Measurement Political Trust: A Structural Equation Modelling Study

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Course

Structural Equation & Latent Variable Modelling

Abstract:

Along this essay, I attempt to address the requirement in this assignment (Section 1: testing hypothesis and Section 2: questions) taking‘’ professional’’ scientific papers as referent format to report CFA, MGCFA and LCA methods. I will present a path diagram that clearly explain the full assignment by section 1 and section 2.

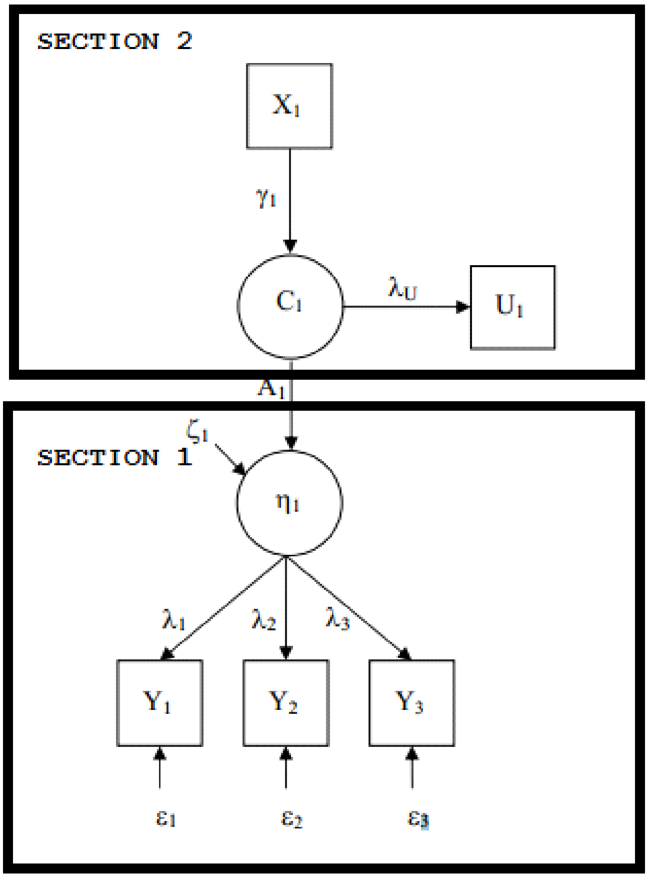


Figure 1: Path diagram for the proposed latent-class factor-analysis model.

Source: (Nick Shryane et al, 2006)

SECTION 1

Models of Political Trust

A number of scholars differ on measurement models to draw the relations with Political Trust in sociology framework. There is array of different theories that support, one-factor model (H1) as the most adequate to represent Political Trust, (Oskarsson 2010) in which, the sum of all observed variables are taken. However, other authors have been worked out with alternative models (multi dimensional model). Briefly, one-factor model (H1) assumes that all items form an integral part of the underlying factor. The two-factor model (and three-factor) suggested by some researchers, differentiate between the national and international institutions and, in the third model also distinguish between partisan and order institution. (Rothstein and Stolle, 2008 and Papadakis, 1999).

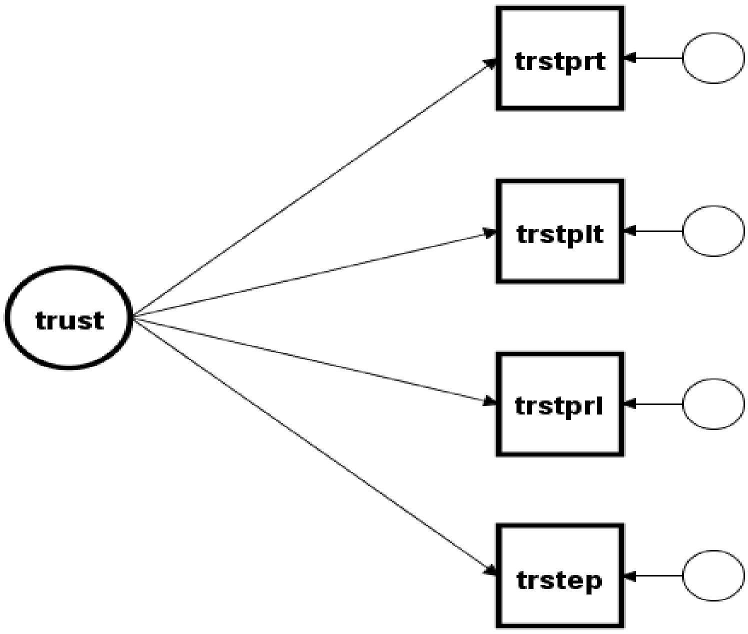


Fig 1. One-factor Model of ''Political Trust''

Cross Country Comparisons of Political Trust

Attempting to establish cross-country equivalence, measurement invariance of parameters is required condition. (Ariely and Davidov 2011). This will allow to establish ''meaningful'' comparisons of ''political trust'' latent factor among different countries.(i.e, equal meaning in Eire and UK). (LluisCoromina and EldadDavidov, 2013).

Three type of invariance should be tested as Steenkamp and Baumgartner (1998) suggested:

Configural invariance: if the factor model fit for UK and Eire (equal model structure ''items'' but different values of parameters estimated) then, configural equivalence is established. This represents the baseline model for more restrictive model (being least restrictive level of invariance).

Metric invariance *(weak invariance):* this level of invariance assumes equal contribution of factor loadings (λ) across UK and Eire eliciting equivalence of meaning but, not same intercepts indicators. Hence, one unit increase in UK and Eire in the measurement scale on latent variable should be same meaning in both. (Meuleman et al, 2009).

Scalar invariance *(strong invariance):* establishing scalar invariance in the model, we are able to compare means of the latent factor across UK and Eire being meaningfully. (Meredith, 1993). This is most restrictive level of invariance being model structure, factor loadings and intercepts invariant across the country. **(H2)**

A Cross-political comparison among countries is still possible although scalar invariance is not holding in our model by ***partial scalar invariance***. (Byrne, Shavelson and Muthén 2007).

Broadly, all requirements of invariant are necessary but allowing a condition of *''at least two items per latent variable are the same (loadings and intercept) across group''.* (Steenkamp and Baumgartner,1998). In this case, *''trust in EU institution''* is relaxed while remaining three items hold with strong factorial invariance. ***(H2a)***.

Measurement and Methods

Firstly, the existence of Trust underlying dimension (one-factor vs. two-factor model) is tested with a confirmatory factor analysis with Mplus software (Muthen and Muthen 1998-2010).

The indicators (Ys) are continuous observed variables as indicators of the latent factor (TRUST). The latent factor represents the unobserved relation of the correlations upon the observed variables(Y) and has been treated as continuous. Indicator (Ys) assume to be conditionally independent. (see Es uncorrelated Appendix A. Table 3b). It is specified as normally distributed and maximum likelihood (ML) estimation was reasonably robust to violations of distributional assumption in CFA.(Coenders, Satorra, & Saris, 1997). . To test the fit of our models for each level of invariance, we made use of different criteria: on one side, Chi square (exact fit) test whether the null-hypothesis of ''good fit model'' can be rejected or not. In addition, to help assess the decision to constrain or not the parameters in nested model, we performed likelihood ratio using chi-square differences and degrees of freedom. Also, we made use of a set model fit combination to calculate enhancements over competing model.

Secondly, we bear in mind the country-level and attempt to establish cross-country equivalence with MGCFA.

Results

We first tested the one-factor model against two-factor model **(H1).** Table 1 displays the fit indices of these different models. We found that one-factor model has good comparative fit (TLI =.99) as well as good indicator for residual correlation (SRMR=0.007), considered as strongly acceptable. However, the largest $\chi 2$, showing the misfit between observed and expected values being still significant ($p<0.05$); thus, the hypothesis of "exact fit" is rejected. Adding a cross loading factors seems to significantly improve in model fit (based in test likelihood ratio Chi-Square). The rest of indicators shows a slight improvement of comparative model fit (TLI=0.998, RMSEA=0.882) and Chi-square is lower (better) than in the one factor model, but still large and significant. Using MLR estimator assessing the extent to which data might be non normally distributed and taking into account violations of the homoscedasticity assumption, shows similar results. We can see in table 1 that RMSEA are lower in both models (i.e. no interval accompanies MLR). The likelihood ratio test produced by MLR (with unbiased Chi-square-corrected) demonstrates the same conclusion as ML. Hence, we can release the assumption and keep model with ML estimator for further analysis and interpretations.

Table 1. Fit of one, two factor model in the UK and Eire

	$\chi 2$	*df*	p	CFI	TLI	RMSEA	SRMR
UK & EIRE (N= 4760)							
ML Estimator							
One-factor	18.809	2	0.000	0.999	0.996	0.042	0.007
Two-factor	5.136	1	0.023	1.000	0.998	0.029	0.002
MLR Estimator							
One-factor				0.998	0.993	0.034	0.007
Two-factor				1.000	0.997	0.002	0.002

We consider it inappropriate to continue fitting the model beyond this point because we would add some residual covariance or cross-loading onto but we will get over identified model. Other variant is to including other items (e.g. Trust in the United Nations) and create additional models. As shortcoming gathered from other studies, including ''correlated error'' between ''political parties'' and ''politician's is adequate since politicians are in political parties and the correlation between these items would be higher than trust in parliament. (Stefanie Andre, 2013) The cross-loading between factors is very strong (0.969, see STDYX Std. Table 3, appendix A). This correlation suggests that there is a link between trust in politics and trust in institutions.

The hypothesized one-factor model provides an adequate representation of the data albeit adding ‘’trust in institutions’’ latent factor shows an improvement in the model.

Fig. 2 Two-factor model of political trust

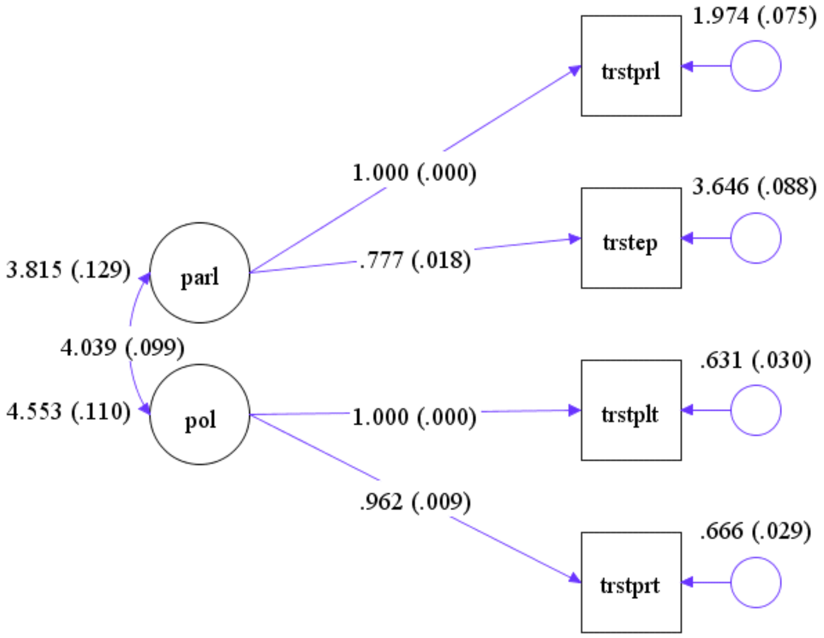


Table 2 shows the global fit indices of MGCGA model of different levels of invariance measurement of MGCFA performed with one-factor model.

We established ***configural invariance***. This model fit in adequately with data, being RMSEA(0.069) and SMRM(.011) within acceptable limits. We also established ***metric invariance*** (weak): this model (2.a Model) showed an acceptable fit (RSMSEA=0.060, TLI=0.992 and SRMR=0.024) lower than the critical values for an acceptable fit.

However, the ***scalar invariance*** model (2.b. Model), did not hold with two countries (strong invariance). An inspection of fit values shows that, RMSEA=0.178 and SRMR=0.098, are higher than the critical values for consider an acceptable fit. This suggest that the equality constraint of the factor loading and intercept of the indicators measuring ‘’political trust’’, had to be released. **(H2)**

For *partial scalar invariance* (2.d. Model Table 2), ‘the constraints of at least two items are the same (loading and items)”, after releasing the equality constraint of the item ‘’trust in the European Parliament’’ and keep equality constraints of factor loadings for the rest three items (albeit not loadings). The fit of the model turn into tolerable limits (RSMEA=0.057, SRMR=0.013) meaning that, it is possible the meaningfully comparability of political trust another theoretical construct of significance between UK and EIRE. (Hox et al 2010). Finally, the Model 2c (*partial scalar*) is constructed by release equality constraints of factors loadings and intercept of ‘’trust in the European Parliament’’, and the constraints on the parameters of other three items, were equal across the country (loadings and intercept). As Table 2 noted, the fit model indicator (2c) provides an adequate representation of the data (except RMSEA=0.08). However, Wald Test on the model proved to reject the hypothesis of partial invariance.

Table 2. Global Fit Measures for Models Testing for Measurement Invariance for Political Trust

One-factor Model: Political Trust	*χ2*	*df*	**CFI**	**TLI**	**RMSEA**	**SRMR**
1. No constraints						
a. Configural Invariance	49.644	4	0.996	0.989	0.069	0.011
2. Measurement parameters						
a. Metric Invariance (*all factor invariance*)	66.668	7	0.995	0.992	0.060	0.024
b. Scalar Invariance (*all factor and loading invariance*)	764.8	10	0.941	0.929	0.178	0.098
c. Partial (1)	177.078	9	0.987	0.982	0.089	0.067
d. Partial (2)	12751.02	12	0.996	0.993	0.057	0.013

Notes: Model 2.c refers partial invariance where all factor, loading, intercept invariance except trstep item. Model 2.d. refers partial invariance all factor loading invariance except trstep item. χ2 = chi-square; df = degrees of freedom; CFI = comparative fi t index; TLI = Tucker-Lewis index; RMSEA = root

Based on our results, these demonstrate that political trust are not (partially) scalar invariant across Eire and England in 2012, that is not compatible with a comparison analysis of latent means between Eire and England.(Byrne, Barbara M., Richard J. Shavelson and Bengt. O. Muthén, 1989):

Table 3. Unstandardized Factor Loadings

TRUST BY	*Estimate*	Standard Error
TRSTPRT	1.000	0.000
TRSTPLT	1.039	0.010
TRSTPRL	0.925	0.013
TRSTEP	0.722	0.016

The least trust indicator proved to be Trust in European Institution which actually is better correlated with trust in institutions. We also found that Political Trust latent factor is best represented by the variable measuring ‘’trust in politicians’’. This latent factor could be indentify as Nick Shryane et al (2006) mentioned in his study, ‘’Diffuse political support’’ constructed by ‘’sense of trust in regime, institutions and authorities’’. (Easton’s, 1965)

SECTION 2

Latent Class Factor Analysis

LCA has been performed in order to describe unobserved heterogeneity of the sample, i.e. different group of individual that has different characteristics within the population. This modelling assumes conditionally independent of the observed class indicators given latent class variable. (Nich Shryane, Ed. Fieldhouse, Andrew Pickles, 2006). However, this assumption can be relaxed if there is previous theoretical reason that justified dependence among indicator in the factor structure. (Muthén, et al. 2007) Based on this model, we classifies types of political trust (by combining ‘’trust politicians’’, ‘’trust in parliament’’, ‘’trust in political parties’’ and ‘’trust in the EU Parliament’’) in different groups in the pooled sample of UK and Eire. **(Q1).**

Additionally, we included in the model covariates affecting type of Trust (i.e. distribution of type of trust by country and age variable. **(Q2)** In this sense, multinomial logistic regression analysis is performed to find out how affect the individual condition (i.e. where they born, age) by treating political trust as dependent variable. The rationale of adding covariates in the latent class analysis is to take into account the hypothetical critical impact in political trust profiling. Also, voting as vote propensity or not depend on their underlying political trust (as binary indicator of latent class). **(Q3).**

Results

Table 4 and Figure 2 to 5 display LCA results. Local Maxima forces to use the estimation algorithm 20 times per each model using randomly perturbed starting values. (Muthén, et al. 2007)

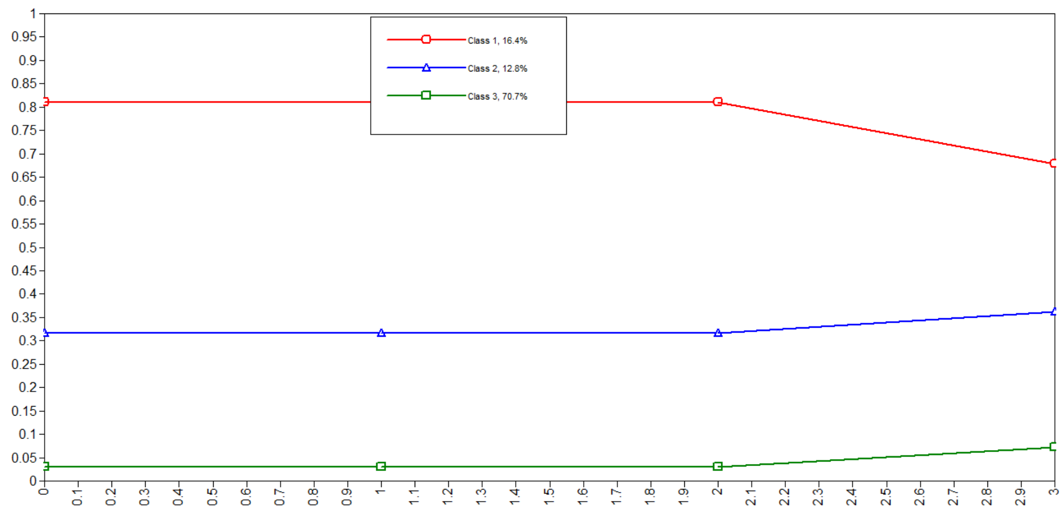
LCA statistical criteria of the parsimony and good-fit model are showed in Table 6. Hence, BIC, AIC, aLRT and bLRT was used to further evaluations. LCA is performed by clustering from 1-group to a 5-groups model. The result of fitness index, appears to be 3-group model as the most suitable. This model have indices are the lowest (AIC and BIC) within the rest. However, there is statistically significant improvement from extending to 4-groups model. (p=0.00). The 4-groups model appears to be the best model with slight improving in Loglikelihood and BIC, albeit this model is overlapping categories. (i.e. Entropy) In addition, 3-group model provide an adequate class discrimination probability and better quality classification.(We did not consider five class model since the adjusted LR Test advises to do not extent in five member class, $p>0.05$).

Table 4: Model Fitness Index for latent Class analysis

	AIC	BIC	Loglikelihood	Entropy	*LRT p-value for k-1*
1 group model	19482.61	19508.48	-9737.303	*NA*	*NA*
2 groups model	13647.62	13705.83	-6814.81	0.94	0.0
3 groups model	13608.84	13699.39	-6790.42	0.82	0.0
4 groups model	13610.82	13733.72	-6786.412	0.668	0.0
5 groups model	13620.82	13776.06	-6786.412	0.568	0.7

Figure 3 and 4(see also appendix B Table 3) shows the conditional probabilities of each indicator of the latent factor constructed above. Each line on the graph describes characteristics and nature of these classes in relation with their type of trust. The class 1, (red line) represents a class of respondents who are completely skeptical about politics institutions. Special feature of this respondent is that the conditional probability to trust EU Parliament is 32,1%, caused, likely, by missing data and, if they believe in ‘’something’’, the trust in institutions. As opposed to this class, full politic ‘’believers’’ responded that they could trust in politics institutions (>. 97%).

Fig 3. Conditional Probabilities to answer "0-1" = low political trust and answer "2-10" = high political trust



As mentioned above (latent factor constructed), ‘’trust in politicians’’ was the variable that best explained the latent factor(R squared = .87, see appendix A). We can also see how this dimension of trust is the most discriminate among the classes. For instance, class 1 ‘’political skeptics’’, has 100% probabilities to respond as not trust in politicians when class 3 full politic ‘’believers’’ has 99,6% to follow and belief in ‘’theoretical’’ politic leader. Those respondent clustered in 3 full politic ‘’believers’’, has the lower conditional probabilities in believe in EU parliament than rest of institutions. The odds of have high level of trust in politics institutions appears to decrease if you are in the on ‘’political skeptics’’ profile respect of the rest of the group. It is interesting that those respondents clustered on class 2 reduces the level of politician in 483,746 compared with full politic ‘’believers’’ class. (see table 3 Appendix). Thus, this class 2, belong to respondent who believe in ‘’Politics without Politicians’’.

Table 4a display the result of analysis (threshold estimates) to verify which conditions (i.e. country) affect in the probability to be in our member class. Those respondent in Eire prove a higher probability (more likely) than British respondent of belonging to ‘’political skeptics’’ and ‘’Politics without Politicians’’. Finally, table 4b displays the threshold estimated for voting, so the interpretation will be equal as mentioned before. It appears that full trust respondents tend to use their right as citizen relatively more than trust oriented type. It is also revealed that respondent belonging to in distrust are not the best target profile for political campaign as it proved more likely to turn out abstentions.

Table 4a. Estimates for covariates predicting latent class, relative to class 3

Covariate	Class 1	Class 2
Eire (Great Bretain)	0.515	0.551
Age	0.042	0.043

Note: log-odds

Table 4b. Estimate for voting

	Class 1	Class 2	Class 3
Participation in elections (yes=1/no=0)	-0.603	-1.237	-1.2

Note: log-odds

By analysing the result, we can conclude that different type of trust has substantive influence over voting. The reason why people use to vote more in class 2 and class 3 could be that those that they are skeptics, the administrative and government institutions will not resolve their social issues.

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APPENDIX A:

CFA 1-Factor Model (ML)

TABLE 1: STDYX Standardization

	Estimate	S.E.	Est./S.E.	P-Value
TRUST BY				
TRSTPRT	0.929	0.003	277.343	0.000
TRSTPLT	0.936	0.003	288.201	0.000
TRSTPRL	0.789	0.006	129.200	0.000
TRSTEP	0.607	0.010	59.636	0.000
Intercepts				
TRSTPRL	1.602	0.022	72.676	0.000
TRSTPLT	1.445	0.021	69.527	0.000
TRSTPRT	1.474	0.021	70.171	0.000
TRSTEP	1.578	0.023	69.404	0.000
Variances				
TRUST	1.000	0.000	999.000	999.000
Residual Variances				
TRSTPRL	0.378	0.010	39.205	0.000
TRSTPLT	0.123	0.006	20.249	0.000
TRSTPRT	0.137	0.006	21.966	0.000
TRSTEP	0.631	0.012	51.081	0.000

TABLE 2: R-SQUARE

	Estimate	S.E.	Est./S.E.	P-Value
TRSTPRL	0.622	0.010	64.600	0.000
TRSTPLT	0.877	0.006	144.100	0.000
TRSTPRT	0.863	0.006	138.672	0.000
TRSTEP	0.369	0.012	29.818	0.000

TABLE 2 a: Residual ERROR

Residuals for Covariances/Correlations/Residual Correlations

	TRSTPRL	TRSTPLT	TRSTPRT	TRSTEP
TRSTPRL	0.000			
TRSTPLT	0.005	0.000		
TRSTPRT	-0.023	0.004	0.000	
TRSTEP	0.153	-0.050	0.014	0.001

Standardized Residuals (z-scores) for Covariances/Correlations/Residual Corr

	TRSTPRL	TRSTPLT	TRSTPRT	TRSTEP
TRSTPRL	0.298			
TRSTPLT	0.825	999.000		
TRSTPRT	-4.205	1.668	999.000	
TRSTEP	3.536	-3.715	0.870	0.456

Normalized Residuals for Covariances/Correlations/Residual Correlations

	TRSTPRL	TRSTPLT	TRSTPRT	TRSTEP
TRSTPRL	0.003			
TRSTPLT	0.055	-0.002		
TRSTPRT	-0.244	0.043	-0.003	
TRSTEP	1.545	-0.528	0.151	0.010

CFA 2-Factor Model (ML)

TABLE 3: STDYX Standardization

	Estimate	S.E.	Est./S.E.	P-Value
PARL BY				
TRSTPRL	0.812	0.008	97.328	0.000
TRSTEP	0.622	0.011	58.209	0.000
POL BY				
TRSTPLT	0.937	0.003	280.042	0.000
TRSTPRT	0.929	0.003	269.539	0.000
POL WITH				
PARL	0.969	0.008	118.865	0.000
Intercepts				
TRSTPRL	1.602	0.022	72.683	0.000
TRSTPLT	1.445	0.021	69.526	0.000
TRSTPRT	1.474	0.021	70.169	0.000
TRSTEP	1.578	0.023	69.403	0.000
Variances				
PARL	1.000	0.000	999.000	999.000
POL	1.000	0.000	999.000	999.000

Loglikelihood Ratio

TABLE 4a: nested model ML

	l0(null)	l1(alternative)
log	-35196.582	-35189.746
standard Chi-square	13.672	
K	12	13
df	1	
p	**0.000217676**	significant

TABLE 4b: nested model MLR

	h0 (one-factor)	h1(two factor)
log likelihood	-35,197	-35,190
Correction factor	1.567	1.5479
parameters	12	13

Correction	1.319
corrected Chi-square	10.368
df	1
p	0.001
standard Chi-square	13.672
p	0.000

APPENDIX B:

Table 1: UNIVARIATE PROPORTIONS AND COUNTS FOR CATEGORICAL VARIABLES

ITEMS	LEVEL TRUST	%	n
Trust Parliament			
Category 1	High	80.5%	3751
Category 2	Low	19.5%	907
Trust in Politicians			
Category 1	High	75.0%	3522
Category 2	Low	25.0%	1175
Trust in Political Parties			
Category 1	High	75.1%	3511
Category 2	Low	24.9%	1166
Trust in the EU Parliament			
Category 1	High	79.2%	3370*
Category 2	Low	20.8%	883*
**missing values*			

Table 2: Classification Probabilities for the Most Likely Latent Class Membership (Row) by Latent Class (Column)

	political skeptics	Politics without	Believers
political skeptics	**0.913**	0.084	0.003
Politics without	0.205	**0.656**	0.139
Believers	0	0.019	**0.981**

Table 3: Conditional Probabilities to answer ''0-1'' = low political trust and answer ''2-10'' = high political trust

	Class 1 ‘’ skeptics’’		Class 2 ‘’Politics without politicians’’		Class 3 ‘’Believers’’	
TRUST LEVEL	high	Low	high	Low	high	Low
Trust Parliament	19.0%	81.0%	68.4%	31.6%	97.0%	3.0%
Trust in Politicians	0.0%	100.0%	35.9%	64.1%	99.6%	0.4%
Trust in Political Parties	0.8%	99.2%	40.8%	59.2%	98.8%	1.2%
Trust in the EU Parliament	32.1%	67.9%	63.7%	36.3%	92.8%	7.2%

MPLUS syntaxis

SECTION 1:

H1:

CFA 1 factor ML

```
Variable:
  Names are
     trstprl trstlgl trstplc trstplt trstprt trstep trstun vote age country;
  Missing are
     all (-999) ;

Usevariables are
                    trstprl trstplt trstprt trstep                  ;
Analysis:
                    Estimator = ML                                  ;
Model:
                   TRUST    BY    trstprt trstplt trstprl trstep     ;
Output:
                    Standardized cinterval residual  mod             ;
```

CFA 1 factor MLR

```
Variable:
  Names are
     trstprl trstlgl trstplc trstplt trstprt trstep trstun vote age country;
  Missing are
     all (-999) ;

Usevariables are
                    trstprl trstplt trstprt trstep                  ;
Analysis:
                    Estimator = MLR                                 ;
Model:
                   TRUST    BY    trstprt trstplt trstprl trstep     ;
Output:
                    Standardized cinterval residual  mod             ;
```

CFA 2 factor ML

```
Variable:
  Names are
     trstprl trstlgl trstplc trstplt trstprt trstep trstun vote age country;
  Missing are
     all (-999) ;

Usevariables are
                    trstprl trstplt trstprt trstep                    ;
```

```
Analysis:
            Estimator = ML                      ;
Model:
             PARL    BY    trstprl trstep                ;

                  POL    BY    trstplt trstprt


Output:          Standardized cinterval residual  mod            ;
```

CFA 2 factor MLR

```
Variable:
  Names are
    trstprl trstlgl trstplc trstplt trstprt trstep trstun vote age country;
  Missing are
    all (-999) ;

Usevariables are
            trstprl trstplt trstprt trstep                ;
Analysis:
            Estimator = MLR                        ;
Model:
             PARL    BY    trstprl trstep                ;

                  POL    BY    trstplt trstprt

Output:
            Standardized cinterval residual  mod            ;
```

H2:

CONFIGURAL INVARIANCE:

```
Usevariables are
            trstprl trstplt trstprt trstep              ;

Grouping is
            country ( 11 = UK   12 = Eire)              ;
Analysis:
            Estimator = ML                      ;
Model:
            TRUST BY  trstprl trstplt trstprt trstep       ;
            [TRUST@0]                           ;
Model Eire:
            [trstprl trstplt trstprt trstep]            ;
            TRUST BY trstplt trstprt trstep             ;

Output:
            Standardized cinterval residual             ;
```

WEAK INVARIANCE:

```
Usevariables are
            trstprl trstplt trstprt trstep              ;

Grouping is
            country ( 11 = UK   12 = Eire)              ;
Analysis:
```

```
            Estimator = ML                  ;
Model:
            TRUST BY  trstprl trstplt trstprt trstep      ;
            [TRUST@0]                       ;
Model Eire:
            [trstprl trstplt trstprt trstep]          ;

Output:
            Standardized cinterval residual           ;
```

STRONG INVARIANCE:

```
Usevariables are
            trstprl trstplt trstprt trstep            ;

Grouping is
            country ( 11 = UK   12 = Eire)            ;
Analysis:
            Estimator = ML                  ;
Model:
            TRUST BY    trstplt trstprl trstprt trstep     ;


Output:
            Standardized cinterval residual           ;
```

H2a:

WEAK VS CONFIGURAL

```
Variable:
  Names are
    trstprl trstlgl trstplc trstplt trstprt trstep trstun vote age country;
  Missing are
    all (-999) ;

Usevariables are
            trstprl trstplt trstprt trstep            ;

Grouping is
            country ( 11 = UK   12 = Eire)            ;
Analysis:
            Estimator = ML                  ;
Model:
            TRUST BY  trstprl trstplt trstprt trstep      ;
            [TRUST@0]                       ;
Model Eire:
            [trstprl trstplt trstprt trstep]          ;
            TRUST BY trstep                    ;

Output:
            Standardized cinterval residual           ;
```

STRONG VS CONFIGURAL

```
Usevariables are
                trstprl trstplt trstprt trstep              ;

Grouping is
                country ( 11 = UK   12 = Eire)              ;
Analysis:
                Estimator = ML                              ;
Model:
                TRUST BY  trstprl trstplt trstprt trstep    ;
                [TRUST@0]                                   ;
Model Eire:
                [trstep]                      ;
                TRUST BY trstep                             ;

Output:
                Standardized cinterval residual             ;
```

MODEL TEST ''STRONG VS CONFIGURAL''

```
Usevariables are
                trstprl trstplt trstprt trstep              ;

Grouping is
                country ( 11 = UK   12 = Eire)              ;
Analysis:
                Estimator = ML                              ;
Model:
                TRUST BY  trstprl trstplt trstprt trstep    ;
                [trstprl] (g1I1)
                [trstplt] (g1I2)
                [trstprt] (g1I3)
                [trstep]  (g1I4)                            ;


                [TRUST@0]                                   ;
Model Eire:
                [trstprl trstplt trstprt trstep]            ;
                [trstprl] (g2I1)
                [trstplt] (g2I2)
                [trstprt] (g2I3)
                [trstep]  (g2I4)                            ;

Model test:
                g1l1 = g2I1 ;
                g1I2 = g2I2 ;
                g1I3 = g2I3 ;


Output:
                Standardized cinterval residual             ;
```

SECTION 2:

Q1:

LCA 1-CLASS

```
Usevariables are
    no_trstprl no_trstplt no_trstprt no_trstep              ;

Categorical  are
            no_trstprl no_trstplt no_trstprt no_trstep     ;
classes are  c (1) ;

Define:
  if trstprl LE 1 then no_trstprl = 1 ;
  if trstprl GE 2 then no_trstprl = 0 ;

  if trstplt LE 1 then no_trstplt = 1 ;
  if trstplt GE 2 then no_trstplt = 0 ;

  if trstprt LE 1 then no_trstprt = 1 ;
  if trstprt GE 2 then no_trstprt = 0 ;

  if trstep LE 1 then no_trstep = 1 ;
  if trstep GE 2 then no_trstep = 0 ;

Analysis:
  Type = mixture ;
  STARTS = 300 20;
  Output:
  tech11;
Plot:
  type is plot3 ;
```

LCA 2-CLASS

```
Usevariables are
    no_trstprl no_trstplt no_trstprt no_trstep              ;

Categorical  are
            no_trstprl no_trstplt no_trstprt no_trstep     ;
classes are  c (2) ;

Define:
  if trstprl LE 1 then no_trstprl = 1 ;
  if trstprl GE 2 then no_trstprl = 0 ;

  if trstplt LE 1 then no_trstplt = 1 ;
  if trstplt GE 2 then no_trstplt = 0 ;

  if trstprt LE 1 then no_trstprt = 1 ;
  if trstprt GE 2 then no_trstprt = 0 ;

  if trstep LE 1 then no_trstep = 1 ;
  if trstep GE 2 then no_trstep = 0 ;

Analysis:
  Type = mixture ;
  STARTS = 300 20;
  Output:
  tech11;
```

```
Plot:
  type is plot3 ;
```

LCA 3-CLASS

```
Usevariables are
     no_trstprl no_trstplt no_trstprt no_trstep                ;

Categorical  are
               no_trstprl no_trstplt no_trstprt no_trstep     ;
classes are  c (3) ;

Define:
  if trstprl LE 1 then no_trstprl = 1 ;
  if trstprl GE 2 then no_trstprl = 0 ;

  if trstplt LE 1 then no_trstplt = 1 ;
  if trstplt GE 2 then no_trstplt = 0 ;

  if trstprt LE 1 then no_trstprt = 1 ;
  if trstprt GE 2 then no_trstprt = 0 ;

  if trstep LE 1 then no_trstep = 1 ;
  if trstep GE 2 then no_trstep = 0 ;

Analysis:
  Type = mixture ;
  STARTS = 300 20;
  Output:
  tech11;
Plot:
  type is plot3 ;
```

LCA 4-CLASS

```
Usevariables are
     no_trstprl no_trstplt no_trstprt no_trstep                ;

Categorical  are
               no_trstprl no_trstplt no_trstprt no_trstep     ;
classes are  c (4) ;

Define:
  if trstprl LE 1 then no_trstprl = 1 ;
  if trstprl GE 2 then no_trstprl = 0 ;

  if trstplt LE 1 then no_trstplt = 1 ;
  if trstplt GE 2 then no_trstplt = 0 ;

  if trstprt LE 1 then no_trstprt = 1 ;
  if trstprt GE 2 then no_trstprt = 0 ;

  if trstep LE 1 then no_trstep = 1 ;
  if trstep GE 2 then no_trstep = 0 ;

Analysis:
  Type = mixture ;
  STARTS = 300 20;
```

```
  Output:
  tech11;
Plot:
  type is plot3 ;
```

LCA 5-CLASS

```
Usevariables are
     no_trstprl no_trstplt no_trstprt no_trstep                ;

Categorical  are
               no_trstprl no_trstplt no_trstprt no_trstep     ;
classes are  c (5) ;

Define:
  if trstprl LE 1 then no_trstprl = 1 ;
  if trstprl GE 2 then no_trstprl = 0 ;

  if trstplt LE 1 then no_trstplt = 1 ;
  if trstplt GE 2 then no_trstplt = 0 ;

  if trstprt LE 1 then no_trstprt = 1 ;
  if trstprt GE 2 then no_trstprt = 0 ;

  if trstep LE 1 then no_trstep = 1 ;
  if trstep GE 2 then no_trstep = 0 ;

Analysis:
  Type = mixture ;
  STARTS = 300 20;
  Output:
  tech11;
Plot:
  type is plot3 ;
```

LCA 3-CLASS-Alrt

```
Usevariables are
     no_trstprl no_trstplt no_trstprt no_trstep                ;
Categorical  are
               no_trstprl no_trstplt no_trstprt no_trstep     ;
classes are  c (3) ;

Define:
  if trstprl LE 1 then no_trstprl = 1 ;
  if trstprl GE 2 then no_trstprl = 0 ;

  if trstplt LE 1 then no_trstplt = 1 ;
  if trstplt GE 2 then no_trstplt = 0 ;

  if trstprt LE 1 then no_trstprt = 1 ;
  if trstprt GE 2 then no_trstprt = 0 ;

  if trstep LE 1 then no_trstep = 1 ;
  if trstep GE 2 then no_trstep = 0 ;
Analysis:
  Type = mixture ;
  STARTS = 0;
```

```
OPTSEED = 836515 ;
PROCESSORS = 4(STARTS);
  Output:
  tech11;
Plot:
  type is plot3 ;
```

LCA 3-CLASS-blrt

```
Usevariables are
     no_trstprl no_trstplt no_trstprt no_trstep                ;
Categorical  are
               no_trstprl no_trstplt no_trstprt no_trstep      ;
classes are  c (3) ;

Define:
  if trstprl LE 1 then no_trstprl = 1 ;
  if trstprl GE 2 then no_trstprl = 0 ;

  if trstplt LE 1 then no_trstplt = 1 ;
  if trstplt GE 2 then no_trstplt = 0 ;

  if trstprt LE 1 then no_trstprt = 1 ;
  if trstprt GE 2 then no_trstprt = 0 ;

  if trstep LE 1 then no_trstep = 1 ;
  if trstep GE 2 then no_trstep = 0 ;

Analysis:
  Type = mixture ;
  STARTS = 0;
OPTSEED = 836515 ;
PROCESSORS = 4(STARTS);
LRtSTARTS = 0 0 100 20;
OUTPUT:
Tech11 Tech14;

Plot:
  type is plot3 ;
  series is no_trstprl no_trstplt no_trstprt no_trstep (*) ;
```

LCA 4-CLASS-blrt

```
Usevariables are
     no_trstprl no_trstplt no_trstprt no_trstep                ;
Categorical  are
               no_trstprl no_trstplt no_trstprt no_trstep                  ;
classes are  c (4) ;

Define:
  if trstprl LE 1 then no_trstprl = 1 ;
  if trstprl GE 2 then no_trstprl = 0 ;

  if trstplt LE 1 then no_trstplt = 1 ;
  if trstplt GE 2 then no_trstplt = 0 ;

  if trstprt LE 1 then no_trstprt = 1 ;
  if trstprt GE 2 then no_trstprt = 0 ;
```

```
  if trstep LE 1 then no_trstep = 1 ;
  if trstep GE 2 then no_trstep = 0 ;

Analysis:
  Type = mixture ;
  STARTS = 0;
OPTSEED = 462228 ;
PROCESSORS = 4(STARTS);
LRtSTARTS = 0 0 100 20;
OUTPUT:
Tech11 Tech14;
Plot:
  type is plot3 ;
```

Q2:

LCA with covariate:

```
Usevariables are
     no_trstprl no_trstplt no_trstprt no_trstep E_country              ;
Categorical  are
      no_trstprl no_trstplt no_trstprt no_trstep                   ;
classes are  c (3) ;

Define:
  if trstprl LE 1 then no_trstprl = 1 ;
  if trstprl GE 2 then no_trstprl = 0 ;

  if trstplt LE 1 then no_trstplt = 1 ;
  if trstplt GE 2 then no_trstplt = 0 ;

  if trstprt LE 1 then no_trstprt = 1 ;
  if trstprt GE 2 then no_trstprt = 0 ;

  if trstep LE 1 then no_trstep = 1 ;
  if trstep GE 2 then no_trstep = 0 ;

  if country == 11 then E_country = 0 ;
  if country == 12 then E_country = 1 ;

Analysis:
  Type = mixture ;
  STARTS = 0;
OPTSEED = 836515 ;
PROCESSORS = 4(STARTS);
LRtSTARTS = 0 0 100 20;
OUTPUT:
Tech11 Tech14;
```

```
Model:
          %overall%
          c on E_country ;
Plot:
  type is plot3 ;
  series is no_trstprl no_trstplt no_trstprt no_trstep (*) ;
  SAVEDATA:

  FILE IS "threeclass.dat";
save is cprob;
```

Q3:

LCA with predictor:

```
Usevariables are
     age vote no_trstprl no_trstplt no_trstprt no_trstep               ;
Categorical  are
      vote  no_trstprl no_trstplt no_trstprt no_trstep                   ;
classes are  c (3) ;

Define:
  if trstprl LE 1 then no_trstprl = 1 ;
  if trstprl GE 2 then no_trstprl = 0 ;

  if trstplt LE 1 then no_trstplt = 1 ;
  if trstplt GE 2 then no_trstplt = 0 ;

  if trstprt LE 1 then no_trstprt = 1 ;
  if trstprt GE 2 then no_trstprt = 0 ;

  if trstep LE 1 then no_trstep = 1 ;
  if trstep GE 2 then no_trstep = 0 ;

  if country == 11 then E_country = 0 ;
  if country == 12 then E_country = 1 ;

  center age (grandmean);

Analysis:
  Type = mixture ;
  STARTS = 0;
OPTSEED = 836515 ;
```

```
PROCESSORS = 4(STARTS);
LRtSTARTS = 0 0 100 20;
OUTPUT:
Tech11 Tech14;

Model:
          %overall%
           vote on age;

Plot:
  type is plot3 ;
  TYPE = PLOT2;
  series is no_trstprl no_trstplt no_trstprt no_trstep (*) ;
  SAVEDATA:

  FILE IS "threeclass.dat";
  save is cprob;
```