0.000    0.447    0.498
##   C1_8          3.133    0.528    5.937   0.000    0.868    0.836
## CS_GT =~
##   C1_1          1.000
##   C1_3          0.746    0.070   10.706   0.000    0.466    0.432
##   C1_4          1.614    0.105   15.403   0.000    1.007    0.639
##   C1_5          0.412    0.072    5.688   0.000    0.257    0.216
##   C1_6          1.014    0.071   14.316   0.000    0.633    0.558
##   C1_10         1.010    0.077   13.164   0.000    0.630    0.521
##   C1_11         0.654    0.068    9.626   0.000    0.408    0.392
##
## Covariances:
##      Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
## VAA_LR ~~
## VAA_GT (r.VA)   0.650    0.043   15.095   0.000    0.586    0.586
## CS_LR ~~
## CS_GT (r.CS)   0.029    0.010    2.950   0.003    0.166    0.166
## VAA_LR ~~
## CS_LR (r.LR)   0.204    0.036    5.616   0.000    0.714    0.714
## VAA_GT ~~
## CS_GT (r.GT)   0.670    0.042   16.001   0.000    1.000    1.000
## VAA_LR ~~
## CS_GT (r.d1)   0.353    0.030   11.841   0.000    0.548    0.548
## VAA_GT ~~
## CS_LR (r.d2)   0.064    0.018    3.604   0.000    0.214    0.214
## .y4 ~~
## .C1_4          0.898    0.065   13.882   0.000    0.898    0.627
## .y5 ~~
## .C1_10         0.376    0.047    7.946   0.000    0.376    0.367
##
## Intercepts:
##      Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all
##   .y22          2.641    0.033   79.395   0.000    2.641    1.812
##   .y23          2.180    0.030   72.987   0.000    2.180    1.672
##   .y27          3.638    0.030  122.720   0.000    3.638    2.804
##   .y9           3.471    0.031  112.286   0.000    3.471    2.557
##   .y19          2.135    0.030   71.158   0.000    2.135    1.621
##   .y4           2.440    0.036   68.014   0.000    2.440    1.527
##   .y5           3.102    0.034   91.052   0.000    3.102    2.050

```


##	.y21	2.606	0.033	79.835	0.000	2.606	1.846
##	.C1_2	1.884	0.036	51.807	0.000	1.884	1.714
##	.C1_7	1.892	0.029	64.895	0.000	1.892	2.104
##	.C1_8	1.854	0.032	58.020	0.000	1.854	1.785
##	.C1_1	4.019	0.029	138.703	0.000	4.019	4.206
##	.C1_3	1.945	0.034	56.426	0.000	1.945	1.805
##	.C1_4	2.261	0.043	53.015	0.000	2.261	1.436
##	.C1_5	3.399	0.039	86.530	0.000	3.399	2.859
##	.C1_6	3.590	0.035	101.565	0.000	3.590	3.166
##	.C1_10	2.471	0.036	68.447	0.000	2.471	2.044
##	.C1_11	1.642	0.034	48.757	0.000	1.642	1.576
##	VAA_LR	0.000				0.000	0.000
##	VAA_GT	0.000				0.000	0.000
##	CS_LR	0.000				0.000	0.000
##	CS_GT	0.000				0.000	0.000

##

Variances:

##		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
##	.y22	1.060	0.047	22.708	0.000	1.060	0.498
##	.y23	1.170	0.043	27.003	0.000	1.170	0.688
##	.y27	1.283	0.045	28.287	0.000	1.283	0.762
##	.y9	0.966	0.041	23.378	0.000	0.966	0.524
##	.y19	1.011	0.040	25.033	0.000	1.011	0.583
##	.y4	1.400	0.062	22.429	0.000	1.400	0.548
##	.y5	0.985	0.054	18.208	0.000	0.985	0.430
##	.y21	1.316	0.052	25.544	0.000	1.316	0.660
##	.C1_2	1.131	0.055	20.655	0.000	1.131	0.936
##	.C1_7	0.608	0.033	18.396	0.000	0.608	0.752
##	.C1_8	0.326	0.067	4.893	0.000	0.326	0.302
##	.C1_1	0.524	0.031	16.901	0.000	0.524	0.574
##	.C1_3	0.945	0.048	19.894	0.000	0.945	0.813
##	.C1_4	1.465	0.082	17.916	0.000	1.465	0.591
##	.C1_5	1.347	0.064	20.914	0.000	1.347	0.953
##	.C1_6	0.886	0.048	18.600	0.000	0.886	0.689
##	.C1_10	1.065	0.056	18.866	0.000	1.065	0.728
##	.C1_11	0.919	0.046	20.026	0.000	0.919	0.847
##	VAA_LR	1.066	0.067	15.884	0.000	1.000	1.000
##	VAA_GT	1.155	0.080	14.357	0.000	1.000	1.000
##	CS_LR	0.077	0.024	3.249	0.001	1.000	1.000
##	CS_GT	0.389	0.039	10.076	0.000	1.000	1.000

##

Defined Parameters:

##		Estimate	Std.Err	z-value	P(> z)	Std.lv	Std.all
##	test.H1	-0.446	0.053	-8.375	0.000	0.128	0.128
##	test.H2	0.020	0.046	0.440	0.660	0.414	0.414

Remove the weak loading items C1_2 and C1_5

```
model_H1H2.exp.re.4<-"
#loadings
VAA_LR=~y22+y23+y27+y9+y19
VAA_GT=~y4+y5+y21
CS_LR=~C1_7+C1_8
CS_GT=~C1_1+C1_3+C1_4+C1_6+C1_10+C1_11
```

```
#latent correlations
```

```
#cross-dimension same-method
```

```
VAA_LR~~r.VAA*VAA_GT
```

```
CS_LR~~r.CS*CS_GT
```

```
#concurrent validity
```

```
VAA_LR~~r.LR*CS_LR
```

```
VAA_GT~~r.GT*CS_GT
```

```
#cross-dimension cross-method correlations
```

```
VAA_LR~~r.d1*CS_GT
```

```
VAA_GT~~r.d2*CS_LR
```

```
#custom parameters
```

```
test.H1:=r.LR-max(r.VAA,r.CS,r.d1,r.d2)
```

```
test.H2:=r.GT-max(r.VAA,r.CS,r.d1,r.d2)
```

```
y4~~C1_4
```

```
y5~~C1_10
```

```
"
```

```
fit_H1H2.exp.re.4<-cfa(model=model_H1H2.exp.re.4,
  data=dat2011,
  missing="fiml")
```

```
## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some cases
## 573
```

```
## Warning in lav_object_post_check(object): lavaan WARNING: covariance matrix of latent variables
## is not positive definite;
## use lavInspect(fit, "cov.lv") to investigate.
```

```
round(inspect(fit_H1H2.exp.re.3,"fit")
  [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

```
##      npar      df   chisq  pvalue    cfi    tli   rmsea   srmr
## 62.000 127.000 948.797   0.000   0.877   0.852   0.056   0.076
```

```
round(inspect(fit_H1H2.exp.re.4,"fit")
  [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

```
##      npar      df   chisq  pvalue    cfi    tli   rmsea   srmr
## 56.000  96.000 737.799   0.000   0.900   0.875   0.057   0.065
```

```
std.est.H1H2.exp.re.4<-standardizedsolution(fit_H1H2.exp.re.4)
```

```
std.est.H1H2.exp.re.4[std.est.H1H2.exp.re.4$op == "=~" |
  (std.est.H1H2.exp.re.4$op == "~~" &
    std.est.H1H2.exp.re.4$lhs != std.est.H1H2.exp.re.4$rhs),]
```

```
##      lhs op      rhs est.std    se      z  pvalue ci.lower ci.upper
## 1  VAA_LR =~    y22   0.708 0.015 45.934  0.000    0.678    0.738
## 2  VAA_LR =~    y23   0.558 0.019 29.307  0.000    0.521    0.596
## 3  VAA_LR =~    y27   0.487 0.021 23.717  0.000    0.447    0.527
```

## 4	VAA_LR =~	y9	0.690	0.016	43.303	0.000	0.659	0.721
## 5	VAA_LR =~	y19	0.646	0.017	38.197	0.000	0.613	0.679
## 6	VAA_GT =~	y4	0.674	0.018	38.307	0.000	0.640	0.709
## 7	VAA_GT =~	y5	0.755	0.016	47.216	0.000	0.723	0.786
## 8	VAA_GT =~	y21	0.583	0.019	29.961	0.000	0.545	0.621
## 9	CS_LR =~	C1_7	0.499	0.034	14.707	0.000	0.432	0.565
## 10	CS_LR =~	C1_8	0.847	0.040	21.207	0.000	0.768	0.925
## 11	CS_GT =~	C1_1	0.653	0.024	26.843	0.000	0.606	0.701
## 12	CS_GT =~	C1_3	0.416	0.032	13.182	0.000	0.355	0.478
## 13	CS_GT =~	C1_4	0.645	0.023	28.577	0.000	0.601	0.689
## 14	CS_GT =~	C1_6	0.564	0.027	20.691	0.000	0.511	0.618
## 15	CS_GT =~	C1_10	0.522	0.029	18.307	0.000	0.466	0.578
## 16	CS_GT =~	C1_11	0.392	0.033	11.979	0.000	0.328	0.456
## 17	VAA_LR ~~	VAA_GT	0.584	0.024	24.822	0.000	0.538	0.630
## 18	CS_LR ~~	CS_GT	0.107	0.043	2.493	0.013	0.023	0.191
## 19	VAA_LR ~~	CS_LR	0.694	0.040	17.181	0.000	0.614	0.773
## 20	VAA_GT ~~	CS_GT	0.998	0.015	67.587	0.000	0.969	1.027
## 21	VAA_LR ~~	CS_GT	0.538	0.031	17.212	0.000	0.476	0.599
## 22	VAA_GT ~~	CS_LR	0.176	0.042	4.243	0.000	0.095	0.258
## 23	y4 ~~	C1_4	0.624	0.026	23.664	0.000	0.572	0.676
## 24	y5 ~~	C1_10	0.369	0.038	9.718	0.000	0.295	0.444

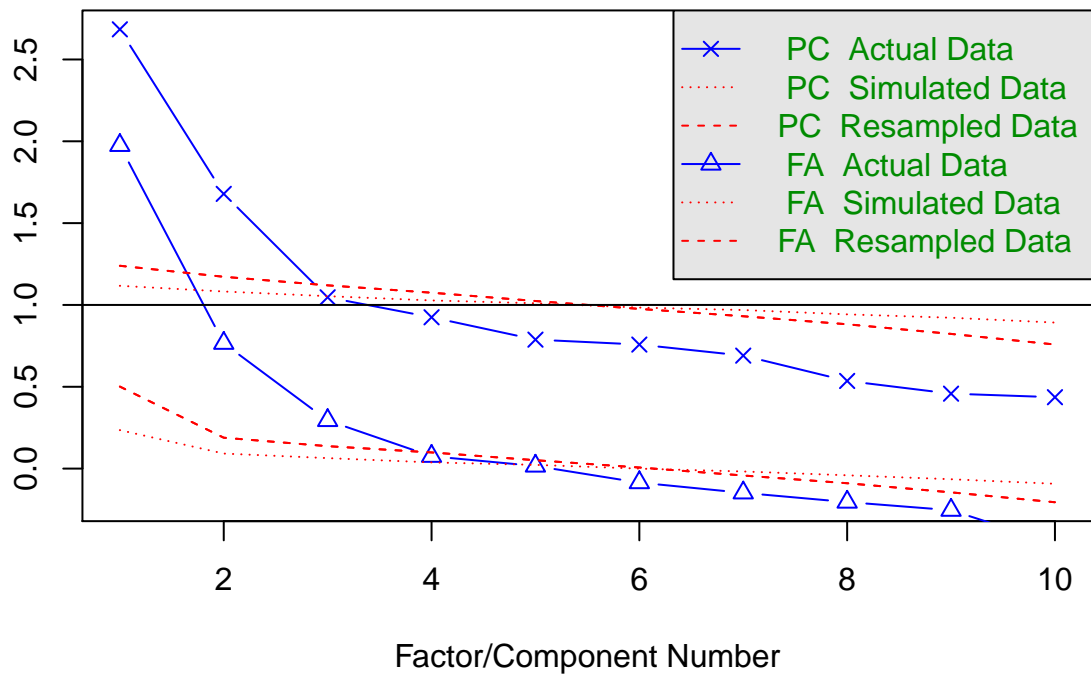
Exploratory factor analysis for CS-data

```
all_CS_items<-c("C1_2","C1_7","C1_8","C1_1","C1_3","C1_4","C1_5","C1_6","C1_10","C1_11")

#conduct a parallel analysis to explore the number of factors
fa.parallel(dat2011[,all_CS_items])
```

eigenvalues of principal components and factor analysis

Parallel Analysis Scree Plots



Parallel analysis suggests that the number of factors = 4 and the number of components = 2

#four factor solution

```
fa(dat2011[,all_CS_items],nfactors = 4,fm = "ml",rotate = "oblimin")
```

Loading required namespace: GPArotation

Factor Analysis using method = ml

Call: fa(r = dat2011[, all_CS_items], nfactors = 4, rotate = "oblimin",

fm = "ml")

Standardized loadings (pattern matrix) based upon correlation matrix

	ML1	ML3	ML2	ML4	h2	u2	com
## C1_2	0.10	0.26	0.20	-0.03	0.14	0.860	2.3
## C1_7	0.04	-0.12	0.34	0.30	0.25	0.745	2.3
## C1_8	0.00	0.01	1.00	0.01	1.00	0.005	1.0
## C1_1	-0.03	0.74	0.02	0.04	0.55	0.450	1.0
## C1_3	0.14	0.13	0.14	0.34	0.26	0.741	2.1
## C1_4	1.00	0.01	0.00	-0.02	1.00	0.005	1.0
## C1_5	-0.04	0.06	0.15	0.42	0.24	0.760	1.3
## C1_6	0.07	0.62	0.03	-0.11	0.41	0.594	1.1
## C1_10	0.08	0.44	-0.19	0.25	0.37	0.627	2.1
## C1_11	0.47	-0.06	-0.03	0.12	0.23	0.770	1.2

##

	ML1	ML3	ML2	ML4
## SS loadings	1.32	1.30	1.27	0.55

## Proportion Var	0.13	0.13	0.13	0.06
-------------------	------	------	------	------

## Cumulative Var	0.13	0.26	0.39	0.44
-------------------	------	------	------	------

```

## Proportion Explained  0.30 0.29 0.29 0.12
## Cumulative Proportion 0.30 0.59 0.88 1.00
##
## With factor correlations of
##      ML1  ML3  ML2  ML4
## ML1 1.00 0.51 0.03 0.21
## ML3 0.51 1.00 0.02 0.27
## ML2 0.03 0.02 1.00 0.29
## ML4 0.21 0.27 0.29 1.00
##
## Mean item complexity = 1.5
## Test of the hypothesis that 4 factors are sufficient.
##
## The degrees of freedom for the null model are 45 and the objective function was 1.65 with Chi Square
## The degrees of freedom for the model are 11 and the objective function was 0.02
##
## The root mean square of the residuals (RMSR) is 0.02
## The df corrected root mean square of the residuals is 0.03
##
## The harmonic number of observations is 897 with the empirical chi square 18.22 with prob < 0.077
## The total number of observations was 2060 with Likelihood Chi Square = 42.16 with prob < 1.5e-08
##
## Tucker Lewis Index of factoring reliability = 0.962
## RMSEA index = 0.037 and the 90 % confidence intervals are 0.026 0.049
## BIC = -41.77
## Fit based upon off diagonal values = 1
## Measures of factor score adequacy
##
##                                     ML1  ML3  ML2  ML4
## Correlation of (regression) scores with factors 1.00 0.86 1.00 0.67
## Multiple R square of scores with factors         0.99 0.73 0.99 0.45
## Minimum correlation of possible factor scores    0.99 0.46 0.99 -0.09

```

First factor is defined by “Samaa sukupuolta olevien avioliitot pitäisi kieltää laissa” to which only other substantial loading is from “Naisilla pitäisi olla vapaus päättää aborttikysymyksistä”. So this represents a conservative dimension.

Second factor (ML3) has loadings from immigration items.

Third factor is defined by “Tuloja ja vaurautta pitäisi uudelleenjakaa tavallisten ihmisten suuntaan” with no substantial loadings from other items.

Some of the items also have very weak variance explained, and high communalities

Fourth factor is some sort of mixed factor. This is not an ideal solution to which VAA responses in GT and LR could be compared to.

Try 3 factor solution.

```

fa(dat2011[,all_CS_items],nfactors = 3,fm = "ml",rotate = "oblimin")

## Factor Analysis using method = ml
## Call: fa(r = dat2011[, all_CS_items], nfactors = 3, rotate = "oblimin",
##      fm = "ml")
## Standardized loadings (pattern matrix) based upon correlation matrix
##      ML3  ML1  ML2  h2    u2 com
## C1_2  0.23  0.10  0.20 0.14 0.862 2.3
## C1_7 -0.03  0.03  0.51 0.26 0.736 1.0
## C1_8 -0.02 -0.01  0.83 0.69 0.312 1.0

```

```

## C1_1  0.77 -0.04  0.02 0.57 0.435 1.0
## C1_3  0.23  0.14  0.30 0.21 0.795 2.3
## C1_4  0.00  1.00  0.00 1.00 0.005 1.0
## C1_5  0.19 -0.04  0.34 0.15 0.847 1.6
## C1_6  0.56  0.08 -0.02 0.36 0.639 1.0
## C1_10 0.52  0.09 -0.11 0.33 0.670 1.1
## C1_11 -0.01  0.47  0.02 0.22 0.784 1.0
##
##                               ML3  ML1  ML2
## SS loadings                 1.38 1.31 1.22
## Proportion Var              0.14 0.13 0.12
## Cumulative Var              0.14 0.27 0.39
## Proportion Explained        0.35 0.34 0.31
## Cumulative Proportion       0.35 0.69 1.00
##
## With factor correlations of
##      ML3  ML1  ML2
## ML3 1.00 0.53 0.07
## ML1 0.53 1.00 0.06
## ML2 0.07 0.06 1.00
##
## Mean item complexity = 1.4
## Test of the hypothesis that 3 factors are sufficient.
##
## The degrees of freedom for the null model are 45 and the objective function was 1.65 with Chi Squ
## The degrees of freedom for the model are 18 and the objective function was 0.08
##
## The root mean square of the residuals (RMSR) is 0.03
## The df corrected root mean square of the residuals is 0.05
##
## The harmonic number of observations is 897 with the empirical chi square 78.71 with prob < 1.4e-0
## The total number of observations was 2060 with Likelihood Chi Square = 166.49 with prob < 4.4e-5
##
## Tucker Lewis Index of factoring reliability = 0.889
## RMSEA index = 0.063 and the 90 % confidence intervals are 0.055 0.072
## BIC = 29.14
## Fit based upon off diagonal values = 0.98
## Measures of factor score adequacy
##                               ML3  ML1  ML2
## Correlation of (regression) scores with factors 0.86 1.00 0.86
## Multiple R square of scores with factors        0.74 1.00 0.74
## Minimum correlation of possible factor scores    0.48 0.99 0.49

```

First factor (ML3) has loadings from immigration items.

Second (ML1) is a conservativeness factor (factors 1 and 2 also correlate with .50)

Third factor is right-wing factor, although environment and some women's right items seem to weakly load there as well.

See what the two-factor solution looks like

```
fa(dat2011[,all_CS_items],nfactors = 2,fm = "ml",rotate = "oblimin")
```

```

## Factor Analysis using method = ml
## Call: fa(r = dat2011[, all_CS_items], nfactors = 2, rotate = "oblimin",
##      fm = "ml")

```

```

## Standardized loadings (pattern matrix) based upon correlation matrix
##      ML2   ML1   h2   u2 com
## C1_2  0.31  0.20  0.14  0.86  1.7
## C1_7  0.01  0.50  0.25  0.75  1.0
## C1_8 -0.02  0.86  0.73  0.27  1.0
## C1_1  0.64  0.02  0.41  0.59  1.0
## C1_3  0.35  0.28  0.22  0.78  1.9
## C1_4  0.66  0.01  0.44  0.56  1.0
## C1_5  0.16  0.32  0.14  0.86  1.5
## C1_6  0.58 -0.02  0.33  0.67  1.0
## C1_10 0.59 -0.12  0.35  0.65  1.1
## C1_11 0.39  0.01  0.15  0.85  1.0
##
##                               ML2  ML1
## SS loadings                   1.94 1.24
## Proportion Var                 0.19 0.12
## Cumulative Var                 0.19 0.32
## Proportion Explained           0.61 0.39
## Cumulative Proportion          0.61 1.00
##
## With factor correlations of
##      ML2  ML1
## ML2 1.00 0.07
## ML1 0.07 1.00
##
## Mean item complexity = 1.2
## Test of the hypothesis that 2 factors are sufficient.
##
## The degrees of freedom for the null model are 45 and the objective function was 1.65 with Chi Squ
## The degrees of freedom for the model are 26 and the objective function was 0.24
##
## The root mean square of the residuals (RMSR) is 0.05
## The df corrected root mean square of the residuals is 0.07
##
## The harmonic number of observations is 897 with the empirical chi square 210.65 with prob < 8e-3
## The total number of observations was 2060 with Likelihood Chi Square = 485.41 with prob < 3.6e-4
##
## Tucker Lewis Index of factoring reliability = 0.762
## RMSEA index = 0.093 and the 90 % confidence intervals are 0.086 0.1
## BIC = 287.02
## Fit based upon off diagonal values = 0.95
## Measures of factor score adequacy
##                               ML2  ML1
## Correlation of (regression) scores with factors 0.87 0.88
## Multiple R square of scores with factors         0.75 0.77
## Minimum correlation of possible factor scores    0.50 0.54

```

This, at least partially, reflects the intended structure. Some loadings, however, are very weak ($< .40$), and some items show also larger (but $< .40$) cross-loadings than intended loadings.

Such items are: C1_2: Poliitiikan ei pitäisi puuttua talouden toimintaan C1_3: Luonnon suojelemiseksi pitäisi ryhtyä vahvempiin toimenpiteisiin C1_5: Naisia pitäisi suosia työhönotossa ja ylennyksissä C1_11: Naisilla pitäisi olla vapaus päättää aborttikysymyksistä

Exclude these items and see if the solution produces a better criteria to which VAA responses can be compared

```

subset_CS_items<-c("C1_7","C1_8","C1_1","C1_4","C1_6","C1_10")

fa(dat2011[,subset_CS_items],nfactors = 2,fm = "ml",rotate = "oblimin")

## Factor Analysis using method = ml
## Call: fa(r = dat2011[, subset_CS_items], nfactors = 2, rotate = "oblimin",
##      fm = "ml")
## Standardized loadings (pattern matrix) based upon correlation matrix
##      ML2  ML1  h2   u2 com
## C1_7  0.01  0.42 0.18 0.822 1.0
## C1_8  0.00  1.00 1.00 0.005 1.0
## C1_1  0.71  0.04 0.51 0.493 1.0
## C1_4  0.56  0.02 0.31 0.686 1.0
## C1_6  0.63  0.01 0.40 0.600 1.0
## C1_10 0.56 -0.12 0.33 0.672 1.1
##
##
##      ML2  ML1
## SS loadings      1.53 1.19
## Proportion Var    0.26 0.20
## Cumulative Var    0.26 0.45
## Proportion Explained 0.56 0.44
## Cumulative Proportion 0.56 1.00
##
## With factor correlations of
##      ML2  ML1
## ML2 1.00 0.02
## ML1 0.02 1.00
##
## Mean item complexity = 1
## Test of the hypothesis that 2 factors are sufficient.
##
## The degrees of freedom for the null model are 15 and the objective function was 0.92 with Chi Squ
## The degrees of freedom for the model are 4 and the objective function was 0.02
##
## The root mean square of the residuals (RMSR) is 0.02
## The df corrected root mean square of the residuals is 0.05
##
## The harmonic number of observations is 898 with the empirical chi square 16.45 with prob < 0.002
## The total number of observations was 2060 with Likelihood Chi Square = 44.44 with prob < 5.2e-0
##
## Tucker Lewis Index of factoring reliability = 0.919
## RMSEA index = 0.07 and the 90 % confidence intervals are 0.052 0.089
## BIC = 13.92
## Fit based upon off diagonal values = 0.99
## Measures of factor score adequacy
##
##      ML2  ML1
## Correlation of (regression) scores with factors 0.85 1.00
## Multiple R square of scores with factors 0.72 1.00
## Minimum correlation of possible factor scores 0.45 0.99

```

It's better, although, the CS-LR dimension seems to be very strongly defined by a single item C1_8: Tuloja ja vaurautta pitäisi uudelleenjakaa tavallisten ihmisten suuntaan

H1 and H2 with a subset of CS-items

Model

```
model_H1H2.sub<-"
#loadings
VAA_LR=~y22+y23+y26+y27+y9+y19
VAA_GT=~y4+y5+y1+y21
CS_LR=~C1_7+C1_8
CS_GT=~C1_1+C1_4+C1_6+C1_10

#latent correlations

#cross-dimension same-method
VAA_LR~~r.VAA*VAA_GT
CS_LR~~r.CS*CS_GT

#concurrent validity
VAA_LR~~r.LR*CS_LR
VAA_GT~~r.GT*CS_GT

#cross-dimension cross-method correlations
VAA_LR~~r.d1*CS_GT
VAA_GT~~r.d2*CS_LR

#custom parameters
test.H1:=r.LR-max(r.VAA,r.CS,r.d1,r.d2)
test.H2:=r.GT-max(r.VAA,r.CS,r.d1,r.d2)

"
```

```
fit_H1H2.sub<-cfa(model=model_H1H2.sub,
  data=dat2011,
  missing="fiml")
```

```
## Warning in lav_object_post_check(object): lavaan WARNING: covariance matrix of latent variables
##           is not positive definite;
##           use lavInspect(fit, "cov.lv") to investigate.
```

Problems again

Add the preregistered residual correlation.

```
model_H1H2.sub.re<-paste0(model_H1H2.sub,
  "y4~~C1_4\n")
```

```
fit_H1H2.sub.re<-cfa(model=model_H1H2.sub.re,
  data=dat2011,
  missing="fiml")
```

```
round(inspect(fit_H1H2.sub,"fit")
  [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

Fit the respecified model

```
##      npar      df    chisq  pvalue    cfi    tli    rmsea    srmr
##    54.000    98.000 1583.723    0.000    0.799    0.753    0.086    0.094
```

```
round(inspect(fit_H1H2.sub.re,"fit")
      [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

```
##      npar      df    chisq  pvalue    cfi    tli    rmsea    srmr
##    55.000    97.000 1256.316    0.000    0.843    0.805    0.076    0.090
```

Fit is quite poor

Hypotheses 1 and 2

Print standardized estimates to test the difference between correlations

```
std.est_H1H2.sub.re<-standardizedsolution(fit_H1H2.sub.re)
std.est_H1H2.sub.re[std.est_H1H2.sub.re$op=="!=" |
                    std.est_H1H2.sub.re$op=="~" &
                    std.est_H1H2.sub.re$lhs!=std.est_H1H2.sub.re$rhs,]
```

```
##      lhs op      rhs est.std    se      z pvalue
## 17  VAA_LR ~ VAA_GT  0.446 0.025 17.531  0.000
## 18  CS_LR ~ CS_GT  0.033 0.042  0.785  0.432
## 19  VAA_LR ~ CS_LR  0.741 0.038 19.722  0.000
## 20  VAA_GT ~ CS_GT  0.987 0.016 62.249  0.000
## 21  VAA_LR ~ CS_GT  0.426 0.034 12.520  0.000
## 22  VAA_GT ~ CS_LR  0.099 0.039  2.509  0.012
## 23    y4 ~ C1_4  0.673 0.022 30.634  0.000
## 64 test.H1 := r.LR-max(r.VAA,r.CS,r.d1,r.d2) 0.295 0.047  6.295  0.000
## 65 test.H2 := r.GT-max(r.VAA,r.CS,r.d1,r.d2) 0.541 0.030 18.175  0.000
##      ci.lower ci.upper
## 17    0.396    0.496
## 18   -0.049    0.114
## 19    0.667    0.814
## 20    0.956    1.018
## 21    0.359    0.492
## 22    0.022    0.176
## 23    0.630    0.716
## 64    0.203    0.386
## 65    0.482    0.599
```

H1: There is strong (.741, $p < .001$) correlation between VAA-LR and CS-LR, and it is notably stronger (difference in correlations .295, $p < .001$) than the strongest of correlations between different dimensions (.446 between VAA_LR and VAA_GT, $p < .001$)

H2: There is very strong (.987, $p < .001$) correlation between VAA-GT and CS-GT, and it is notably stronger (difference in correlations .541, $p < .001$) than the strongest of correlations between different dimensions (.446 between VAA_LR and VAA_GT, $p < .001$)

Seek misspecifications

```
mis.H1H2<-miPowerFit(fit_H1H2.sub.re,stdLoad=.40,cor=.20)
mis.H1H2<-mis.H1H2[mis.H1H2$op=="~" |
                  (mis.H1H2$op=="~" &
                   mis.H1H2$lhs!=mis.H1H2$rhs),]
#see summary of the decisions
table(mis.H1H2$decision.pow)
```

```
##
```

```
## EPC:M EPC:NM      I      M      NM
##      5      73      6      3      79

#there are eight misspecifications

rounded.vars<-c("mi","epc","target.epc",
               "std.epc","se.epc")

num.round<-function(var){
  var<-as.numeric(var)
  var<-round(var,2)
  return(var)
}

mis.H1H2[,rounded.vars]<-sapply(mis.H1H2[,rounded.vars],num.round)

printed.vars<-c("lhs","op","rhs","mi","epc","target.epc",
               "std.epc","std.target.epc","significant.mi",
               "high.power","decision.pow","se.epc")

#print the output

mis.H1H2 %>%
  filter(mis.H1H2$decision.pow=="M" |
         mis.H1H2$decision.pow=="EPC:M") %>%
  dplyr::select(all_of(printed.vars))
```

```
##      lhs op      rhs      mi      epc target.epc std.epc std.target.epc significant.mi
## 1 VAA_LR =~      y1 398.57 -0.76      0.53 -0.57      0.4      TRUE
## 2 VAA_GT =~    C1_6  4.43 -1.08      0.45 -0.96      0.4      TRUE
## 3 CS_LR =~      y26 134.67  1.66      1.03  0.65      0.4      TRUE
## 4 CS_LR =~      y9  61.16 -1.29      1.24 -0.42      0.4      TRUE
## 5 CS_LR =~      y1 355.24 -1.66      1.22 -0.55      0.4      TRUE
## 6 CS_GT =~      y1  91.57  9.72      0.83  4.68      0.4      TRUE
## 7 CS_GT =~     y21  14.56 -3.93      0.88 -1.78      0.4      TRUE
## 8      y1 ~~ C1_10 63.48  0.37      0.32  0.23      0.2      TRUE
## high.power decision.pow se.epc
## 1      TRUE      EPC:M  0.04
## 2     FALSE          M  0.51
## 3      TRUE      EPC:M  0.14
## 4      TRUE      EPC:M  0.17
## 5      TRUE      EPC:M  0.09
## 6     FALSE          M  1.02
## 7     FALSE          M  1.03
## 8      TRUE      EPC:M  0.05
```

In this model as well, similarly to the model with the original set of items, y1 (Finland should continue to financially assist EU countries that are facing economic hardship (r.)) is indicated to crossload on all factor, and it also has a residual correlation with C1_10 (Maahanmuutto on hyvä asia Suomen taloudelle). Add this residual correlation.

```
model_H1H2.sub.exp.re<-paste0(model_H1H2.sub.re,
                              "y1~~C1_10\n")

fit_H1H2.sub.exp.re<-cfa(model=model_H1H2.sub.exp.re,
                        data=dat2011,
```

```

missing="fiml")

round(inspect(fit_H1H2.sub.re,"fit")
      [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)

##      npar      df    chisq  pvalue    cfi     tli    rmsea    srmr
##  55.000   97.000 1256.316   0.000   0.843   0.805   0.076   0.090

round(inspect(fit_H1H2.sub.exp.re,"fit")
      [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)

##      npar      df    chisq  pvalue    cfi     tli    rmsea    srmr
##  56.000   96.000 1188.944   0.000   0.852   0.815   0.074   0.089

```

Fit is not improved much

Hypotheses 1 and 2

Print standardized estimates to test the difference between correlations

```

std.est_H1H2.sub.exp.re<-standardizedsolution(fit_H1H2.sub.exp.re)
std.est_H1H2.sub.exp.re[std.est_H1H2.sub.exp.re$op=="==" |
  std.est_H1H2.sub.exp.re$op=="~" &
  std.est_H1H2.sub.exp.re$lhs!=std.est_H1H2.sub.exp.re$rhs,]

##      lhs op      rhs est.std   se      z pvalue
## 17 VAA_LR ~~      VAA_GT  0.456 0.025 18.015 0.000
## 18 CS_LR ~~      CS_GT   0.067 0.041  1.616 0.106
## 19 VAA_LR ~~      CS_LR   0.740 0.038 19.687 0.000
## 20 VAA_GT ~~      CS_GT   0.974 0.015 63.019 0.000
## 21 VAA_LR ~~      CS_GT   0.468 0.033 14.242 0.000
## 22 VAA_GT ~~      CS_LR   0.103 0.039  2.603 0.009
## 23    y4 ~~      C1_4   0.680 0.021 31.639 0.000
## 24    y1 ~~      C1_10  0.312 0.034  9.092 0.000
## 65 test.H1 := r.LR-max(r.VAA,r.CS,r.d1,r.d2) 0.273 0.052  5.208 0.000
## 66 test.H2 := r.GT-max(r.VAA,r.CS,r.d1,r.d2) 0.507 0.036 14.222 0.000
##      ci.lower ci.upper
## 17    0.407    0.506
## 18   -0.014    0.148
## 19    0.667    0.814
## 20    0.944    1.004
## 21    0.403    0.532
## 22    0.025    0.180
## 23    0.638    0.722
## 24    0.245    0.379
## 65    0.170    0.375
## 66    0.437    0.576

```

Hypothesis inference seems almost identical

H1: There is strong (.740, $p < .001$) correlation between VAA-LR and CS-LR, and it is notably stronger (difference in correlations .273, $p < .001$) than the strongest of correlations between different dimensions (.456 between VAA_LR and VAA_GT, $p < .001$)

H2: There is very strong (.974, $p < .001$) correlation between VAA-GT and CS-GT, and it is notably stronger (difference in correlations .507, $p < .001$) than the strongest of correlations between different dimensions (.456 between VAA_LR and VAA_GT, $p < .001$)

Seek misspecifications

```

mis.H1H2<-miPowerFit(fit_H1H2.sub.exp.re,stdLoad=.40,cor=.20)
mis.H1H2<-mis.H1H2[mis.H1H2$op=="~" |
                    (mis.H1H2$op=="~~" &
                     mis.H1H2$lhs!=mis.H1H2$rhs),]
#see summary of the decisions
table(mis.H1H2$decision.pow)

```

```

##
##  EPC:M EPC:NM      I      M      NM
##    4    65      4      5     87

```

#there are eight misspecifications

```

rounded.vars<-c("mi","epc","target.epc",
                "std.epc","se.epc")

```

```

num.round<-function(var){
  var<-as.numeric(var)
  var<-round(var,2)
  return(var)
}

```

```

mis.H1H2[,rounded.vars]<-sapply(mis.H1H2[,rounded.vars],num.round)

```

```

printed.vars<-c("lhs","op","rhs","mi","epc","target.epc",
                "std.epc","std.target.epc","significant.mi",
                "high.power","decision.pow","se.epc")

```

#print the output

```

mis.H1H2 %>%
  filter(mis.H1H2$decision.pow=="M" |
         mis.H1H2$decision.pow=="EPC:M") %>%
  dplyr::select(all_of(printed.vars))

```

```

##      lhs op   rhs      mi   epc target.epc std.epc std.target.epc significant.mi
## 1 VAA_LR =~   y1 341.78 -0.70      0.53  -0.53          0.4          TRUE
## 2 VAA_GT =~ C1_6  18.38 -1.94      0.45  -1.73          0.4          TRUE
## 3 VAA_GT =~ C1_10 25.31  2.38      0.48   2.00          0.4          TRUE
## 4 CS_LR =~   y26 134.90  1.65      1.03   0.64          0.4          TRUE
## 5 CS_LR =~   y9  61.54 -1.29      1.24  -0.42          0.4          TRUE
## 6 CS_LR =~   y1 311.10 -1.53      1.22  -0.50          0.4          TRUE
## 7 CS_GT =~   y5  23.64  5.37      0.92   2.33          0.4          TRUE
## 8 CS_GT =~   y1  25.81 -4.12      0.81  -2.02          0.4          TRUE
## 9 CS_GT =~  y21   7.84 -2.37      0.86  -1.10          0.4          TRUE
##  high.power decision.pow se.epc
## 1      TRUE          EPC:M  0.04
## 2     FALSE           M    0.45
## 3     FALSE           M    0.47
## 4      TRUE          EPC:M  0.14
## 5      TRUE          EPC:M  0.16
## 6      TRUE          EPC:M  0.09
## 7     FALSE           M    1.10
## 8     FALSE           M    0.81

```

```
## 9      FALSE      M    0.85
```

The cross-loadings with y1 did not go away with the residual correlation. Exclude the item entirely.

```
model_H1H2.sub.exp.re.2<-"
#loadings
VAA_LR=~y22+y23+y26+y27+y9+y19
VAA_GT=~y4+y5+y21
CS_LR=~C1_7+C1_8
CS_GT=~C1_1+C1_4+C1_6+C1_10

#latent correlations

#cross-dimension same-method
VAA_LR~~r.VAA*VAA_GT
CS_LR~~r.CS*CS_GT

#concurrent validity
VAA_LR~~r.LR*CS_LR
VAA_GT~~r.GT*CS_GT

#cross-dimension cross-method correlations
VAA_LR~~r.d1*CS_GT
VAA_GT~~r.d2*CS_LR

#custom parameters
test.H1:=r.LR-max(r.VAA,r.CS,r.d1,r.d2)
test.H2:=r.GT-max(r.VAA,r.CS,r.d1,r.d2)

y4   ~~  C1_4
"
```

```
fit_H1H2.sub.exp.re.2<-cfa(model=model_H1H2.sub.exp.re.2,
  data=dat2011,
  missing="fiml")
```

```
## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some cases
## 573
```

```
round(inspect(fit_H1H2.sub.exp.re,"fit")
  [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

```
##      npar      df    chisq  pvalue    cfi    tli    rmsea    srmr
## 56.000  96.000 1188.944   0.000   0.852   0.815   0.074   0.089
```

```
round(inspect(fit_H1H2.sub.exp.re.2,"fit")
  [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

```
##      npar      df    chisq  pvalue    cfi    tli    rmsea    srmr
## 52.000  83.000  752.004   0.000   0.900   0.874   0.063   0.069
```

Now the fit seems to be adequate (These models are not nested, and can't be compared, therefore)

Hypotheses 1 and 2

Print standardized estimates to test the difference between correlations

```
std.est_H1H2.sub.exp.re.2<-standardizedsolution(fit_H1H2.sub.exp.re.2)
std.est_H1H2.sub.exp.re.2[std.est_H1H2.sub.exp.re.2$op=="!=" |
```

```
std.est_H1H2.sub.exp.re.2$op=="~~" &
std.est_H1H2.sub.exp.re.2$lhs!=std.est_H1H2.sub.exp.re.2$rhs,]
```

```
##      lhs op      rhs est.std   se      z pvalue
## 16 VAA_LR ~~      VAA_GT  0.501 0.025 20.373  0.0
## 17 CS_LR ~~      CS_GT   0.043 0.042  1.037  0.3
## 18 VAA_LR ~~      CS_LR   0.741 0.038 19.758  0.0
## 19 VAA_GT ~~      CS_GT   0.988 0.016 60.121  0.0
## 20 VAA_LR ~~      CS_GT   0.442 0.034 13.018  0.0
## 21 VAA_GT ~~      CS_LR   0.143 0.040  3.594  0.0
## 22      y4 ~~      C1_4   0.671 0.022 30.211  0.0
## 61 test.H1 := r.LR-max(r.VAA,r.CS,r.d1,r.d2) 0.240 0.046  5.211  0.0
## 62 test.H2 := r.GT-max(r.VAA,r.CS,r.d1,r.d2) 0.488 0.029 16.739  0.0
##      ci.lower ci.upper
## 16    0.453    0.549
## 17   -0.038    0.125
## 18    0.668    0.815
## 19    0.956    1.021
## 20    0.375    0.508
## 21    0.065    0.221
## 22    0.627    0.714
## 61    0.150    0.331
## 62    0.430    0.545
```

Hypothesis inference seems almost identical

H1: There is strong (.741, $p < .001$) correlation between VAA-LR and CS-LR, and it is notably stronger (difference in correlations .240, $p < .001$) than the strongest of correlations between different dimensions (.442 between VAA_LR and VAA_GT, $p < .001$)

H2: There is very strong (.988, $p < .001$) correlation between VAA-GT and CS-GT, and it is notably stronger (difference in correlations .488, $p < .001$) than the strongest of correlations between different dimensions (.442 between VAA_LR and VAA_GT, $p < .001$)

Print all model parameters

```
std.est_H1H2.sub.exp.re.2
```

```
##      lhs op      rhs est.std   se      z pvalue
## 1  VAA_LR =~      y22  0.692 0.015 44.991  0.0
## 2  VAA_LR =~      y23  0.604 0.018 33.963  0.0
## 3  VAA_LR =~      y26  0.566 0.019 30.154  0.0
## 4  VAA_LR =~      y27  0.475 0.020 23.192  0.0
## 5  VAA_LR =~      y9   0.674 0.016 42.279  0.0
## 6  VAA_LR =~      y19  0.650 0.016 39.664  0.0
## 7  VAA_GT =~      y4   0.625 0.018 34.091  0.0
## 8  VAA_GT =~      y5   0.810 0.015 52.273  0.0
## 9  VAA_GT =~      y21  0.562 0.020 28.253  0.0
## 10 CS_LR =~      C1_7  0.488 0.032 15.141  0.0
## 11 CS_LR =~      C1_8  0.866 0.036 23.873  0.0
## 12 CS_GT =~      C1_1  0.681 0.023 29.599  0.0
## 13 CS_GT =~      C1_4  0.588 0.023 25.212  0.0
## 14 CS_GT =~      C1_6  0.574 0.027 21.332  0.0
## 15 CS_GT =~      C1_10 0.620 0.025 24.409  0.0
## 16 VAA_LR =~      VAA_GT 0.501 0.025 20.373  0.0
## 17 CS_LR =~      CS_GT  0.043 0.042  1.037  0.3
```

## 18	VAA_LR	~~	CS_LR	0.741	0.038	19.758	0.0
## 19	VAA_GT	~~	CS_GT	0.988	0.016	60.121	0.0
## 20	VAA_LR	~~	CS_GT	0.442	0.034	13.018	0.0
## 21	VAA_GT	~~	CS_LR	0.143	0.040	3.594	0.0
## 22	y4	~~	C1_4	0.671	0.022	30.211	0.0
## 23	y22	~~	y22	0.522	0.021	24.528	0.0
## 24	y23	~~	y23	0.636	0.021	29.607	0.0
## 25	y26	~~	y26	0.680	0.021	32.042	0.0
## 26	y27	~~	y27	0.775	0.019	39.846	0.0
## 27	y9	~~	y9	0.546	0.021	25.445	0.0
## 28	y19	~~	y19	0.578	0.021	27.177	0.0
## 29	y4	~~	y4	0.609	0.023	26.599	0.0
## 30	y5	~~	y5	0.345	0.025	13.743	0.0
## 31	y21	~~	y21	0.684	0.022	30.589	0.0
## 32	C1_7	~~	C1_7	0.762	0.031	24.268	0.0
## 33	C1_8	~~	C1_8	0.250	0.063	3.982	0.0
## 34	C1_1	~~	C1_1	0.536	0.031	17.106	0.0
## 35	C1_4	~~	C1_4	0.654	0.027	23.862	0.0
## 36	C1_6	~~	C1_6	0.670	0.031	21.656	0.0
## 37	C1_10	~~	C1_10	0.615	0.032	19.520	0.0
## 38	VAA_LR	~~	VAA_LR	1.000	0.000	NA	NA
## 39	VAA_GT	~~	VAA_GT	1.000	0.000	NA	NA
## 40	CS_LR	~~	CS_LR	1.000	0.000	NA	NA
## 41	CS_GT	~~	CS_GT	1.000	0.000	NA	NA
## 42	y22	~1		1.810	0.037	48.564	0.0
## 43	y23	~1		1.671	0.036	47.079	0.0
## 44	y26	~1		1.601	0.035	46.306	0.0
## 45	y27	~1		2.803	0.051	55.082	0.0
## 46	y9	~1		2.555	0.047	54.061	0.0
## 47	y19	~1		1.619	0.035	46.623	0.0
## 48	y4	~1		1.527	0.033	46.240	0.0
## 49	y5	~1		2.053	0.040	51.498	0.0
## 50	y21	~1		1.846	0.038	48.624	0.0
## 51	C1_7	~1		2.109	0.059	35.776	0.0
## 52	C1_8	~1		1.797	0.051	35.436	0.0
## 53	C1_1	~1		4.208	0.100	41.992	0.0
## 54	C1_4	~1		1.434	0.040	35.409	0.0
## 55	C1_6	~1		3.167	0.079	39.909	0.0
## 56	C1_10	~1		2.040	0.056	36.585	0.0
## 57	VAA_LR	~1		0.000	0.000	NA	NA
## 58	VAA_GT	~1		0.000	0.000	NA	NA
## 59	CS_LR	~1		0.000	0.000	NA	NA
## 60	CS_GT	~1		0.000	0.000	NA	NA
## 61	test.H1 := r.LR-max(r.VAA,r.CS,r.d1,r.d2)			0.240	0.046	5.211	0.0
## 62	test.H2 := r.GT-max(r.VAA,r.CS,r.d1,r.d2)			0.488	0.029	16.739	0.0
##	ci.lower ci.upper						
## 1				0.662		0.722	
## 2				0.569		0.639	
## 3				0.529		0.602	
## 4				0.435		0.515	
## 5				0.642		0.705	
## 6				0.617		0.682	
## 7				0.589		0.661	
## 8				0.779		0.840	

## 9	0.523	0.601
## 10	0.425	0.551
## 11	0.795	0.937
## 12	0.636	0.726
## 13	0.542	0.634
## 14	0.522	0.627
## 15	0.570	0.670
## 16	0.453	0.549
## 17	-0.038	0.125
## 18	0.668	0.815
## 19	0.956	1.021
## 20	0.375	0.508
## 21	0.065	0.221
## 22	0.627	0.714
## 23	0.480	0.563
## 24	0.593	0.678
## 25	0.638	0.722
## 26	0.736	0.813
## 27	0.504	0.588
## 28	0.536	0.620
## 29	0.565	0.654
## 30	0.295	0.394
## 31	0.640	0.728
## 32	0.701	0.824
## 33	0.127	0.373
## 34	0.475	0.598
## 35	0.601	0.708
## 36	0.609	0.731
## 37	0.554	0.677
## 38	1.000	1.000
## 39	1.000	1.000
## 40	1.000	1.000
## 41	1.000	1.000
## 42	1.737	1.883
## 43	1.602	1.741
## 44	1.534	1.669
## 45	2.703	2.903
## 46	2.463	2.648
## 47	1.551	1.687
## 48	1.463	1.592
## 49	1.974	2.131
## 50	1.771	1.920
## 51	1.994	2.225
## 52	1.697	1.896
## 53	4.012	4.405
## 54	1.354	1.513
## 55	3.012	3.323
## 56	1.931	2.149
## 57	0.000	0.000
## 58	0.000	0.000
## 59	0.000	0.000
## 60	0.000	0.000
## 61	0.150	0.331
## 62	0.430	0.545

H3 and H4

Exclude other than members of the eight parties that have multiple members in the parliament

```
dat2011.party<-dat2011 %>%  
  filter(puolue=="KD" |  
         puolue=="KESK" |  
         puolue=="KOK" |  
         puolue=="PS" |  
         puolue=="RKP" |  
         puolue=="SDP" |  
         puolue=="VAS" |  
         puolue=="VIHR")
```

```
table(dat2011.party$puolue)
```

```
##  
##    KD KESK  KOK   PS  RKP  SDP  VAS VIHR  
##   170  220  227  213   77  222  217  226
```

Define the model

Use the subset of items that were used for H1 and H2

```
model_H3H4<-"  
#loadings  
VAA_LR=~y22+y23+y26+y27+y9+y19  
VAA_GT=~y4+y5+y21  
CS_LR=~C1_7+C1_8  
CS_GT=~C1_1+C1_4+C1_6+C1_10  
  
#cross-dimension same-method  
VAA_LR~~c(r.VAA.KD,r.VAA.KESK,r.VAA.KOK,r.VAA.PS,r.VAA.RKP,r.VAA.SDP,r.VAA.VAS,r.VAA.VIHR)*VAA_GT  
CS_LR~~c(r.CS.KD,r.CS.KESK,r.CS.KOK,r.CS.PS,r.CS.RKP,r.CS.SDP,r.CS.VAS,r.CS.VIHR)*CS_GT  
  
#concurrent validity  
VAA_LR~~c(r.LR.KD,r.LR.KESK,r.LR.KOK,r.LR.PS,r.LR.RKP,r.LR.SDP,r.LR.VAS,r.LR.VIHR)*CS_LR  
VAA_GT~~c(r.GT.KD,r.GT.KESK,r.GT.KOK,r.GT.PS,r.GT.RKP,r.GT.SDP,r.GT.VAS,r.GT.VIHR)*CS_GT  
  
#cross-dimension cross-method correlations  
VAA_LR~~c(r.d1.KD,r.d1.KESK,r.d1.KOK,r.d1.PS,r.d1.RKP,r.d1.SDP,r.d1.VAS,r.d1.VIHR)*CS_GT  
VAA_GT~~c(r.d2.KD,r.d2.KESK,r.d2.KOK,r.d2.PS,r.d2.RKP,r.d2.SDP,r.d2.VAS,r.d2.VIHR)*CS_LR  
  
#custom parameters  
mean.r.VAA:=mean(r.VAA.KD,r.VAA.KESK,r.VAA.KOK,r.VAA.PS,r.VAA.RKP,r.VAA.SDP,r.VAA.VAS,r.VAA.VIHR)  
mean.r.CS:=mean(r.CS.KD,r.CS.KESK,r.CS.KOK,r.CS.PS,r.CS.RKP,r.CS.SDP,r.CS.VAS,r.CS.VIHR)  
mean.r.LR:=mean(r.LR.KD,r.LR.KESK,r.LR.KOK,r.LR.PS,r.LR.RKP,r.LR.SDP,r.LR.VAS,r.LR.VIHR)  
mean.r.GT:=mean(r.GT.KD,r.GT.KESK,r.GT.KOK,r.GT.PS,r.GT.RKP,r.GT.SDP,r.GT.VAS,r.GT.VIHR)  
mean.r.d1:=mean(r.d1.KD,r.d1.KESK,r.d1.KOK,r.d1.PS,r.d1.RKP,r.d1.SDP,r.d1.VAS,r.d1.VIHR)  
mean.r.d2:=mean(r.d2.KD,r.d2.KESK,r.d2.KOK,r.d2.PS,r.d2.RKP,r.d2.SDP,r.d2.VAS,r.d2.VIHR)  
  
test.H3:=mean.r.LR-max(mean.r.VAA,mean.r.CS,mean.r.d1,mean.r.d2)  
test.H4:=mean.r.GT-max(mean.r.VAA,mean.r.CS,mean.r.d1,mean.r.d2)
```

```
"
```

Fit the configural model

```
fit_H3H4<-cfa(model=model_H3H4,  
              data=dat2011.party,  
              group=c("puolue"),  
              group.label=c("KD", "KESK", "KOK", "PS", "RKP", "SDP", "VAS", "VIHR"),  
              missing="fiml")
```

```
## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some cases  
## 452
```

```
## Warning in lav_model_estimate(lavmodel = lavmodel, lavpartable = lavpartable, : lavaan WARNING: the  
## but not all elements of the gradient are (near) zero;  
## the optimizer may not have found a local solution  
## use check.gradient = FALSE to skip this check.
```

Add the preregistered residual correlation

```
model_H3H4.re<-paste0(model_H3H4,  
                      "y4~~C1_4\n")
```

```
fit_H3H4.re<-cfa(model=model_H3H4.re,  
                 data=dat2011.party,  
                 group=c("puolue"),  
                 group.label=c("KD", "KESK", "KOK", "PS", "RKP", "SDP", "VAS", "VIHR"),  
                 missing="fiml")
```

Fit the respecified model

```
## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some cases  
## 452
```

```
## Warning in lav_model_estimate(lavmodel = lavmodel, lavpartable = lavpartable, : lavaan WARNING: the  
## but not all elements of the gradient are (near) zero;  
## the optimizer may not have found a local solution  
## use check.gradient = FALSE to skip this check.
```

The model does not converge.

```
summary(fit_H3H4.re,fit=T,standardized=T)
```

```
## lavaan 0.6-5 did NOT end normally after 1906 iterations  
## ** WARNING ** Estimates below are most likely unreliable  
##  
## Estimator ML  
## Optimization method NLMINB  
## Number of free parameters 416  
##  
## Number of observations per group:  
## KD 170  
## KESK 220  
## KOK 227
```

```

##      PS                      213
##      RKP                      77
##      SDP                      222
##      VAS                      216
##      VIHR                     226
##      Number of missing patterns per group:
##      KD                      11
##      KESK                     13
##      KOK                      11
##      PS                      15
##      RKP                      17
##      SDP                      14
##      VAS                      11
##      VIHR                     14
##
## Model Test User Model:
##
##      Test statistic            NA
##      Degrees of freedom        NA
##      Test statistic for each group:
##      KD                      NA
##      KESK                     NA
##      KOK                      NA
##      PS                      NA
##      RKP                      NA
##      SDP                      NA
##      VAS                      NA
##      VIHR                     NA
##
## Warning in .local(object, ...): lavaan WARNING: fit measures not available if model did not converge
## Warning in sqrt(ETA2): NaNs produced
##
## Warning in sqrt(ETA2): NaNs produced
##
## Warning in sqrt(ETA2): NaNs produced
##
## Warning in sqrt(ETA2): NaNs produced
##
## Warning in sqrt(ETA2): NaNs produced
##
## Warning in sqrt(ETA2): NaNs produced
##
##
## Parameter Estimates:
##
##      Information                Observed
##      Observed information based on      Hessian
##      Standard errors                  Standard
##
##
## Group 1 [KD]:
##
## Latent Variables:
##      Estimate  Std.Err  z-value  P(>|z|)  Std.lv  Std.all

```

```

## VAA_LR =~
## y22          1.000          0.364  0.277
## y23          1.252          NA      0.456  0.392
## y26          1.673          NA      0.609  0.642
## y27          0.084          NA      0.031  0.035
## y9           0.485          NA      0.176  0.172
## y19          0.889          NA      0.323  0.257
## VAA_GT =~
## y4           1.000          0.024  0.025
## y5           1.117          NA      0.026  0.021
## y21          340.250        NA      8.059  6.340
## CS_LR =~
## C1_7         1.000          0.233  0.273
## C1_8         3.191          NA      0.742  0.907
## CS_GT =~
## C1_1         1.000          0.364  0.646
## C1_4         0.055          NA      0.020  0.020
## C1_6         1.129          NA      0.411  0.610
## C1_10        0.859          NA      0.312  0.355
##
## Covariances:
##          Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## VAA_LR ~~
## VAA_GT (r.VA) -0.000      NA      -0.002 -0.002
## CS_LR ~~
## CS_GT (r.CS)  0.038      NA      0.452  0.452
## VAA_LR ~~
## CS_LR (r.LR)  0.094      NA      1.113  1.113
## VAA_GT ~~
## CS_GT (r.GT) -0.000      NA     -0.031 -0.031
## VAA_LR ~~
## CS_GT (r.1.)  0.051      NA      0.386  0.386
## VAA_GT ~~
## CS_LR (r.2.)  0.000      NA      0.018  0.018
## .y4 ~~
## .C1_4        0.476      NA      0.476  0.504
##
## Intercepts:
##          Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .y22        3.248      NA      3.248  2.476
## .y23        2.385      NA      2.385  2.050
## .y26        1.809      NA      1.809  1.907
## .y27        4.199      NA      4.199  4.757
## .y9         3.834      NA      3.834  3.742
## .y19        2.888      NA      2.888  2.295
## .y4         4.448      NA      4.448  4.606
## .y5         3.314      NA      3.314  2.610
## .y21        2.948      NA      2.948  2.319
## .C1_7        2.039      NA      2.039  2.392
## .C1_8        1.832      NA      1.832  2.239
## .C1_1        4.395      NA      4.395  7.807
## .C1_4        4.366      NA      4.366  4.467
## .C1_6        4.038      NA      4.038  5.996
## .C1_10       2.454      NA      2.454  2.788

```

```

##      VAA_LR      0.000      0.000      0.000
##      VAA_GT      0.000      0.000      0.000
##      CS_LR       0.000      0.000      0.000
##      CS_GT       0.000      0.000      0.000
##
## Variances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      .y22      1.588    NA      1.588 0.923
##      .y23      1.146    NA      1.146 0.847
##      .y26      0.529    NA      0.529 0.588
##      .y27      0.778    NA      0.778 0.999
##      .y9       1.019    NA      1.019 0.970
##      .y19      1.480    NA      1.480 0.934
##      .y4       0.932    NA      0.932 0.999
##      .y5       1.612    NA      1.612 1.000
##      .y21     -63.339    NA     -63.339 -39.201
##      .C1_7      0.673    NA      0.673 0.926
##      .C1_8      0.118    NA      0.118 0.177
##      .C1_1      0.184    NA      0.184 0.582
##      .C1_4      0.955    NA      0.955 1.000
##      .C1_6      0.285    NA      0.285 0.628
##      .C1_10     0.677    NA      0.677 0.874
##      VAA_LR     0.132    NA      1.000 1.000
##      VAA_GT     0.001    NA      1.000 1.000
##      CS_LR      0.054    NA      1.000 1.000
##      CS_GT      0.132    NA      1.000 1.000
##
##
## Group 2 [KESK]:
##
## Latent Variables:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      VAA_LR =~
##      y22      1.000      0.770 0.652
##      y23     -0.213    NA     -0.164 -0.130
##      y26     -0.127    NA     -0.098 -0.103
##      y27      0.403    NA      0.310 0.255
##      y9       0.381    NA      0.293 0.354
##      y19      0.757    NA      0.583 0.467
##      VAA_GT =~
##      y4       1.000      0.738 0.506
##      y5       1.257    NA      0.927 0.841
##      y21      0.391    NA      0.289 0.234
##      CS_LR =~
##      C1_7      1.000      6.275 6.552
##      C1_8      0.005    NA      0.034 0.037
##      CS_GT =~
##      C1_1      1.000      0.303 0.478
##      C1_4      2.318    NA      0.703 0.458
##      C1_6      1.132    NA      0.343 0.386
##      C1_10     1.363    NA      0.413 0.454
##
## Covariances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all

```

```

## VAA_LR ~~
## VAA_GT (r.VA) 0.191 NA 0.337 0.337
## CS_LR ~~
## CS_GT (r.CS) -0.014 NA -0.007 -0.007
## VAA_LR ~~
## CS_LR (r.LR) 0.143 NA 0.030 0.030
## VAA_GT ~~
## CS_GT (r.GT) 0.190 NA 0.848 0.848
## VAA_LR ~~
## CS_GT (r.1.) 0.126 NA 0.540 0.540
## VAA_GT ~~
## CS_LR (r.2.) -0.120 NA -0.026 -0.026
## .y4 ~~
## .C1_4 1.338 NA 1.338 0.781
##
## Intercepts:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .y22 3.496 NA 3.496 2.961
## .y23 2.721 NA 2.721 2.160
## .y26 2.001 NA 2.001 2.107
## .y27 3.251 NA 3.251 2.671
## .y9 4.241 NA 4.241 5.122
## .y19 2.869 NA 2.869 2.300
## .y4 3.060 NA 3.060 2.100
## .y5 3.496 NA 3.496 3.170
## .y21 3.586 NA 3.586 2.912
## .C1_7 2.221 NA 2.221 2.319
## .C1_8 2.294 NA 2.294 2.499
## .C1_1 4.064 NA 4.064 6.401
## .C1_4 2.694 NA 2.694 1.757
## .C1_6 3.815 NA 3.815 4.289
## .C1_10 2.222 NA 2.222 2.442
## VAA_LR 0.000 0.000 0.000
## VAA_GT 0.000 0.000 0.000
## CS_LR 0.000 0.000 0.000
## CS_GT 0.000 0.000 0.000
##
## Variances:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .y22 0.802 NA 0.802 0.575
## .y23 1.561 NA 1.561 0.983
## .y26 0.892 NA 0.892 0.989
## .y27 1.385 NA 1.385 0.935
## .y9 0.600 NA 0.600 0.875
## .y19 1.215 NA 1.215 0.782
## .y4 1.578 NA 1.578 0.744
## .y5 0.357 NA 0.357 0.293
## .y21 1.433 NA 1.433 0.945
## .C1_7 -38.463 NA -38.463 -41.932
## .C1_8 0.842 NA 0.842 0.999
## .C1_1 0.311 NA 0.311 0.772
## .C1_4 1.857 NA 1.857 0.790
## .C1_6 0.673 NA 0.673 0.851
## .C1_10 0.658 NA 0.658 0.794

```

```

##      VAA_LR      0.592      NA      1.000      1.000
##      VAA_GT      0.544      NA      1.000      1.000
##      CS_LR      39.380      NA      1.000      1.000
##      CS_GT      0.092      NA      1.000      1.000
##
##
## Group 3 [KOK]:
##
## Latent Variables:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      VAA_LR =~
##      y22      1.000      0.653      0.662
##      y23      0.596      NA      0.389      0.310
##      y26      0.062      NA      0.041      0.034
##      y27      0.600      NA      0.392      0.421
##      y9       0.354      NA      0.231      0.351
##      y19      0.954      NA      0.623      0.507
##      VAA_GT =~
##      y4       1.000      0.571      0.383
##      y5       1.415      NA      0.808      0.705
##      y21      0.756      NA      0.432      0.341
##      CS_LR =~
##      C1_7      1.000      0.685      0.725
##      C1_8      0.263      NA      0.180      0.173
##      CS_GT =~
##      C1_1      1.000      0.371      0.565
##      C1_4      2.016      NA      0.748      0.481
##      C1_6      1.109      NA      0.411      0.407
##      C1_10     0.537      NA      0.199      0.278
##
## Covariances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      VAA_LR ~~
##      VAA_GT (r.VA) 0.157      NA      0.421      0.421
##      CS_LR ~~
##      CS_GT (r.CS) -0.016      NA     -0.062     -0.062
##      VAA_LR ~~
##      CS_LR (r.LR) 0.066      NA      0.147      0.147
##      VAA_GT ~~
##      CS_GT (r.GT) 0.215      NA      1.017      1.017
##      VAA_LR ~~
##      CS_GT (r.1.) 0.092      NA      0.380      0.380
##      VAA_GT ~~
##      CS_LR (r.2.) 0.085      NA      0.217      0.217
##      .y4 ~~
##      .C1_4      1.123      NA      1.123      0.599
##
## Intercepts:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      .y22      3.846      NA      3.846      3.898
##      .y23      3.585      NA      3.585      2.851
##      .y26      3.076      NA      3.076      2.580
##      .y27      4.186      NA      4.186      4.492
##      .y9       4.531      NA      4.531      6.871

```



```

##      .y19      3.354      NA      3.354      2.728
##      .y4       2.558      NA      2.558      1.717
##      .y5       3.565      NA      3.565      3.109
##      .y21      2.686      NA      2.686      2.122
##      .C1_7     2.416      NA      2.416      2.556
##      .C1_8     3.448      NA      3.448      3.317
##      .C1_1     4.210      NA      4.210      6.417
##      .C1_4     2.358      NA      2.358      1.517
##      .C1_6     3.787      NA      3.787      3.745
##      .C1_10    1.688      NA      1.688      2.359
##      VAA_LR     0.000      NA      0.000      0.000
##      VAA_GT     0.000      NA      0.000      0.000
##      CS_LR      0.000      NA      0.000      0.000
##      CS_GT      0.000      NA      0.000      0.000
##
## Variances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      .y22      0.547      NA      0.547      0.562
##      .y23      1.430      NA      1.430      0.904
##      .y26      1.419      NA      1.419      0.999
##      .y27      0.714      NA      0.714      0.823
##      .y9       0.381      NA      0.381      0.877
##      .y19      1.123      NA      1.123      0.743
##      .y4       1.893      NA      1.893      0.853
##      .y5       0.662      NA      0.662      0.503
##      .y21      1.416      NA      1.416      0.884
##      .C1_7     0.424      NA      0.424      0.475
##      .C1_8     1.049      NA      1.049      0.970
##      .C1_1     0.293      NA      0.293      0.680
##      .C1_4     1.859      NA      1.859      0.769
##      .C1_6     0.853      NA      0.853      0.835
##      .C1_10    0.472      NA      0.472      0.923
##      VAA_LR     0.427      NA      1.000      1.000
##      VAA_GT     0.326      NA      1.000      1.000
##      CS_LR      0.470      NA      1.000      1.000
##      CS_GT      0.138      NA      1.000      1.000
##
##
## Group 4 [PS]:
##
## Latent Variables:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      VAA_LR =~
##      y22      1.000      NA      0.854      0.600
##      y23      0.571      NA      0.488      0.444
##      y26      0.398      NA      0.340      0.390
##      y27      0.390      NA      0.333      0.462
##      y9       0.708      NA      0.605      0.578
##      y19      0.529      NA      0.452      0.369
##      VAA_GT =~
##      y4       1.000      NA      NaN      NaN
##      y5     -318.172      NA      NaN      NaN
##      y21      1.348      NA      NaN      NaN
##      CS_LR =~

```

```

##      C1_7      1.000      0.358      0.484
##      C1_8      1.196      NA      0.428      0.598
##      CS_GT =~
##      C1_1      1.000      0.247      0.614
##      C1_4      2.362      NA      0.584      0.428
##      C1_6      2.102      NA      0.519      0.599
##      C1_10     1.789      NA      0.442      0.463
##
## Covariances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      VAA_LR ~~
##      VAA_GT (r.VA) -0.000      NA      -0.036      -0.036
##      CS_LR ~~
##      CS_GT (r.CS)  0.002      NA      0.022      0.022
##      VAA_LR ~~
##      CS_LR (r.LR)  0.187      NA      0.611      0.611
##      VAA_GT ~~
##      CS_GT (r.GT) -0.000      NA      -0.058      -0.058
##      VAA_LR ~~
##      CS_GT (r.1.)  0.072      NA      0.340      0.340
##      VAA_GT ~~
##      CS_LR (r.2.)  0.000      NA      0.014      0.014
##      .y4 ~~
##      .C1_4      0.745      NA      0.745      0.463
##
## Intercepts:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      .y22      3.001      NA      3.001      2.109
##      .y23      2.075      NA      2.075      1.888
##      .y26      1.521      NA      1.521      1.746
##      .y27      4.459      NA      4.459      6.189
##      .y9       3.924      NA      3.924      3.745
##      .y19      2.353      NA      2.353      1.918
##      .y4       3.907      NA      3.907      2.987
##      .y5       4.870      NA      4.870     10.757
##      .y21      3.613      NA      3.613      2.920
##      .C1_7      1.829      NA      1.829      2.469
##      .C1_8      1.620      NA      1.620      2.260
##      .C1_1      4.797      NA      4.797     11.930
##      .C1_4      3.557      NA      3.557      2.611
##      .C1_6      4.184      NA      4.184      4.826
##      .C1_10     3.761      NA      3.761      3.940
##      VAA_LR     0.000      0.000      0.000      0.000
##      VAA_GT     0.000      NaN      NaN      NaN
##      CS_LR      0.000      0.000      0.000      0.000
##      CS_GT      0.000      0.000      0.000      0.000
##
## Variances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      .y22      1.296      NA      1.296      0.640
##      .y23      0.970      NA      0.970      0.803
##      .y26      0.644      NA      0.644      0.848
##      .y27      0.408      NA      0.408      0.786
##      .y9       0.732      NA      0.732      0.666

```

```

##      .y19      1.301      NA      1.301      0.864
##      .y4       1.711      NA      1.711      1.000
##      .y5      12.498      NA     12.498     60.970
##      .y21      1.531      NA      1.531      1.000
##      .C1_7      0.420      NA      0.420      0.766
##      .C1_8      0.330      NA      0.330      0.643
##      .C1_1      0.101      NA      0.101      0.623
##      .C1_4      1.515      NA      1.515      0.817
##      .C1_6      0.482      NA      0.482      0.641
##      .C1_10     0.716      NA      0.716      0.786
##      VAA_LR      0.730      NA      1.000      1.000
##      VAA_GT     -0.000      NA       NaN       NaN
##      CS_LR      0.128      NA      1.000      1.000
##      CS_GT      0.061      NA      1.000      1.000
##
##
## Group 5 [RKP]:
##
## Latent Variables:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      VAA_LR =~
##      y22      1.000      0.696      0.522
##      y23      0.872      NA      0.607      0.476
##      y26      1.042      NA      0.725      0.535
##      y27      0.282      NA      0.196      0.198
##      y9       0.588      NA      0.409      0.406
##      y19      0.665      NA      0.463      0.347
##      VAA_GT =~
##      y4       1.000      0.301      0.308
##      y5       0.492      NA      0.148      0.173
##      y21      2.732      NA      0.823      0.657
##      CS_LR =~
##      C1_7      1.000      0.290      0.303
##      C1_8      5.616      NA      1.631      1.449
##      CS_GT =~
##      C1_1      1.000      NaN      NaN
##      C1_4      0.697      NA      NaN      NaN
##      C1_6     -0.149      NA      NaN      NaN
##      C1_10    -5.766      NA      NaN      NaN
##
## Covariances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      VAA_LR ~~
##      VAA_GT (r.VA) -0.023      NA      -0.108      -0.108
##      CS_LR ~~
##      CS_GT (r.CS) -0.001      NA      -0.025      -0.025
##      VAA_LR ~~
##      CS_LR (r.LR)  0.068      NA      0.339      0.339
##      VAA_GT ~~
##      CS_GT (r.GT) -0.022      NA      -0.361      -0.361
##      VAA_LR ~~
##      CS_GT (r.1.) -0.019      NA      -0.135      -0.135
##      VAA_GT ~~
##      CS_LR (r.2.) -0.001      NA      -0.013      -0.013

```

```

## .y4 ~~
## .C1_4          0.599      NA          0.599      0.627
##
## Intercepts:
##           Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .y22          3.034      NA          3.034      2.276
## .y23          3.299      NA          3.299      2.588
## .y26          3.071      NA          3.071      2.268
## .y27          4.080      NA          4.080      4.121
## .y9           3.935      NA          3.935      3.910
## .y19          2.751      NA          2.751      2.065
## .y4           1.461      NA          1.461      1.496
## .y5           1.590      NA          1.590      1.854
## .y21          2.605      NA          2.605      2.080
## .C1_7          2.213      NA          2.213      2.311
## .C1_8          3.069      NA          3.069      2.727
## .C1_1          3.298      NA          3.298      3.212
## .C1_4          1.357      NA          1.357      1.333
## .C1_6          3.220      NA          3.220      3.073
## .C1_10         1.402      NA          1.402      2.031
## VAA_LR         0.000          0.000      0.000
## VAA_GT         0.000          0.000      0.000
## CS_LR          0.000          0.000      0.000
## CS_GT          0.000          NaN      NaN
##
## Variances:
##           Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .y22          1.293      NA          1.293      0.728
## .y23          1.257      NA          1.257      0.773
## .y26          1.309      NA          1.309      0.713
## .y27          0.942      NA          0.942      0.961
## .y9           0.846      NA          0.846      0.835
## .y19          1.561      NA          1.561      0.879
## .y4           0.863      NA          0.863      0.905
## .y5           0.713      NA          0.713      0.970
## .y21          0.892      NA          0.892      0.569
## .C1_7          0.833      NA          0.833      0.908
## .C1_8         -1.394      NA         -1.394     -1.101
## .C1_1          1.097      NA          1.097      1.040
## .C1_4          1.058      NA          1.058      1.020
## .C1_6          1.099      NA          1.099      1.001
## .C1_10         1.885      NA          1.885      3.955
## VAA_LR         0.484      NA          1.000      1.000
## VAA_GT         0.091      NA          1.000      1.000
## CS_LR          0.084      NA          1.000      1.000
## CS_GT         -0.042      NA          NaN      NaN
##
##
## Group 6 [SDP]:
##
## Latent Variables:
##           Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## VAA_LR =~
## y22           1.000          0.601      0.558

```

```

##      y23      0.221      NA      0.133      0.231
##      y26      0.466      NA      0.280      0.474
##      y27      0.283      NA      0.170      0.166
##      y9       0.903      NA      0.543      0.411
##      y19      0.495      NA      0.298      0.543
## VAA_GT =~
##      y4       1.000      NA      0.514      0.486
##      y5       1.369      NA      0.704      0.584
##      y21      0.953      NA      0.490      0.407
## CS_LR =~
##      C1_7      1.000      NA      0.463      0.587
##      C1_8      0.739      NA      0.343      0.535
## CS_GT =~
##      C1_1      1.000      NA      0.446      0.512
##      C1_4      1.504      NA      0.671      0.632
##      C1_6      1.117      NA      0.498      0.486
##      C1_10     0.988      NA      0.441      0.583
##
## Covariances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## VAA_LR ~~
## VAA_GT (r.VA) 0.085      NA      0.276      0.276
## CS_LR ~~
## CS_GT (r.CS) 0.004      NA      0.021      0.021
## VAA_LR ~~
## CS_LR (r.LR) 0.073      NA      0.262      0.262
## VAA_GT ~~
## CS_GT (r.GT) 0.217      NA      0.945      0.945
## VAA_LR ~~
## CS_GT (r.1.) 0.072      NA      0.269      0.269
## VAA_GT ~~
## CS_LR (r.2.) 0.017      NA      0.072      0.072
## .y4 ~~
## .C1_4      0.422      NA      0.422      0.554
##
## Intercepts:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .y22      1.879      NA      1.879      1.744
## .y23      1.328      NA      1.328      2.304
## .y26      1.301      NA      1.301      2.199
## .y27      3.744      NA      3.744      3.652
## .y9       3.047      NA      3.047      2.304
## .y19      1.160      NA      1.160      2.115
## .y4       1.784      NA      1.784      1.686
## .y5       2.798      NA      2.798      2.321
## .y21      2.396      NA      2.396      1.989
## .C1_7      1.805      NA      1.805      2.287
## .C1_8      1.455      NA      1.455      2.273
## .C1_1      3.874      NA      3.874      4.453
## .C1_4      1.596      NA      1.596      1.502
## .C1_6      3.386      NA      3.386      3.303
## .C1_10     2.067      NA      2.067      2.737
## VAA_LR     0.000      NA      0.000      0.000
## VAA_GT     0.000      NA      0.000      0.000

```

```

##      CS_LR      0.000      0.000      0.000
##      CS_GT      0.000      0.000      0.000
##
## Variances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      .y22      0.799      NA      0.799      0.688
##      .y23      0.315      NA      0.315      0.947
##      .y26      0.271      NA      0.271      0.776
##      .y27      1.022      NA      1.022      0.972
##      .y9       1.455      NA      1.455      0.831
##      .y19      0.212      NA      0.212      0.705
##      .y4       0.855      NA      0.855      0.764
##      .y5       0.958      NA      0.958      0.659
##      .y21      1.211      NA      1.211      0.835
##      .C1_7      0.408      NA      0.408      0.655
##      .C1_8      0.293      NA      0.293      0.714
##      .C1_1      0.558      NA      0.558      0.737
##      .C1_4      0.678      NA      0.678      0.601
##      .C1_6      0.803      NA      0.803      0.764
##      .C1_10     0.376      NA      0.376      0.660
##      VAA_LR     0.362      NA      1.000      1.000
##      VAA_GT     0.264      NA      1.000      1.000
##      CS_LR     0.215      NA      1.000      1.000
##      CS_GT     0.199      NA      1.000      1.000
##
##
## Group 7 [VAS]:
##
## Latent Variables:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      VAA_LR =~
##      y22      1.000      0.162      0.203
##      y23      0.993      NA      0.161      0.281
##      y26      0.443      NA      0.072      0.339
##      y27      3.421      NA      0.554      0.489
##      y9       4.646      NA      0.753      0.601
##      y19      0.138      NA      0.022      0.063
##      VAA_GT =~
##      y4       1.000      0.582      0.563
##      y5       1.683      NA      0.979      0.841
##      y21      1.103      NA      0.642      0.544
##      CS_LR =~
##      C1_7      1.000      0.336      0.444
##      C1_8      1.306      NA      0.439      0.677
##      CS_GT =~
##      C1_1      1.000      0.650      0.665
##      C1_4      0.629      NA      0.409      0.442
##      C1_6      0.993      NA      0.645      0.583
##      C1_10     0.711      NA      0.462      0.472
##
## Covariances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      VAA_LR ~~
##      VAA_GT (r.VA) 0.063      NA      0.669      0.669

```

```

## CS_LR ~~
## CS_GT (r.CS) 0.038 NA 0.176 0.176
## VAA_LR ~~
## CS_LR (r.LR) 0.035 NA 0.640 0.640
## VAA_GT ~~
## CS_GT (r.GT) 0.336 NA 0.887 0.887
## VAA_LR ~~
## CS_GT (r.1.) 0.065 NA 0.613 0.613
## VAA_GT ~~
## CS_LR (r.2.) 0.020 NA 0.103 0.103
## .y4 ~~
## .C1_4 0.338 NA 0.338 0.476
##
## Intercepts:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .y22 1.363 NA 1.363 1.706
## .y23 1.227 NA 1.227 2.142
## .y26 1.051 NA 1.051 4.958
## .y27 2.283 NA 2.283 2.013
## .y9 2.320 NA 2.320 1.852
## .y19 1.069 NA 1.069 3.015
## .y4 1.539 NA 1.539 1.488
## .y5 2.028 NA 2.028 1.740
## .y21 2.086 NA 2.086 1.769
## .C1_7 1.649 NA 1.649 2.182
## .C1_8 1.209 NA 1.209 1.867
## .C1_1 3.700 NA 3.700 3.790
## .C1_4 1.333 NA 1.333 1.440
## .C1_6 3.377 NA 3.377 3.053
## .C1_10 2.252 NA 2.252 2.302
## VAA_LR 0.000 0.000 0.000
## VAA_GT 0.000 0.000 0.000
## CS_LR 0.000 0.000 0.000
## CS_GT 0.000 0.000 0.000
##
## Variances:
## Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## .y22 0.613 NA 0.613 0.959
## .y23 0.302 NA 0.302 0.921
## .y26 0.040 NA 0.040 0.885
## .y27 0.979 NA 0.979 0.761
## .y9 1.002 NA 1.002 0.639
## .y19 0.125 NA 0.125 0.996
## .y4 0.731 NA 0.731 0.683
## .y5 0.398 NA 0.398 0.293
## .y21 0.980 NA 0.980 0.704
## .C1_7 0.459 NA 0.459 0.802
## .C1_8 0.227 NA 0.227 0.541
## .C1_1 0.531 NA 0.531 0.557
## .C1_4 0.690 NA 0.690 0.805
## .C1_6 0.807 NA 0.807 0.660
## .C1_10 0.744 NA 0.744 0.777
## VAA_LR 0.026 NA 1.000 1.000
## VAA_GT 0.339 NA 1.000 1.000

```

```

##      CS_LR      0.113      NA      1.000      1.000
##      CS_GT      0.422      NA      1.000      1.000
##
##
## Group 8 [VIHR]:
##
## Latent Variables:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## VAA_LR =~
##      y22      1.000      NA      0.813      0.636
##      y23      0.150      NA      0.122      0.105
##      y26      0.362      NA      0.294      0.339
##      y27      0.513      NA      0.417      0.354
##      y9       0.892      NA      0.725      0.584
##      y19      0.559      NA      0.454      0.415
## VAA_GT =~
##      y4       1.000      NA      0.174      0.384
##      y5       3.018      NA      0.525      0.576
##      y21      1.341      NA      0.233      0.424
## CS_LR =~
##      C1_7      1.000      NA      0.451      0.553
##      C1_8      0.547      NA      0.247      0.328
## CS_GT =~
##      C1_1      1.000      NA      0.542      0.615
##      C1_4      0.532      NA      0.289      0.499
##      C1_6      1.185      NA      0.643      0.588
##      C1_10     0.478      NA      0.260      0.445
##
## Covariances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
## VAA_LR ~~
## VAA_GT (r.VA)  0.087      NA      0.614      0.614
## CS_LR ~~
## CS_GT (r.CS)  -0.194      NA     -0.794     -0.794
## VAA_LR ~~
## CS_LR (r.LR)   0.060      NA      0.164      0.164
## VAA_GT ~~
## CS_GT (r.GT)   0.116      NA      1.231      1.231
## VAA_LR ~~
## CS_GT (r.1.)   0.213      NA      0.483      0.483
## VAA_GT ~~
## CS_LR (r.2.)  -0.043      NA     -0.542     -0.542
## .y4 ~~
## .C1_4          0.062      NA      0.062      0.295
##
## Intercepts:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      .y22      2.450      NA      2.450      1.916
##      .y23      2.096      NA      2.096      1.810
##      .y26      1.580      NA      1.580      1.818
##      .y27      3.560      NA      3.560      3.019
##      .y9       3.028      NA      3.028      2.437
##      .y19      1.957      NA      1.957      1.787
##      .y4       1.146      NA      1.146      2.527

```



```

##      .y5      1.704      NA      1.704      1.870
##      .y21     1.216      NA      1.216      2.210
##      .C1_7     1.920      NA      1.920      2.355
##      .C1_8     1.808      NA      1.808      2.407
##      .C1_1     3.571      NA      3.571      4.049
##      .C1_4     1.129      NA      1.129      1.953
##      .C1_6     3.027      NA      3.027      2.771
##      .C1_10    1.591      NA      1.591      2.725
##      VAA_LR     0.000      NA      0.000      0.000
##      VAA_GT     0.000      NA      0.000      0.000
##      CS_LR      0.000      NA      0.000      0.000
##      CS_GT      0.000      NA      0.000      0.000
##
## Variances:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      .y22      0.975      NA      0.975      0.596
##      .y23      1.326      NA      1.326      0.989
##      .y26      0.669      NA      0.669      0.885
##      .y27      1.217      NA      1.217      0.875
##      .y9       1.018      NA      1.018      0.659
##      .y19      0.994      NA      0.994      0.828
##      .y4       0.175      NA      0.175      0.853
##      .y5       0.555      NA      0.555      0.668
##      .y21      0.248      NA      0.248      0.820
##      .C1_7     0.461      NA      0.461      0.694
##      .C1_8     0.503      NA      0.503      0.892
##      .C1_1     0.483      NA      0.483      0.622
##      .C1_4     0.251      NA      0.251      0.751
##      .C1_6     0.780      NA      0.780      0.654
##      .C1_10    0.274      NA      0.274      0.802
##      VAA_LR     0.661      NA      1.000      1.000
##      VAA_GT     0.030      NA      1.000      1.000
##      CS_LR      0.203      NA      1.000      1.000
##      CS_GT      0.294      NA      1.000      1.000
##
## Defined Parameters:
##      Estimate Std.Err z-value P(>|z|) Std.lv Std.all
##      mean.r.VAA -0.000      NA      -0.002      -0.002
##      mean.r.CS   0.038      NA      0.452      0.452
##      mean.r.LR   0.094      NA      1.113      1.113
##      mean.r.GT  -0.000      NA     -0.031     -0.031
##      mean.r.d1   0.051      NA      0.386      0.386
##      mean.r.d2   0.000      NA      0.018      0.018
##      test.H3     0.043      NA      0.661      0.661
##      test.H4    -0.051      NA     -0.483     -0.483

```

Try to fit the model separately for each group

```
fit_H3H4.re.KD<-cfa(model=model_H1H2.re,
  data=dat2011.party,
  group=c("puolue"),
  group.label=c("KD"),
  missing="fiml")
```

Model for KD

```
## Warning in lav_model_estimate(lavmodel = lavmodel, lavpartable = lavpartable, : lavaan WARNING: the
## but not all elements of the gradient are (near) zero;
## the optimizer may not have found a local solution
## use check.gradient = FALSE to skip this check.
```

Model for KD does not converge

Fit is poor

Print standardized estimates to test the difference between correlations

```
std.est_H3H4.re.KD<-standardizedsolution(fit_H3H4.re.KD)
```

```
## Warning in sqrt(ETA2): NaNs produced
## Warning in computeOmega(Sigma.hat = Sigma.hat, Mu.hat = Mu.hat, lavsamplestats = lavsamplestats, : 1
## Error in chol.default(S) :
## the leading minor of order 13 is not positive definite
```

```
std.est_H3H4.re.KD[std.est_H3H4.re.KD$op=="==" |
  std.est_H3H4.re.KD$op=="~" &
  std.est_H3H4.re.KD$lhs!=std.est_H3H4.re.KD$rhs,]
```

##	lhs op	rhs	est	std	se	z	pvalue	ci.lower
## 21	VAA_LR ~~	VAA_GT	0.122	NA	NA		NA	NA
## 22	CS_LR ~~	CS_GT	-0.028	NA	NA		NA	NA
## 23	VAA_LR ~~	CS_LR	-0.071	NA	NA		NA	NA
## 24	VAA_GT ~~	CS_GT	3.010	NA	NA		NA	NA
## 25	VAA_LR ~~	CS_GT	0.480	NA	NA		NA	NA
## 26	VAA_GT ~~	CS_LR	0.022	NA	NA		NA	NA
## 27	y4 ~~	C1_4	0.510	NA	NA		NA	NA
## 76	test.H1 := r.LR-max(r.VAA,r.CS,r.d1,r.d2)		-0.551	NA	NA		NA	NA
## 77	test.H2 := r.GT-max(r.VAA,r.CS,r.d1,r.d2)		2.530	NA	NA		NA	NA
##	ci.upper							
## 21	NA							
## 22	NA							
## 23	NA							
## 24	NA							
## 25	NA							
## 26	NA							
## 27	NA							
## 76	NA							
## 77	NA							

```
fit_H3H4.re.KESK<-cfa(model=model_H1H2.re,
  data=dat2011.party,
  group=c("puolue"),
  group.label=c("KESK"),
  missing="fiml")
```

Model for KESK Model for KESK does converge

```
round(inspect(fit_H3H4.re.KESK,"fit")
  [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

```
##      npar      df    chisq  pvalue      cfi      tli    rmsea    srmr
##  67.000 163.000 287.143   0.000   0.662   0.606   0.059   0.114
```

Fit is poor

Print standardized estimates to test the difference between correlations

```
std.est_H3H4.re.KESK<-standardizedsolution(fit_H3H4.re.KESK)
std.est_H3H4.re.KESK[std.est_H3H4.re.KESK$op=="==" |
  std.est_H3H4.re.KESK$op=="~" &
  std.est_H3H4.re.KESK$lhs!=std.est_H3H4.re.KESK$rhs,]
```

```
##      lhs op      rhs est.std    se      z pvalue
## 21 VAA_LR ~~      VAA_GT  0.254 0.113  2.250  0.024
## 22 CS_LR  ~~      CS_GT  0.241 0.276  0.873  0.383
## 23 VAA_LR ~~      CS_LR -0.192 0.348 -0.552  0.581
## 24 VAA_GT ~~      CS_GT  0.884 0.092  9.593  0.000
## 25 VAA_LR ~~      CS_GT  0.392 0.176  2.229  0.026
## 26 VAA_GT ~~      CS_LR  0.025 0.250  0.100  0.921
## 27      y4 ~~      C1_4  0.766 0.063 12.131  0.000
## 76 test.H1 := r.LR-max(r.VAA,r.CS,r.d1,r.d2) -0.584 0.351 -1.665  0.096
## 77 test.H2 := r.GT-max(r.VAA,r.CS,r.d1,r.d2)  0.492 0.209  2.353  0.019
##      ci.lower ci.upper
## 21    0.033    0.475
## 22   -0.300    0.781
## 23   -0.874    0.490
## 24    0.704    1.065
## 25    0.047    0.737
## 26   -0.465    0.515
## 27    0.643    0.890
## 76   -1.272    0.104
## 77    0.082    0.902
```

```
fit_H3H4.re.KOK<-cfa(model=model_H1H2.re,
  data=dat2011.party,
  group=c("puolue"),
  group.label=c("KOK"),
  missing="fiml")
```

Model for KOK

```
## Warning in lav_object_post_check(object): lavaan WARNING: covariance matrix of latent variables
## is not positive definite;
## use lavInspect(fit, "cov.lv") to investigate.
```

Model for KOK has problems

```
round(inspect(fit_H3H4.re.KOK,"fit")
  [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

```
##      npar      df    chisq  pvalue      cfi      tli    rmsea    srmr
## 67.000 163.000 214.323   0.004   0.799   0.766   0.037   0.108
```

Fit is poor

Print standardized estimates to test the difference between correlations

```
std.est_H3H4.re.KOK<-standardizedsolution(fit_H3H4.re.KOK)
std.est_H3H4.re.KOK[std.est_H3H4.re.KOK$op=="==" |
  std.est_H3H4.re.KOK$op=="~" &
  std.est_H3H4.re.KOK$lhs!=std.est_H3H4.re.KOK$rhs,]
```

```
##      lhs op      rhs est.std    se      z pvalue
## 21  VAA_LR ~~      VAA_GT  0.431 0.112  3.838  0.000
## 22  CS_LR  ~~      CS_GT  0.533 0.290  1.838  0.066
## 23  VAA_LR ~~      CS_LR  0.348 0.243  1.431  0.152
## 24  VAA_GT ~~      CS_GT  1.295 0.162  7.980  0.000
## 25  VAA_LR ~~      CS_GT  0.512 0.187  2.730  0.006
## 26  VAA_GT ~~      CS_LR  0.282 0.261  1.079  0.280
## 27      y4 ~~      C1_4  0.549 0.100  5.497  0.000
## 76 test.H1 := r.LR-max(r.VAA,r.CS,r.d1,r.d2) -0.185 0.359 -0.515  0.607
## 77 test.H2 := r.GT-max(r.VAA,r.CS,r.d1,r.d2)  0.762 0.326  2.339  0.019
##      ci.lower ci.upper
## 21    0.211    0.652
## 22   -0.035    1.101
## 23   -0.129    0.824
## 24    0.977    1.613
## 25    0.144    0.879
## 26   -0.230    0.794
## 27    0.353    0.745
## 76   -0.889    0.519
## 77    0.124    1.401
```

Correlations larger than 1.00

```
fit_H3H4.re.PS<-cfa(model=model_H1H2.re,
  data=dat2011.party,
  group=c("puolue"),
  group.label=c("PS"),
  missing="fiml")
```

Model for PS

```
## Warning in lav_object_post_check(object): lavaan WARNING: some estimated ov
## variances are negative
```

Model for PS has problems with negative variances

```
round(inspect(fit_H3H4.re.PS,"fit")
  [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

```
##      npar      df    chisq  pvalue      cfi      tli    rmsea    srmr
##  67.000 163.000 204.859   0.015   0.849   0.823   0.035   0.092
```

Fit is poor, but not very poor

Print standardized estimates to test the difference between correlations

```
std.est_H3H4.re.PS<-standardizedsolution(fit_H3H4.re.PS)
std.est_H3H4.re.PS[std.est_H3H4.re.PS$op=="==" |
  std.est_H3H4.re.PS$op=="~" &
  std.est_H3H4.re.PS$lhs!=std.est_H3H4.re.PS$rhs,]
```

```
##      lhs op      rhs est.std    se      z pvalue
## 21 VAA_LR ~~ VAA_GT  0.380 0.132  2.880  0.004
## 22 CS_LR  ~~ CS_GT  -0.042 0.122 -0.345  0.730
## 23 VAA_LR ~~ CS_LR   0.300 0.242  1.242  0.214
## 24 VAA_GT ~~ CS_GT   0.921 0.158  5.834  0.000
## 25 VAA_LR ~~ CS_GT   0.378 0.143  2.639  0.008
## 26 VAA_GT ~~ CS_LR  -0.077 0.154 -0.499  0.618
## 27      y4 ~~ C1_4   0.403 0.096  4.194  0.000
## 76 test.H1 := r.LR-max(r.VAA,r.CS,r.d1,r.d2) -0.080 0.282 -0.285  0.776
## 77 test.H2 := r.GT-max(r.VAA,r.CS,r.d1,r.d2)  0.541 0.194  2.785  0.005
##      ci.lower ci.upper
## 21    0.122    0.639
## 22   -0.282    0.198
## 23   -0.174    0.774
## 24    0.612    1.231
## 25    0.097    0.658
## 26   -0.378    0.225
## 27    0.214    0.591
## 76   -0.632    0.472
## 77    0.160    0.921
```

```
fit_H3H4.re.RKP<-cfa(model=model_H1H2.re,
  data=dat2011.party,
  group=c("puolue"),
  group.label=c("RKP"),
  missing="fiml")
```

Model for RKP

```
## Warning in lav_object_post_check(object): lavaan WARNING: some estimated ov
## variances are negative
```

```
## Warning in lav_object_post_check(object): lavaan WARNING: some estimated lv
## variances are negative
```

Model for RKP converges, but has problem with negative variances

```
round(inspect(fit_H3H4.re.RKP,"fit")
  [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

##	npar	df	chisq	pvalue	cfi	tli	rmsea	srmr
##	67.000	163.000	251.461	0.000	0.463	0.374	0.084	0.132

Fit is poor

Print standardized estimates to test the difference between correlations

```
std.est_H3H4.re.RKP<-standardizedsolution(fit_H3H4.re.RKP)
```

```
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
```

[illegible]

[illegible]

[illegible]

[illegible]

```
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
## Warning in sqrt(ETA2): NaNs produced
```

```
std.est_H3H4.re.RKP[std.est_H3H4.re.RKP$op=="==" |
  std.est_H3H4.re.RKP$op=="~" &
  std.est_H3H4.re.RKP$lhs!=std.est_H3H4.re.RKP$rhs,]
```

##	lhs op	rhs	est	std	se	z	pvalue
## 21	VAA_LR ~~	VAA_GT	0.352	0.245	1.439	0.150	
## 22	CS_LR ~~	CS_GT	0.069	0.238	0.289	0.773	
## 23	VAA_LR ~~	CS_LR	-0.269	0.281	-0.960	0.337	
## 24	VAA_GT ~~	CS_GT	0.421	0.289	1.454	0.146	
## 25	VAA_LR ~~	CS_GT	0.656	0.251	2.611	0.009	
## 26	VAA_GT ~~	CS_LR	0.003	0.093	0.037	0.970	
## 27	y4 ~~	C1_4	0.556	0.102	5.463	0.000	
## 76	test.H1 := r.LR-max(r.VAA,r.CS,r.d1,r.d2)		-0.925	0.370	-2.505	0.012	
## 77	test.H2 := r.GT-max(r.VAA,r.CS,r.d1,r.d2)		-0.235	0.369	-0.638	0.524	
##	ci.lower ci.upper						
## 21	-0.128 0.832						
## 22	-0.398 0.535						
## 23	-0.819 0.281						
## 24	-0.146 0.988						
## 25	0.164 1.149						
## 26	-0.179 0.186						
## 27	0.357 0.756						
## 76	-1.650 -0.201						
## 77	-0.959 0.488						

```
fit_H3H4.re.SDP<-cfa(model=model_H1H2.re,
  data=dat2011.party,
  group=c("puolue"),
  group.label=c("SDP"),
  missing="fiml")
```

Model for SDP Model for SDP converges

```
round(inspect(fit_H3H4.re.SDP,"fit")
  [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

```
##      npar      df    chisq  pvalue      cfi      tli    rmsea    srmr
##  67.000 163.000 227.918   0.001   0.781   0.745   0.042   0.095
```

Fit is poor

Print standardized estimates to test the difference between correlations

```
std.est_H3H4.re.SDP<-standardizedsolution(fit_H3H4.re.SDP)
std.est_H3H4.re.SDP[std.est_H3H4.re.SDP$op=="==" |
  std.est_H3H4.re.SDP$op=="~" &
  std.est_H3H4.re.SDP$lhs!=std.est_H3H4.re.SDP$rhs,]
```

```
##      lhs op      rhs est.std    se      z pvalue
## 21 VAA_LR ~~      VAA_GT   0.195 0.126 1.542  0.123
## 22 CS_LR  ~~      CS_GT   0.174 0.211 0.824  0.410
## 23 VAA_LR ~~      CS_LR   0.328 0.241 1.364  0.173
## 24 VAA_GT ~~      CS_GT   0.932 0.097 9.602  0.000
## 25 VAA_LR ~~      CS_GT   0.298 0.152 1.961  0.050
## 26 VAA_GT ~~      CS_LR   0.138 0.233 0.593  0.553
## 27      y4 ~~      C1_4   0.537 0.094 5.695  0.000
## 76 test.H1 := r.LR-max(r.VAA,r.CS,r.d1,r.d2) 0.031 0.269 0.114  0.910
## 77 test.H2 := r.GT-max(r.VAA,r.CS,r.d1,r.d2) 0.635 0.186 3.411  0.001
##      ci.lower ci.upper
## 21   -0.053    0.442
## 22   -0.240    0.589
## 23   -0.143    0.800
## 24    0.742    1.123
## 25    0.000    0.595
## 26   -0.319    0.595
## 27    0.352    0.722
## 76   -0.496    0.558
## 77    0.270    0.999
```

```
fit_H3H4.re.VAS<-cfa(model=model_H1H2.re,
  data=dat2011.party,
  group=c("puolue"),
  group.label=c("VAS"),
  missing="fiml")
```

Model for VAS

```
## Warning in lav_object_post_check(object): lavaan WARNING: covariance matrix of latent variables
## is not positive definite;
## use lavInspect(fit, "cov.lv") to investigate.
```

Model for VAS has problems

```
round(inspect(fit_H3H4.re.VAS,"fit")
  [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

```
##      npar      df    chisq  pvalue      cfi      tli    rmsea    srmr
## 67.000 163.000 260.989   0.000   0.760   0.720   0.053   0.113
```

Print standardized estimates to test the difference between correlations

```
std.est_H3H4.re.VAS<-standardizedsolution(fit_H3H4.re.VAS)
std.est_H3H4.re.VAS[std.est_H3H4.re.VAS$op=="==" |
  std.est_H3H4.re.VAS$op=="~" &
  std.est_H3H4.re.VAS$lhs!=std.est_H3H4.re.VAS$rhs,]
```

```
##      lhs op      rhs est.std    se      z pvalue
## 21  VAA_LR ~ VAA_GT  0.658 0.097  6.786  0.000
## 22  CS_LR ~ CS_GT   1.107 0.603  1.835  0.067
## 23  VAA_LR ~ CS_LR   1.401 0.724  1.934  0.053
## 24  VAA_GT ~ CS_GT   0.965 0.071 13.635  0.000
## 25  VAA_LR ~ CS_GT   0.582 0.149  3.908  0.000
## 26  VAA_GT ~ CS_LR   0.716 0.498  1.439  0.150
## 27      y4 ~ C1_4    0.437 0.099  4.430  0.000
## 76 test.H1 := r.LR-max(r.VAA,r.CS,r.d1,r.d2) 0.294 0.430  0.683  0.495
## 77 test.H2 := r.GT-max(r.VAA,r.CS,r.d1,r.d2) -0.142 0.607 -0.234  0.815
##      ci.lower ci.upper
## 21    0.468    0.848
## 22   -0.076    2.290
## 23   -0.019    2.821
## 24    0.826    1.104
## 25    0.290    0.875
## 26   -0.259    1.692
## 27    0.244    0.631
## 76   -0.550    1.137
## 77   -1.332    1.047
```

Correlations are impossible

```
fit_H3H4.re.VIHR<-cfa(model=model_H1H2.re,
  data=dat2011.party,
  group=c("puolue"),
  group.label=c("VIHR"),
  missing="fiml")
```

Model for VIHR

```
## Warning in lav_model_estimate(lavmodel = lavmodel, lavpartable = lavpartable, : lavaan WARNING: the
## but not all elements of the gradient are (near) zero;
## the optimizer may not have found a local solution
## use check.gradient = FALSE to skip this check.
```

Model for VIHR does not converge

Fit is poor

Print standardized estimates to test the difference between correlations

```
std.est_H3H4.re.VIHR<-standardizedsolution(fit_H3H4.re.VIHR)
```

```
## Warning in sqrt(ETA2): NaNs produced
```

```
## Warning in computeOmega(Sigma.hat = Sigma.hat, Mu.hat = Mu.hat, lavsamplestats = lavsamplestats, : 1
```

```
## Error in chol.default(S) :
```

```
## the leading minor of order 13 is not positive definite
```

```
std.est_H3H4.re.VIHR[std.est_H3H4.re.VIHR$op=="==" |
  std.est_H3H4.re.VIHR$op=="~" &
  std.est_H3H4.re.VIHR$lhs!=std.est_H3H4.re.VIHR$rhs,]
```

##	lhs op	rhs	est	std	se	z	pvalue	ci.lower
## 21	VAA_LR ~~	VAA_GT	0.556	NA	NA	NA	NA	NA
## 22	CS_LR ~~	CS_GT	0.004	NA	NA	NA	NA	NA
## 23	VAA_LR ~~	CS_LR	-0.011	NA	NA	NA	NA	NA
## 24	VAA_GT ~~	CS_GT	1.144	NA	NA	NA	NA	NA
## 25	VAA_LR ~~	CS_GT	0.591	NA	NA	NA	NA	NA
## 26	VAA_GT ~~	CS_LR	-0.001	NA	NA	NA	NA	NA
## 27	y4 ~~	C1_4	0.317	NA	NA	NA	NA	NA
## 76	test.H1 := r.LR-max(r.VAA,r.CS,r.d1,r.d2)		-0.602	NA	NA	NA	NA	NA
## 77	test.H2 := r.GT-max(r.VAA,r.CS,r.d1,r.d2)		0.553	NA	NA	NA	NA	NA
##	ci.upper							
## 21	NA							
## 22	NA							
## 23	NA							
## 24	NA							
## 25	NA							
## 26	NA							
## 27	NA							
## 76	NA							
## 77	NA							

Summary of H3-H4 with MG-CFA approach

The configural model did not converge, even after respecification. Single group model also were non-converging or had other type of problems, except for KD and KOK, for which the fit of the model nevertheless was poor, and therefore not interpretable.

This most likely is an indication that the sample sizes of the parties are too small for this model with 21 indicators and 4 factors.

The alternative way to test hypotheses 4-6 is presented below. It unconfounds the associations in the model by using party-mean centered observed variables for estimating the similar type of model that was used for H1 and H2, and H5, respectively. Because this approach does not have any grouping structure, it uses the overall sample size for the eight parties, which is 1572. It is nevertheless only conducted among the eight focal parties, and other parties are excluded. Because the misspecification in the model with centered variables might be entirely different to raw score variables, the modeling is again started with no residual correlations and they are examined if the fit of the model is inadequate.

H3 and H4 with group-mean centered variables and no grouping structure

Estimate how much of the variation in each item is between-groups

```
#there was problems running the mult.icc function to the data structure so  
#data observed data was extracted from one of the previously fitted models  
#to get rid of all labels etc.  
  
num.dat.2011<-data.frame(fit_H1H2@Data@X,dat2011$puolue)  
names(num.dat.2011)<-c(fit_H1H2@Data@ov$name,"puolue")  
num.dat.2011<-num.dat.2011 %>%  
  filter(puolue=="KD" |  
         puolue=="KESK" |  
         puolue=="KOK" |  
         puolue=="PS" |  
         puolue=="RKP" |  
         puolue=="SDP" |  
         puolue=="VAS" |  
         puolue=="VIHR")  
  
ICC<-data.frame(multilevel::mult.icc(x=num.dat.2011[,obs_items[2:length(obs_items)]],  
                                   grpId=num.dat.2011$puolue))  
  
ICC[,2:3]<-round(ICC[,2:3],3)  
ICC  
  
##      Variable  ICC1  ICC2  
## 1      y22 0.338 0.990  
## 2      y23 0.385 0.992  
## 3      y26 0.421 0.993  
## 4      y27 0.318 0.989  
## 5       y9 0.326 0.990  
## 6      y19 0.379 0.992  
## 7       y4 0.525 0.995  
## 8       y5 0.531 0.996  
## 9       y1 0.505 0.995  
## 10     y21 0.319 0.989  
## 11    C1_2 0.078 0.943  
## 12    C1_7 0.071 0.937  
## 13    C1_8 0.477 0.994  
## 14    C1_1 0.266 0.986  
## 15    C1_3 0.205 0.981  
## 16    C1_4 0.479 0.994  
## 17    C1_5 0.054 0.918  
## 18    C1_6 0.137 0.969  
## 19   C1_10 0.428 0.993  
## 20   C1_11 0.480 0.995  
  
describe(ICC$ICC1,fast=T)  
  
##    vars  n mean  sd min  max range  se  
## X1     1 20 0.34 0.16 0.05 0.53 0.48 0.03  
  
ICC$label<-get_label(df2011[,as.character(ICC[,1])])  
  
#export to .csv file
```



```
write.csv2(ICC,"ICC_2011.csv")
```

ICC gives the proportion (%) of variance that is between the parties. There is quite a lot between-party variance.

Center all observed variables

```
ind.items<-obs_items[2:length(obs_items)]
```

```
dat2011.gmc<-data.frame(dat2011.party)
```

```
na.mean<-function(var){  
  mean(var,na.rm=T)  
}
```

```
group.means<-dat2011.gmc %>%  
  group_by(puolue) %>%  
  summarise_at(ind.items,na.mean)
```

```
dat2011.gmc<-left_join(x=dat2011.gmc,  
  y=group.means,  
  by=c("puolue"),  
  suffix=c("", ".pm"))
```

```
ind.items %in% names(dat2011.gmc)
```

```
## [1] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE  
## [16] TRUE TRUE TRUE TRUE TRUE
```

```
paste0(ind.items, ".pm") %in% names(dat2011.gmc)
```

```
## [1] TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE  
## [16] TRUE TRUE TRUE TRUE TRUE
```

```
for(i in 1:length(ind.items)){  
  dat2011.gmc[,which(names(dat2011.gmc)==ind.items[i])]<-  
    dat2011.gmc[,which(names(dat2011.gmc)==ind.items[i])]-  
    dat2011.gmc[,which(names(dat2011.gmc)==paste0(ind.items[i], ".pm"))]  
}
```

```
psych::describe(dat2011.gmc[,ind.items],fast=T)
```

```
##      vars    n mean   sd   min  max range   se  
## y22      1 1479    0 1.17 -2.85 3.64  6.49 0.03  
## y23      2 1482    0 1.07 -2.58 3.78  6.37 0.03  
## y26      3 1494    0 0.89 -2.08 3.48  5.56 0.02  
## y27      4 1496    0 1.03 -3.46 2.74  6.20 0.03  
## y9       5 1490    0 1.07 -3.53 2.72  6.25 0.03  
## y19      6 1495    0 1.07 -2.35 3.93  6.29 0.03  
## y4       7 1490    0 1.16 -3.44 3.53  6.97 0.03  
## y5       8 1496    0 1.05 -2.87 3.30  6.17 0.03  
## y1       9 1503    0 1.00 -3.80 2.69  6.49 0.03  
## y21     10 1439    0 1.15 -2.61 3.79  6.40 0.03  
## C1_2     11  639    0 0.91 -1.16 3.50  4.65 0.04  
## C1_7     12  637    0 0.84 -1.41 3.20  4.61 0.03
```

```
## C1_8    13  638    0 0.81 -2.08 3.75  5.83 0.03
## C1_1    14  639    0 0.77 -2.88 1.70  4.58 0.03
## C1_3    15  640    0 0.96 -1.64 3.89  5.53 0.04
## C1_4    16  636    0 1.18 -3.39 3.87  7.25 0.05
## C1_5    17  639    0 1.09 -2.76 2.00  4.76 0.04
## C1_6    18  639    0 0.97 -3.17 1.98  5.15 0.04
## C1_10   19  640    0 0.84 -2.75 2.80  5.55 0.03
## C1_11   20  633    0 0.81 -2.56 3.75  6.31 0.03
```

Define the model

Use the subset of items used for H1 and H2

```
model_H3H4<-"
#loadings
VAA_LR=~y22+y23+y26+y27+y9+y19
VAA_GT=~y4+y5+y21
CS_LR=~C1_7+C1_8
CS_GT=~C1_1+C1_4+C1_6+C1_10

#latent correlations

#cross-dimension same-method
VAA_LR~~r.VAA*VAA_GT
CS_LR~~r.CS*CS_GT

#concurrent validity
VAA_LR~~r.LR*CS_LR
VAA_GT~~r.GT*CS_GT

#cross-dimension cross-method correlations
VAA_LR~~r.d1*CS_GT
VAA_GT~~r.d2*CS_LR

#custom parameters
test.H3:=r.LR-max(r.VAA,r.CS,r.d1,r.d2)
test.H4:=r.GT-max(r.VAA,r.CS,r.d1,r.d2)

"
```

Fit the model

```
fit_H3H4<-cfa(model=model_H3H4,
              data=dat2011.gmc,
              missing="fiml")
```

```
## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some cases
##    452

## Warning in lav_object_post_check(object): lavaan WARNING: covariance matrix of latent variables
##           is not positive definite;
##           use lavInspect(fit, "cov.lv") to investigate.
```

Problems with the covariance structure, add the preregistered residual correlation.

```
model_H3H4.re<-paste0(model_H3H4,
                        "y4~~C1_4\n")
```

```
fit_H3H4.re<-cfa(model=model_H3H4.re,
                  data=dat2011.gmc,
                  missing="fiml")
```

Fit the respecified model

```
## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some cases
## 452
```

Problem was solved with the residual correlation

Inspect fit of the model

```
round(inspect(fit_H3H4.re,"fit")
      [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

```
##      npar      df   chisq  pvalue    cfi    tli   rmsea   srmr
## 52.000  83.000 268.505   0.000   0.873   0.840   0.038   0.048
```

The fit of the model is adequate.

Hypotheses 3 and 4

Print standardized estimates to test the difference between correlations

```
std.est_H3H4.re<-standardizedsolution(fit_H3H4.re)
std.est_H3H4.re[std.est_H3H4.re$op=="==" |
                 std.est_H3H4.re$op=="~~" &
                 std.est_H3H4.re$lhs!=std.est_H3H4.re$rhs,]
```

```
##      lhs op      rhs est.std   se      z pvalue
## 16 VAA_LR ~~      VAA_GT   0.373 0.046  8.094  0.000
## 17 CS_LR  ~~      CS_GT   0.031 0.074  0.422  0.673
## 18 VAA_LR ~~      CS_LR   0.424 0.093  4.582  0.000
## 19 VAA_GT ~~      CS_GT   0.863 0.053 16.277  0.000
## 20 VAA_LR ~~      CS_GT   0.439 0.063  6.939  0.000
## 21 VAA_GT ~~      CS_LR   0.060 0.077  0.773  0.439
## 22 y4    ~~      C1_4    0.587 0.028 21.117  0.000
## 61 test.H3 := r.LR-max(r.VAA,r.CS,r.d1,r.d2) -0.015 0.114 -0.129 0.897
## 62 test.H4 := r.GT-max(r.VAA,r.CS,r.d1,r.d2)  0.425 0.082  5.209  0.000
##      ci.lower ci.upper
## 16    0.283    0.463
## 17   -0.114    0.177
## 18    0.243    0.605
## 19    0.759    0.967
## 20    0.315    0.562
## 21   -0.092    0.211
## 22    0.532    0.641
## 61   -0.238    0.208
## 62    0.265    0.584
```

H3: There is a moderately strong (.424, $p < .001$) correlation between VAA-LR and CS-LR, and it is not stronger (difference in correlations -.015, $p = .897$) than the strongest of correlations between different dimensions (.439 between VAA_LR and CS_GT, $p < .001$)

H4: There is a strong (.863, $p < .001$) correlation between VAA-GT and CS-GT, and it is notably stronger (difference in correlations .425, $p < .001$) than the strongest of correlations between different dimensions (.439 between VAA_LR and CS_GT, $p < .001$)

```
mis.H3H4<-miPowerFit(fit_H3H4.re,stdLoad=.40,cor=.20)
mis.H3H4<-mis.H3H4[mis.H3H4$op=="=~" | mis.H3H4$op=="~~",]
#see summary of the decisions
table(mis.H3H4$decision.pow)
```

Exploratory for H3 and H4: Seek misspecification to improve the overall model fit

```
##
##  EPC:M EPC:NM      I      M      NM
##      2      33      4      4     105
#there are 6 misspecifications

rounded.vars<-c("mi","epc","target.epc",
               "std.epc","se.epc")

num.round<-function(var){
  var<-as.numeric(var)
  var<-round(var,2)
  return(var)
}

mis.H3H4[,rounded.vars]<-sapply(mis.H3H4[,rounded.vars],num.round)

printed.vars<-c("lhs","op","rhs","mi","epc","target.epc",
               "std.epc","std.target.epc","significant.mi",
               "high.power","decision.pow","se.epc")

#print the output

mis.H3H4 %>%
  filter(mis.H3H4$decision.pow=="M" |
         mis.H3H4$decision.pow=="EPC:M") %>%
  dplyr::select(all_of(printed.vars))

##      lhs op   rhs    mi    epc target.epc std.epc std.target.epc significant.mi
## 1 VAA_GT =~ C1_6 15.56 -1.81      0.86   -0.85          0.4           TRUE
## 2 VAA_GT =~ C1_10 24.92  1.87      0.74    1.01          0.4           TRUE
## 3 CS_GT =~   y5 21.85  4.99      0.93    2.14          0.4           TRUE
## 4 CS_GT =~   y21 11.85 -1.63      1.02   -0.64          0.4           TRUE
## 5   y26 ~~ C1_8 25.76  0.15      0.14    0.20          0.2           TRUE
## 6  C1_1 ~~ C1_6 21.63  0.15      0.15    0.20          0.2           TRUE
##  high.power decision.pow se.epc
## 1      FALSE              M   0.46
## 2      FALSE              M   0.37
## 3      FALSE              M   1.07
## 4      FALSE              M   0.47
## 5       TRUE          EPC:M   0.03
## 6       TRUE          EPC:M   0.03
```

All the proposed loadings would be cross-loadings across methods (from VAA to CS or vice versa), and therefore not applicable for the present approach. Also, the expected parameter changes are indicative that most of these respecification would be Heywood -cases (standardized loadings that would be larger than 1 in absolute magnitude).

There were two misspecified residual correlations: y26. “Taxation of high earners should be increased in the next electoral cycle (r.)” and C1_8. “Tuloja ja vaurautta pitäisi uudelleenjakaa tavallisten ihmisten suuntaan” and between C1.1 “Maahanmuuttajien pitäisi sopeutua suomalaisiin tapoihin” and “Lakia rikkovia ihmisiä pitäisi rangaista kovemmin”

Add these residual correlations to the model.

```
model_H3H4.exp.re<-paste0(model_H3H4.re,
                           "y26~~C1_8\n",
                           "C1_1~~C1_6\n")

fit_H3H4.exp.re<-cfa(model=model_H3H4.exp.re,
                     data=dat2011.gmc,
                     missing="fiml")
```

Exploratory respecification

```
## Warning in lav_data_full(data = data, group = group, cluster = cluster, : lavaan WARNING: some cases
## 452
```

Inspect fit of the model

```
round(inspect(fit_H3H4.re,"fit")
      [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

```
##      npar      df    chisq  pvalue    cfi    tli   rmsea   srmr
## 52.000  83.000 268.505   0.000  0.873  0.840  0.038  0.048
```

```
round(inspect(fit_H3H4.exp.re,"fit")
      [c("npar","df","chisq","pvalue","cfi","tli","rmsea","srmr")],3)
```

```
##      npar      df    chisq  pvalue    cfi    tli   rmsea   srmr
## 54.000  81.000 219.828   0.000  0.905  0.877  0.033  0.042
```

The fit of the model is improved

Retest Hypotheses 4 and 5

Print standardized estimates to test the difference between correlations

```
std.est_H3H4.exp<-standardizedsolution(fit_H3H4.exp.re)
std.est_H3H4.exp[std.est_H3H4.exp$op=="==" |
                  std.est_H3H4.exp$op=="~" &
                  std.est_H3H4.exp$lhs!=std.est_H3H4.exp$rhs,]
```

```
##      lhs op      rhs est.std   se      z pvalue
## 16 VAA_LR ~ VAA_GT  0.373 0.046  8.153  0.000
## 17 CS_LR ~ CS_GT   0.080 0.085  0.947  0.344
## 18 VAA_LR ~ CS_LR   0.379 0.093  4.094  0.000
## 19 VAA_GT ~ CS_GT   0.963 0.056 17.167  0.000
## 20 VAA_LR ~ CS_GT   0.444 0.070  6.340  0.000
## 21 VAA_GT ~ CS_LR   0.080 0.081  0.986  0.324
## 22 y4 ~ C1_4   0.570 0.029 19.349  0.000
```

```

## 23      y26 ~~                                C1_8    0.274 0.055  4.942  0.000
## 24      C1_1 ~~                                C1_6    0.237 0.045  5.285  0.000
## 63 test.H3 := r.LR-max(r.VAA,r.CS,r.d1,r.d2) -0.065 0.117 -0.561  0.575
## 64 test.H4 := r.GT-max(r.VAA,r.CS,r.d1,r.d2)  0.519 0.088  5.924  0.000
##      ci.lower ci.upper
## 16      0.283    0.462
## 17     -0.086    0.247
## 18      0.197    0.560
## 19      0.853    1.073
## 20      0.307    0.582
## 21     -0.079    0.240
## 22      0.512    0.628
## 23      0.165    0.383
## 24      0.149    0.325
## 63     -0.294    0.163
## 64      0.347    0.691

```

The results are virtually identical to those without the additional residual correlations.

H3: There is a moderately strong (.379, $p < .001$) correlation between VAA-LR and CS-LR, and it is not stronger (difference in correlations -.065, $p = .575$) than the strongest of correlations between different dimensions (.444 between VAA_LR and CS_GT, $p < .001$)

H4: There is a very strong (.963, $p < .001$) correlation between VAA-GT and CS-GT, and it is notably stronger (difference in correlations .519, $p < .001$) than the strongest of correlations between different dimensions (.444 between VAA_LR and CS_GT, $p < .001$)

Examine how self-placement on