Profiles of tolerance and respect for the rights of diverse social groups among youth. Comparisons across countries.

submitted

to

Femke De Keulenaer
Maria Magdalena Isac

KU Leuven
Leuven Statistics Research Centre
Femke De Keulenaer

by

Pamela Inostroza Fernández
(r0648901)

in partial fulfillment of the requirements
for the program of
Master in Statistics & Data Science

May 2021

Profiles of tolerance and respect for the rights of diverse social groups among youth. Comparisons across countries.

Pamela Inostroza Fernández

May 2021

Acknowledgements

I want to thank a people that help me ge through this important task, by helping in different ways.

Preface

This is draft version.

Table of Contents

List of Tables

List of Figures

Abstract

This a draft version, not finalized.

Dedication

To my family.

Introduction

The development of civic values and attitudes of tolerance and respect for the rights of diverse social groups among youth are essential for sustainable democratic societies. These values are strongly promoted by families, educational systems and international organizations across the world. The measurements and comparison of these attitudes among youth can provide valuable information about their development in different societies and over time.

Same international studies such as the International Civic and Citizenship Education Study (ICCS) provide extensive comparative information regarding these aspects. The ICCS study is a large-scale assessment (survey) applied in more than 25 educational systems during the last three cycles and focused on secondary education (representative samples of 8th graders, 14-year-olds in each country) addressing topics such as citizenship, diversity and social interactions at school. The study produces internationally comparative data collected via student, school and teacher questionnaires. Data from different waves of the ICCS survey is publicly available to researchers. The first time this study was applied was in 1999 to 28 countries and it was called CIVED, the second wave started using the name ICCS and was implemented in 2009 in 38 countries, the last study was performed in 2016 to 24 countries. The next cycle is scheduled for 2022 and 25 countries will participate.

Previous research using ICCS data has been largely focused on average country comparisons of attitudinal measures such as attitudes toward equal rights for immigrants, ethnic minorities and women, norms of good citizenship behaviour and political participation. Most of these studies employed variable-centered analyses. Nevertheless, recent studies started to show the usefulness of person-centered approaches (i.e. latent class analysis, hereafter LCA) aimed at identifying profiles of young people's attitudes. For example, using ICCS 2009 data, (Hooghe, Oser, & Marien, 2016) compare profiles of good citizenship norms across 38 countries and distinguished distinctive subgroups of the population that share a common understanding of what constitutes good citizenship were identified (e.g. who express either engaged or duty-based citizenship norms).

Another study focused their research on changes over time (where the research design and data gathering methods are strictly comparable) (Hooghe & Oser, 2015). For this, CIVED 1999 and ICCS 2009 was used. The scope of the analysis was threefold. First, distinct profiles of good citizenship norms were identified in both cycles. Second, trends over time were investigated and finally, differences between countries and/over time were analysed in detail. Nevertheless, most of these studies employing LCA with ICCS data focused on patterns within a particular type of attitude described by individual items (e.g. citizenship norms) leaving space for investigations that aim to capture a wider set of attitudinal measures described by scores on different variables.

To address this gap, this research will approach the topic of tolerance and respect for the rights operationalized as a multifaceted set of attitudes toward equal rights for women. This topic was addressed by previous studies aimed at comparing these attitudinal measures mostly in isolation across countries and over time. However, to date, no studies addressed the potential interdependence in these attitudinal dimensions among different subgroups of people (e.g. highly tolerant, highly intolerant regarding all aspects, etc.). Therefore, the current study aims to fill this gap by addressing the following research questions:

1. What profiles of tolerance and respect for the rights of women are observed among adolescents in different countries?
2. Are these profiles comparable across countries and over time?
3. What individual and contextual factors are associated with profile membership? Do they vary depending on the context of the country or the cohort?

Chapter 1

Framework

Categorical modelling The latent class model assumes the existence of a latent categorical variable such that the observed response variables are conditionally independent, given that variable. LCA treat a contingency table as a finite mixture of unobserved tables generated under a conditional independence structure of a latent variable . In other words, LCA can directly assess the theory that distinctive groups of people share specific attitudes. Depending on the response variable in the model the analysis is called Latent Profile Analysis if is continuous (Normal) and Latent Class Analysis if the response variable is categorical (Multinomial).

1.1 Mixture models Latent Class Analysis

Parameters that describe a factor's effects in an ordinary generalized linear model are called fixed effects. Fixed effect applies to all categories of interest, gender, treatments or any other manifest grouping variable. By contrast, random effects apply to a sample of all possible categories. GLM extend ordinary regression by allowing nonnormal responses and a link function of the mean. The generalized linear mixed model (GLMM) is a further extension that permit random an fixed effects in the linear predictor.

In this type of analysis, a contingency table is treated as a finite mixture of unobserved tables generated under a conditional independence structure at categories of a latent variable(Agresti, 2013). A generalized linear mixed model (GLMM) with discrete data, create a mixture of linear predictor values using a latent variable, in this case the unobserved random effect vector instead of being continuous and assumed to have a Normal distribution, it is a qualitative mixture distribution.

1.1.1 Person center approach

Meanwhile ANOVA, multiple regression, mixed models are variable-centered approaches that focus on relations among variables and assume that the sample studied come from a homogeneous population. Mixture models (finite mixture models) have taken the place of framework for person-center analytic approach. The difference between this two approaches is that person-centered approach focus on identifying unobserved subpopulations comprised of similar individuals or cases, and involve a modeling a mixture outcome distribution (usually a Normal distribution). The mixture of different distributions indicates population heterogeneity; ie. sample observations arise from a finite number of unobserved subpopulations in the target populations in the target population.

A tool for building typologies (or clustering) based on dichotomous observed variables, Latent class and finite mixture models can be useful in probabilistic cluster analysis for continuous observed variables, an approach with more advantages over traditional cluster techniques such as k-means clustering.
Latent class modeling defines a model for the probability of having a particular response pattern. This probability is a weighted average (or mixture) of the class-specific probabilities for these patterns. The item responses of an individual are mutually independent given the individual's class membership. Similar to cluster analysis, it is possible to assign individuals to the latent classes. The probability of belonging to a particular class given the responses (posterior class membership probability) can be obtained by the Bayes' rule (Vermunt, 2014).

Mixture modeling provides an important complement to the traditional variable-centered analytical approaches.

In summary, CFA focuses on grouping items, and thus is a variable-centered approach; in contrast, LCA focuses on grouping respondents or cases based on the patterns of item responses, and thus is a person-centered approach.

The most common technique to find homogeneous groups based on observed variables is cluster analysis. There are different methods that can be used to identify this groups of cases, but they are lacking in the giving statistical indices and test for the optimal number of clusters. The most common techniques to determine the best number of groups are based on tabular o graphical output and the researcher's interpretation of this groups.

1.1.2 LCA model

As indicated previously a mixture model assumes that some of its parameters differ across unobserved subgroups, latent classes, or mixture components and particularly a latent class model is a mixture model for a set of categorical items.

Latent Class Analysis is a model based approach to cluster individuals/cases into distinctive groups, called latent classes, based in their responses to a set of observed categorical variables. The first LCA approach was introduced by Lazarsfeld (1950) and then improved by Lazarsfeld and Henry (1968) and Goodman (1974). Now, thanks to the increase of computing availability power and specialized software for mixture models, LCA is a more accessible technique to be used.

The goal of LCA is to identify unobserved subgroups based on similar response patterns. In contrast with cluster analysis, LCA is a model-based approach to clustering. It identifies subgroups based on posterior membership probabilities rather than somewhat adhoc dissimilarity measures such as Euclidean distance. The general probability model underlying LCA allows for formal statistical procedures for determining the number of clusters, and more interpretable results stated in terms of probabilities.

LCA assumes conditional independence, that the observed categorical indicators are mutually independent once the categorical latent variable is conditioned out. Assuming the conditional independence, the joint probability of all observed indicator variables is described as:

$$P(u_1, u_1, ..., u_Q) = \sum_{k=1}^{K} P(C = k)P(u_1|C = k)P(u_2|C = k)...P(u_Q|C = k) \tag{1.1}$$

From Bayes' formula, the posterior probabilities for each individual to be in different classes are estimated as:

$$P(C = k|u_1, u_2, ..u_Q) = \frac{P(C = k)P(u_1|C = k)P(u_2|C = k)...P(u_Q|C = k)}{P(u_1, u_2, ..., u_Q)} \tag{1.2}$$

where $P(C = k)$ are the unconditional probabilities ($\sum_{k=1}^{K} P(C = k) = 1$) and $P(u_Q|C = k)$ are the conditional probabilities.

The unconditional probabilities are latent class probabilities, and the average of the probabilities can be interpreted as the prevalence of latent class (relative frequency of class membership) or the proportion of the population expected to belong to a latent class. The conditional probabilities are conditional item-response probabilities, measurement parameters, representing the likelihood of endorsing specific characteristics of the observed items, given a specific class membership.

Conditional probabilities close to 1.0 indicate that members in the corresponding latent class endorse a category of the item; on the contrary, a very small probability indicate that they do not endorse the characteristic of the item. When a conditional item-response probability is close to $1/J$, where J is the number of categories in the item, the conditional probability is considered as random probability, thus the latent class membership is not predictive of the patterns of item response. The conditional item-response probability is defined

$$P(u_q = u_{qj}|C = k) = \frac{1}{1 + exp(-L_{jk})} \tag{1.3}$$

and

$$L_{jk} = ln(\frac{P_{jk}}{1 - P_{jk}}) \tag{1.4}$$

which is the logit for u_{qj} given in latent class k. A logit of 0 means that the conditional item probability $P_{jk} = 0.5$, when the logit take an extreme value as -15 then $P_{jk} = 0$. On the contrary, a logit with a positive extreme value 15, $P_{jk} = 1$. This conditional item response probabilities provide information about how the latent classes differ from each other, for this reason are used to define the estimated classes.

1.1.3 Number of classes

Determining the number of latent classes is the most important part of a Latent Class Analysis. This cannot be estimated directly from the data. For determine the optimal number of classes, a series of LCA models with an increasing number of latent classes should be fitted. The optimal number of classes will be obtained based on the comparison of the k-class model with the (k-1)class model iteratively.

It is important to consider other aspects before decide the final number of classes, it is recommended to follow a series of step to identify the model that best fit the underlined classes.

a) Compare subsequent models by model fit indices.

b) Evaluate the quality of latent class membership.

c) Confirm that the size of the latent classes are reasonable.

d) Identify that the final classes are interpretable based on a theoretical grounding.

In mixture models, multiple model fit statistics can be used to compare models. Information criterion indices, such as AIC, consistent AIC, BIC, aBIC, Lo-Mendell-Rubin likelihood ratio (LMR LR) test, adjusted LMR LR test and bootstrap likelihood ratio test (BLRT).

Model fit

Akaike's Information Criterion

Akaike's Information Criteria called AIC, is one of the more important indicators to evaluate models performance, with the formula

$$AIC(M) = -2log - likelihood_{max}(M) + 2length(M) \tag{1.5}$$

where $length(M)$ corresponds to the length of parameter vector of the model M. AIC penalizes the log-likelihood, generating a balance between a good fit (high value of log-likelihood) and complexity (simple models are preferable).
AIC prefers a model with few parameters but the fit of the model is good as well.

Numerical results have shown that AIC has a tendency to overfit, it tends to pick models with more parameters than strictly necessary. It can be proven that this effect tend to vary in one parameter more than necessary. The corrected version of AIC can be express as the following.

$$AIC_c f(\theta) = AICf(.;\theta) + \frac{2length(\theta)(length(\theta)+1)}{n - length(\theta) - 1} \tag{1.6}$$

Bayesian information criterion

Based on the probability given the data it is possible to find the best model. This idea is based on Bayesian framework, involving prior probabilities on the candidate models along with prior densities on all parameters in the models.

$$BICf(.;\theta) = -2logL(\hat{\theta}) + log(n)length(\theta) \tag{1.7}$$

where n is the sample size and $length(\theta)$ the number of parameters.
Compared to AIC, BIC include a more severe penalty for complexity.

Smaller values of information criterion indices indicate a better model fit.

Log-likelihood ratio test

The LR test based on model χ^2 statistic is not appropriate in this case, this is because the contingency table usually has a large number of zero cells, for this, the model χ^2 distribution is not correct. In addition, the model with (k-1)-classes is a special case of the k-classes model where the one latent class probability is set to zero, and the difference of the log-likelihood between this two models does not follow a χ^2 distribution.

Lo, Mendell, and Rubin developed a LMR LR test, which is not based on χ^2 distribution but in a correctly derived distribution. A significant P-value ($p < 0.05$) of the LMR LR when comparing model fit in a k-classes and (k-1)-class model indicates a significant improvement in model fit in the k-class model compared to the (k-1)-classes model. Then, if the test is statistically insignificant ($P \geq 0.05$) when comparing the (k+1)-class model with the k-class model, this means that there is no more significant improvement in model fit when including a new class, thus cannot reject the k-class model. Consequently the optimal number of classes will be k.

LMR LR test may inflate Type I error when the sample size is small, for this adjusted LMR LR was proposed by adjusting the number of degrees of freedom and sample size. This two test can perform identical.

An alternative LR test based on non-χ^2 distribution is the BLRT, Bootstrap log-likelihood ratio test where parametric bootstrapping was used to generate a set of bootstrap samples usng the parameters estimates from the (k-1)-class model, and each of the bootstrap samples is analyzed for both k-class and (k-1)-class models. A distribution of the log-likelihood differences between the k-class and (k-1)-class model from all the bootstrap samples is constructed. The BLRT is applied following this empirical distribution of the log-likelihood differences. The P-values are interpreted in the same way as the LMR LR test.

Quality of latent class membership classification

Once the optimal number of classes is identified, the cases or individuals are classified into the latent classes. The probability for an individual to be assigned to a specific latent class is measured by posterior class-membership probability given the individual's response pattern on the observed categorical indicators/items. The latent class memberships of individuals are not definitely determined, but based on their highest posterior class-membership probabilities.
If the posterior probability of a individual is close to 1.0, then the class misclassification or uncertainty is small. The probability for correct class-classification for a individual is the highest probability to be in a class, and the probability of misclassification is the sum of the probability to be classified in the rest of the classes. Posterior probabilities for a specific class of 1.0 are unlikely, consequently zero for the rest of the classes. A rule of thumb for acceptable class classification is 0.70 or greater (Nagin, 2005).

For assessing the quality of class membership classification another criterion is

Entropy, whose values range from 0 to 1 with smaller values indicating a better classification, which is defined as,

$$EN(k) = -\sum_{i=1}^{N}\sum_{k=1}^{K} P_{ik} ln P_{ik} \tag{1.8}$$

where P_{ik} is the posterior probability for the ith individual to be in class k.

The relative entropy that is defined by (Wedel and Kamakura, 2000; Dias and Vermunt, 2006) as

$$REN(k) = 1 - \frac{EN(k)}{Nln(K)} \tag{1.9}$$

for a k-class model with a sample size of N. This rescaled version of entropy range from 0 to 1 and a value closer to 1.0 indicates better classification. A good classification can be defined as Clark (2010) suggest with entropy of 0.8 or higher, 0.6 is medium and 0.4 is low relative entropy.

When defining the final latent classes it is important to check the size of each class, the percentage of individuals in each class represents the prevalence of the corresponding subpopulation in the target population. To have a meaningful class classification, the sizes should not be too small. Latent classes must be theoretically meaningful and interpretable. The researcher need to define and name the classes based on the patterns of item-response probabilities in that class. For this, the classes identified should make sense and if any class is not theoretically interpretable, the model will not be useful regardless of model fit.

After the number of latent classes is defined, the class classification should be checked and interpreted. Class counts are estimated based on the posterior class membership probabilities for each individual to be partially a member of all the classes. Another type of latent class count is estimated based on the most likely latent class membership, this means that each individual is assigned to the most likely class. If this two types of counts differ substantially indicated that the class membership misclassification is large. With a perfect classification (entropy = 1) the two counts would be identical.

Avoid local maxima

A well-known problem of any mixture modeling is that model estimation may not converge on the global maximum of the likelihood, but local maxima, providing incorrect parameter estimates (Goodman, 1974; Muthen and Shedden, 1999). The solution is to estimate the model with different sets of random values to ensure the best likelihood (Muthen and Muthen, 1998-2010; McLachlan and Peel, 2000).
The software automatically generates 10 random sets of starting values in the initial stage for all model parameters; and then maximum likelihood optimization is carried out for 10 iterations using each of the 10 random set starting values; and finally 2 starting values for the final stage optimizations (Muthen and Muthen, 1998-2010). When more than 2 classes are specified it requests a larger number of random sets of starting values to avoid local maxima of the likelihood.

1.1.4 Measurement invariance - Multigroup Latent Class Analysis

Białowolski, 2016; Kankaraš, Vermunt, & Moors, 2011; Magidson & Vermunt, 2004

~The value of cross-country comparisons is at the heart of large-scale international surveys. But as household surveys expand from tools to measure objective attributes (age, household size) and behaviours (e.g. unemployment or job-seeking behaviours) to instruments to assess subjective attitudes (e.g. attitudes towards migrants, or subjective well-being), and as skills assessments aim no longer to measure only knowledge of mathematics, but also psychological traits such as perseverance, new challenges for the validity and comparability of survey results emerge, and old issues acquire renewed salience. Reflective latent constructs measured through self-reports, for example, are particularly affected by subtle linguistic differences in the translated questionnaires and by broader cultural differences. These may introduce variation in participants' understanding of survey questions, and therefore in the relationship between their responses and the target latent construct. Similarly, when confronted with Likert items, with generic frequency scales ("often," "sometimes," "never or almost never," ...), or with subjective rating scales ("on a scale from 1 to 10"), cultural norms may mediate the response process of participants. As a result, international surveys may fall short of their objective to facilitate comparisons across countries (*Invariance analyses in large-scale studies*, 2019).~

~Measurement invariance can be defined as a conditional independence property of the measurement model with respect to a set of sub-populations within the parent population (e.g. language groups, or gender, or time) (Mellenbergh, 1989[103]; Horn and Mcardle, 1992[104]; Meredith, 1993[8]).~

Measurement invariance is an important prerequisite for using multi-indicator assessment instruments to examine group differences. If the measurement properties of an instruments differ between observed groups (non invariance), it is not possible to compare the differences between the groups.

In latent class analysis invariance is necessary to determine whether the number and nature of the latent classes are the same across the different groups. LCA tests whether the number of classes is stable across the known groups and if the measurement part of the model is equivalent across these groups.

1. Heterogenous model

The first model is an unconstrained model in which the compared groups exhibit the same number of classes but the parameters defining those classes are freely estimated across groups. This means that assumes that the only similarity between groups is the number of classes identified and allows that response patterns (conditional probabilities) and class sizes vary among groups. Although the number of classes in all groups may be the same, direct between-country comparisons are not possible in this step because the meaning of latent classes may be substantially different. A completely unrestricted multi-group latent class model is equivalent to the estimation of a separate 3-class LC model for each group.

$$\pi_{ijklmt|g}^{ABCDEX|G} = \pi_{t|g}^{X|G}\pi_{it|g}^{A|X,G}\pi_{jt|g}^{B|X,G}\pi_{kt|g}^{C|X,G}\pi_{lt|g}^{D|X,G}\pi_{mt|g}^{E|X,G} \tag{1.10}$$

Here, $\pi_{ijklmt|g}^{ABCDEX|G}$ denotes the conditional probability that an individual who belongs to the *gth* group will be at level (i, j, k, l, m, t) with respect to variables A, B, C, D, E, and X. The conditional probability of X taking on level t for a member of the *gth* group is denoted by $\pi_{t|g}^{X|G}$, which determines the LC ts proportion for the sth group.

$\pi_{it|g}^{A|X,G}$ is the conditional probability of an individual taking level i of variable A, for a given level t of the latent variable X and for a given group membership s of the grouping variable G. Parameters $\pi_{jt|g}^{B|X,G}$, $\pi_{kt|g}^{C|X,G}$, $\pi_{lt|g}^{D|X,G}$, and $\pi_{mt|g}^{E|X,G}$ are similarly defined conditional probabilities. It should be noted that ~~Equation 14.1~~ implies that indicator variables A, B, C, D and E are independent from each other, given the value of the latent variable X. This is usually referred to as the assumption of local independence ~~(Lazarsfeld & Henry, 1968)~~. The LC and conditional response probabilities are constrained to a sum of 1: $\sum \pi_{t|g}^{X|G} = 1$, $\sum \pi_{it|g}^{A|XG} = 1$, and so on.

$$\pi_{it|g}^{A|XG} = \frac{\exp(\lambda_i^A + \lambda_{it}^{AX} + \lambda_{ig}^{AG} + \lambda_{itg}^{AXG})}{\sum \exp(\lambda_i^A + \lambda_{it}^{AX} + \lambda_{ig}^{AG} + \lambda_{itg}^{AXG})} \tag{1.11}$$

2. Partial homogeneity

The second model to test is the semiconstrained model in which equality constraints are imposed across the observed groups. The measurement part of the model (conditional probabilities) are restricted to be equal in all observed groups. For each group, the meaning of latent classes is invariant of the group and cross-group comparisons are meaningful. Yet, the size of the classes (i.e. the relative importance of each class) may still vary. Most applicable and desirable in cross-cultural studies.

$$\pi_{ijklmt|g}^{ABCDEX|G} = \pi_{t|g}^{X|G}\pi_{it|g}^{A|X}\pi_{jt|g}^{B|X}\pi_{kt|g}^{C|X}\pi_{lt|g}^{D|X}\pi_{mt|g}^{E|X} \tag{1.12}$$

- While it is tempting to interpret class 1 for both samples as representing the 'ideal' respondents, this is not appropriate without first restricting the measurement portion of the models (the conditional probabilities) to be equal. - Latent structures are partially homogenous when across- group equality constraints are imposed on the conditional probabilities.

To test for invariance, the unconstrained model (1) and the semiconstrained models (2) are compared using the likelihood ratio test (LRT) and information criteria such as AIC, BIC, aBIC. A statistically significant LRT indicates a substantial decrease in model fit such that the semiconstrained model should be rejected. The model with the smallest AIC, BIC, aBIC value is selected as the best fitting model.

If the semiconstrained model is rejected, this means, lower information criteria for the unconstrained model and LRT statistically significant, there is no evidence to assume measurement invariance. In this case, latent classes are characterized different

across the observed groups and differences in the prevalence of the profiles across the groups cannot be meaningfully determined.
For invariance to exist, the semicontrained model should show a better fit to the data than the unconstrained model.

Only after establishing the stability of the classes definition across the different groups it is possible to compare groups and evaluate the differences in class prevalence.

3. Complete homogeneity

The more strict level of invariance is where all parameters are constrained across countries, and the prevalence of latent classes are restricted to be equal across groups (i.e. the percentage of individuals assigned to different classes will be equal in all groups). This last assumption will imply that the identified groups of individuals with similar scoring patterns are identical in the all the groups with identical numbers of individuals assigned to each group.

$$\pi_{t|1}^{X|G} = \pi_{t|2}^{X|G}, fort = 1, 2, 3 \tag{1.13}$$

If the fully constrained model fit best it can be concluded that there are no differences in how the known groups are represented in each profile. In contrast, if the fully constrained model is rejected but the semiconstrained model holds means that although the profiles have the same meaning in each group, there are differences in how the individuals are distributed across classes.

1.2 Large scales assessments - IEA ICCS 2016

The International Association for the Evaluation of Educational Achievement (IEA) International Civic and Citizenship Education Study (ICCS) 2016 focus their research in how young people are prepared to undertake their roles as citizens in a range of countries in the second decade of the 21st century (Citizenship Education Study 2016, n.d.). This study evaluate student's knowledge and understanding of civics and citizenship, as well as their attitudes, perceptions, and activities related to civics and citizenship.

ICCS 2016 addressed the following research questions: 1. The way civic and citizenship education is implemented in participating countries, including the aim and principles for this learning area, the curricular approaches chosen to provide it, and changes and/or developments since 2009.
2. The extent of student's knowledge and understanding of civics and citizenship, and the factors associated with its variation across and within countries.
3. Student's current and expected future involvement in civic-related activities, their perceptions of their capacity to engage in these activities, and their perception of the value of civic engagement.
4. Student's belief about contemporary civic and civic issues in society, including those concerned with civic institutions, rules and social principles (democracy, citizenship, and diversity), as well as their perceptions of their communities and threats to the

world's future.
5. The ways in which schools organize civic and citizenship education, with a particular focus on general approaches, the processes used to facilitate civic engagement, interaction with their communities, and schools' and teacher's perceptions of the role of this learning area.

The 2016 study gathered data from more than 94.000 students in 8th grade in about 3800 schools from 24 countries. Also data from more than 37.000 teachers in those schools and contextual data collected from school principals is included. An additional European questionnaire gathered data from almost 53.000 students is 14 European countries and a Latin American student questionnaire from more than 25.000 students from 5 Latin American countries.

From all 24 participants countries, 16 are from Europe, 5 from Latin America, and 3 from Asia. In two of the participant countries a sub-national entity participate. In Belgium, ICCS 2016 was implemented only in the Flemish education system and North Rhine-Westphalia state in Germany participate as a benchmarking participant. The student population is defined as students in 8th grade, in average 13.5 years of age in this study.

The schools samples were designed as stratified two-stage cluster samples, first schools were randomly selected at the first stage with probability proportional to size and intact classrooms were sampled at the second stage. Each country has a sample size of 150 schools approximately and the sample of students around 3.000 and 4.500. Additionally around 15 teachers teaching the target grade from each school were sampled.

The framework of the study consist of two parts:
- The civic and citizenship framework outlines the outcome measures addressed by the cognitive test and the international ans regional student questionnaires;
- The contextual framework maps the contextual factors expected to influence outcomes and explain their variation.

The assessment framework identified the different types of student perceptions and behaviors relevant to civics and citizenship along two affective-behavioural domains:
i. Attitudes: These refer to judgments or evaluations regarding ideas, persons, objects, events, situations, and/or relationships. This include the students' belief about democracy and citizenship, students' attitudes towards the rights and responsibilities of groups in society, and students' attitudes towards institutions.
ii. Engagement: Refers to students' civic engagement , students' expectations of future civic related action, and students' disposition to actively engage in society (interest, sense of efficacy). The sense of engagement also includes preparedness to participate in forms of civic protest, anticipated future political participation as adults, and anticipated future participation in citizenship activities.

1.3 Methodological features

There are two different approaches to conduct a Latent Class Analysis, a confirmatory and exploratory approach.

1.3.1 Confirmatory LCA

The confirmatory approach starts with a specific hypotheses about the latent structure, the researcher can test if there is a defined number of classes that explained the associations between the observed variables. Based on the conditional response probabilities and class sizes computed by the software, the expected frequencies can be estimated. These frequencies can be compared with the observed frequencies with a statistical test such as the Pearson test or the LRT. If the test statistics show that the observed and expected frequencies do not differ significantly, the model is appropiate for explaining the associations of the observed variables. The expected frequency of each possible response pattern should be at least 1 or even 5 to make sure that both statistics follow a χ^2 distribution and that p-values can be used for a valid decision. In case of sparse tables bootstrapping goodness of fit is highly recommended (*Invariance analyses in large-scale studies*, 2019).

1.3.2 Exploratory LCA

When researchers do not have a specific hypotheses but the goal is to identify how many classes are necessary to fit the data a exploratory latent class analysis can be performed. In this case, several latent class models with an increasing number of classes should be computed. The best fitting will be selected, this can be identify by which increasing the number of latent classes would not result in a model that fits the data significantly better. Information criteria such as AIC, BIC and aBIC can also be used to determine the best fit. The best model will have the lowest values of information criteria.

1.3.3 Multigroup LCA

In LCA, studying measurement invariance is necessary to determine whether the number and nature of the latent profiles are the same across the different observed groups (Olivera-Aguilar & Rikoon, 2018). For this, multiple group LCA models are computed, and the relative fit of the unconstrained and semi-constrained models are compared using the LRT, AIC, BIC, and aBIC measures. Also is needed to review any kind of response bias, the most common refers to “a systematic tendency to respond to a range of questionnaire items on some basis other than the specific item content” for example e.g. extreme or agree/disagree (Kankaraš, Vermunt, & Moors, 2011).

The strategy for investigate if the different classes are consistent across the studied groups, is conduct the LCA in several steps:
1. LCA is conducted in each group separately according to the exploratory approach to identify how many classes have to be considered and what the conditional probabilities can say about the meaning of each latent class.
2. If the number of classes is the same in the different groups, the assumption of full invariance is tested by comparing the fit of the model without measurement invariance

by a likelihood ratio test and by information criteria. If the full invariance is rejected, the different forms of partial measurement invariance can be tested. it can be studied if some latent classes are measurement invariant or not and/or if some items are invariant or not. That means that the assumption of measurement invariance can be relaxed for some classes and/or items. This can be done successively until one finds such a less restrictive model that does not fit the data worse that the totally unrestricted model.
3. If the number of classes differ between groups, then it can be tested whether the classes that are present in all groups are measurement invariant or not. This means, if one group has 2 classes and other group has 3 classes a 3-class multigroup model with full measurement invariance can be tested, where the size of the third class in the first group would be zero.

This strategy is recommended for a small number of groups, when a large number of groups is tested another strategy is recommended as it will take so much time in computing and compare all parameters to identify the ones that are invariant or that should be free.

The appropriate strategy for a large amount of groups is to conduct a multigroup LCA where full measurement invariance is assumed across the groups and that the number of classes does not differ across groups. For this the appropriate number of classes should be identified for each group, and test is just one class is different between them, if this is rejected a extra class should be added to identify if there are two different classes among them. If the double of classes is found as the best fit means that none of the classes are measurement invariant, because different classes by country are needed. This strategy has the advantage to have a higher power to detect small classes that exist in several groups but that would not be detected in country-specific analysis because of their size within a group might be too small.

1.4 Study

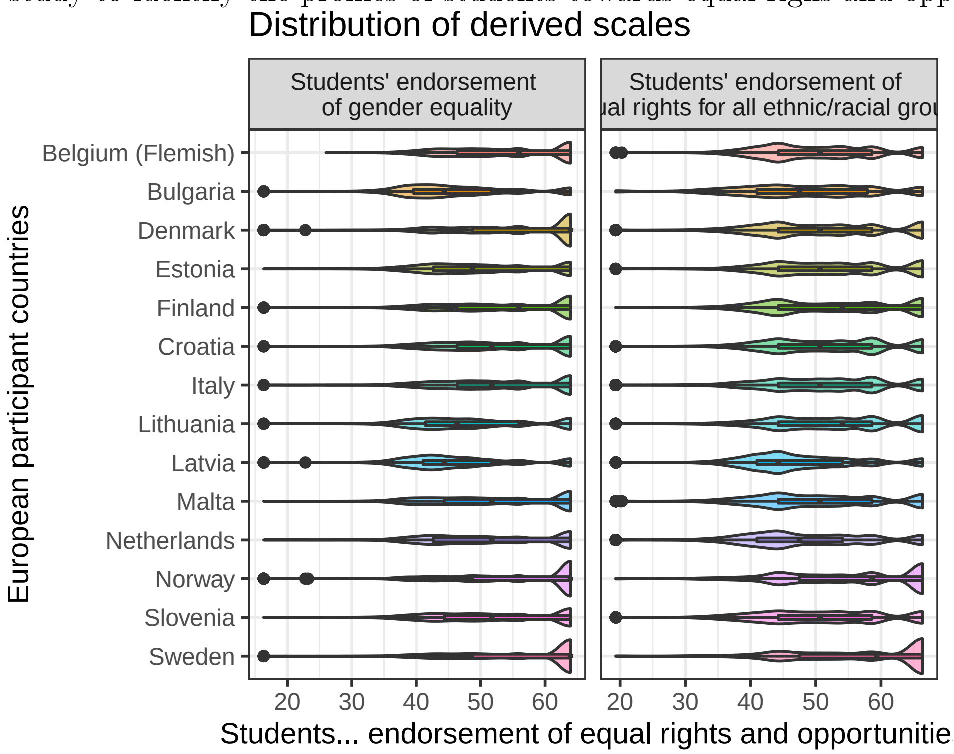
1.4.1 Students' endorsement of equal rights and opportunities

A serie of seven questions in the student questionnaire addressed the roles of women and men in society. Students were asked to indicate their level of agreement (ranging from strongly agree to strongly disagree). The first six items were used to create the scale *attitudes towards gender equality* (S_GENEQL in the dataset). Higher values of this scale reflect stronger agreement with the notion of gender equality or stronger disagreement with negative views of gender equality.

Another set of questions focused on the rights and responsibilities of all different ethnic/racial groups in society. Same as before students' indicate their level of agreement in the same range. This scale called *attitudes towards equal rights for all ethnic/racial groups* (S_ETHRGHT) indicate with higher scores a greater degree of agreement with the idea that ethnic and racial groups should have the same rights as other citizens in a society.

A two dimensional model in a confirmatory factor analysis using these two scales showed a good fit after controlling for the common residual variance between the negatively worded statements on gender equality. This two latent dimensions are highly correlated (0.63) and the measurement invariance was within acceptable ranges, this means that a certain degree of measurement invariance across countries was achieved.

The description of each item can be found in **??**, these 11 items will be used in this study to identify the profiles of students towards equal righs and opportunities.



1.4.2 Countries

Multiple countries had participated in the ICCS 2016 study (detailed participation of the selected countries can be found in Table A.1 in the Annex).

The European countries that participated can be classified by the following grouping:

a) Nordic: Denmark, Finland, Norway, Sweden.
b) Western European: Belgium (Flemish), The Netherlands.
c) Central and Eastern European: Bulgaria, Estonia, Latvia, Lithuania, Croatia, Slovenia.
d) Southern European: Italy, Malta.

These 14 European countries wil be selected to evaluate the scales indicated previously.

Chapter 2

Methods

In this section, the methods used in the research are explained, firstly a description of the data used, characteristics and size. Secondly, the variables used are described. Finally the analytical strategy used in this research in explained.

2.1 Sample

Only European countries were selected for this research, the decision was mainly based on select countries that had a similar background, where no characteristics as language, geographical location or other could influence in unwanted factors that could impact in the results.
Fourteen countries were chosen, from nordic, western, central, eastern an southern Europe. Each country sample size is different, the country with the highest sample is Norway (6.271), followed by Denmark (6.254), and the countries with lowest sample size are Netherlands (2.812) and Slovenia (2.844). But as mentioned in the previous chapter each individual in the sample has a senate weight associated, that sum up 1.000 for each country, this means that each country will have the sample participation in the analysis. The datail of each country sample size can be found in the annex, table A.1.

2.2 Variables

ICCS 2016 scale Students' endorsement of equal rights and opportunities include 2 different scales, attitudes towards gender equality and attitudes towards equal rights for all ethnic/racial groups as indicated in table A.2.

The first scale is composed by six items, first 3 items consult about the level of agreement with statements as "Men and women should have equal opportunities to take part in government," "Men and women should have the same rights in every way" and "Men and women should get equal pay when they are doing the same jobs" and the next items which are negative worded consult for the level of agreement with the following statements, "Women should stay out of politics," "When not many jobs available, men should have more right to a job than women" and "“Men are better qualified to be political leaders than women." These last items were inversely coded, this means that when a individual responded "Agree" to any of these items, this response was coded as "Disagree" and then the question should be interpreted inversely. In the analysis chapter these items will appear with a "(r)" added at the end of the label of these items to easily identify them.

The second scale . . . .

The original response categories for these items are based on 4 points agree/disagree scale, starting by the lower level of agreement "Strongly disagree" (1), "Disagree" (2), "Agree" (3), and "Strongly disagree" (4). These categories were recoded into two levels, "Disagree" (1) and "Agree" (2) to identify patterns of the classes in a clear way.

2.3 Analytical strategy

We define the number of random sets of starting values for initial stage optimizations to 1000, the number of random sets of starting values for final stage optimizations to 250 (a quarter of the number of initial starting values) and the maximum number of iterations in optimization to 20.

To be completely sure that the model has reached the global maximum of likelihood, the model was tested specifying two different random seeds. The model was performed by using two of the seed asociated to one of the optimizations obtained in the first run with a start number of zero.

The multigroup extension of the standard LC model has been developed for the analysis of latent structures of observed categorical variables across two or more groups (Clogg & Goodman, 1984, 1985). When comparing latent structures across groups, a number of possible outcomes can occur: they may turn out to be completely different (heterogeneous model), partially different (partially homogeneous model), or completely the same (homo- geneous model).

Meeting this last assumption ensures the highest level of cross-country comparability but may be difficult to achieve in cross-cultural studies.

Measurement invariance across observed groups is a prerequi- site to making meaningful comparisons in the prevalence of the profiles of those groups. Furthermore, measurement invar- iance is an important practical issue for institutions to evaluate when the goal is to classify individuals (e.g., students, employ- ees) into meaningful groups irrespective of demographic back- ground characteristics. In other words, institutions would be well served by evidence supporting the grouping of people from different known groups into the same latent profiles. For example, a company or educational institution might be inter- ested in grouping employees or students, respectively, accord- ing to a holistic set of behavioral or attitudinal patterns (e.g., to appropriately tailor opportunities or interventions) without explicit regard for background variables such as gender, race, and ethnicity.

~When the number of observations per group is small, likelihood ratio tests have limited power; while with large groups, violations of invariance detected in such tests may be inconsequential for the substantive inferences.(*Invariance analyses in large-scale studies*, 2019) The problem is compounded by the fact that in realistic settings (when violations of measurement invariance may be due to cultural or language specificities), the hypotheses are not independent, neither across items, nor across groups. ~

Mplus only provides a bootstrap likelihood ratio difference test for comparing models differing in the number of classes.

Chapter 3

Results

In this chapter, the relevant findings from every step is analyzed. Following the analytical strategy indicated in the previous chapter. First, a latent class analysis for every country included in the sample selected is performed in order to identify the correct number of classes optimal for each country separately. Secondly, a global analysis is performed to identify how many latent classes are identify including all different countries, with this information it is possible to establish the number of classes that can be compared across countries. Finally, a multigroup latent class analysis is performed considering all the previous information. The multigroup analysis is constructed in multiple steps, starting from the most restricted model until the less restricted model is evaluated. As a final step, a confirmatory latent class analysis is performed using some theoretical hypothesis that were defined based on the previous results.

This procedure is performed for the two scales that were used to create the Students' endorsement of equal rights and opportunities indicators separately. And finally both scales are used together to identify the common classes that underline this construct.

The model fit statistics table include all the statistics that are given by MPLUS. The tables for the different analysis indicate the total number of parameters used in the model, the final and best Log-likelihood, values for information criteria AIC, BIC, aBIC. The entropy indicated in each table correspond to the relative entropy were a perfect classification is 1, the table also indicates the log likelihood reduction from adding one class into the model. Two test for model fit are indicated as well, the value of the statistic and the p-value associated to the Vuong-Lo-Mendell-Rubin likelihood ratio test (VLMR) and Lo-Mendell-Rubin adjusted LRT Test (LMR).

The table by country is listed with models from 1 to 6 latent classes incrementally. The rows in **bold** indicate the best model selected, the values is *italics* indicate the lowest values of each model fit criteria defined previously.

The plot with residuals for each individual model is available,

3.1 Attitudes towards gender equality scale

This scale is composed by 6 items, in the following results, this items were ordered in the output for a easier interpretation of the results. This ordering consider first all the items that were positive worded in the instrument (GND1, GND2 and GND5), followed by the three other items that are negatively worded (GND3, GND4, GND6). As mentioned before all these variables were recoded in two categories, as Agree and Disagree. All 14 countries were analysed independently and then pooled in the same dataset.

3.1.1 Analysis by country

A latent class analysis with 1 to 6-class models were performed in each country in order to evaluate the model fit of each one of them. The results are summarized in table 3.1.

In most European countries, the best model fit based on the different criteria indicated previously are by including 3 or 4 latent classes.

For Belgium, Denmark, Croatia, Latvia and Netherlands there is no significant improvement in the log likelihood from two to three latent classes. In this sense, BIC and aBIC simultaneously have the lowest values in the 3-class model.

On the other hand, Bulgaria, Estonia, Malta, Slovenia, and Sweden according to the statistical tests, BIC, and aBIC criteria, the best model is a 4-class model. In Finland, Italy, Lithuania models, the BIC, aBIC differ from the statistical test indicating a better fit for the 3 class model.

Norway is the only country from the sample that the best model fit is the one with 5 latent classes according to the statistical tests and BIC and aBIC.

It is a common tendency in all the evaluated countries the AIC value is lower in the models with one more class than the indicated by the statistical tests and BIC and aBIC. Which is consistent with the indication that this criteria tends to overfit the data.

Values of Entropy are higher when the tests are significant, but consistent with a better fit of the data the lower entropy found in the 4-class model is in Latvia (73.7%) and the highest value in Norway (96%). The log likelihood reduction is consistent in all countries, where having more than 3 latent classes reduce the log likelihood around 0.2% and 1%.

Table 3.1: Model fit statistics LCA by country Attitudes towards gender equality scale

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
Belgium (Flemish)											
1	6	*-4246*	8504	8540	8521						
2	13	-3843	7713	7790	7749	84.8%	*9.5%*	806	0	791	0
3	**20**	**-3812**	**7664**	***7784***	***7721***	***88.2%***	**0.8%**	***62***	***0.323***	***61***	***0.327***
4	27	-3795	*7645*	7806	7721	68.9%	0.4%	*34*	*0.237*	*33*	*0.24*
5	34	-3789	7646	7849	7741	74.3%	0.2%	*13*	*0.392*	*13*	*0.394*
6	41	-3785	7653	7898	7768	81.8%	0.1%	*7*	*0.64*	*7*	*0.641*
Bulgaria											
1	6	*-8369*	16749	16785	16766						
2	13	-7710	15446	15524	15483	63.6%	*7.9%*	1317	0	1294	0
3	20	-7553	15146	15265	15202	69.8%	2.0%	315	0	309	0
4	**27**	**-7523**	**15100**	***15261***	***15175***	***75.2%***	**0.4%**	***60***	***0.077***	***59***	***0.08***
5	34	-7508	15083	15287	15179	71.2%	0.2%	*30*	*0.445*	*30*	*0.45*
6	41	-7500	*15083*	15328	15198	73.7%	0.1%	*15*	*0.458*	*14*	*0.46*
Denmark											
1	6	*-7273*	14557	14597	14578						
2	13	-6043	12111	12198	12157	*91.7%*	*16.9%*	2460	0	2420	0
3	20	-5951	11943	12077	12013	90.2%	1.5%	*182*	*0.077*	*179*	*0.08*
4	**27**	**-5914**	**11883**	***12063***	**11977**	**91.2%**	**0.6%**	***74***	***0.174***	***73***	***0.178***
5	34	-5894	11856	12084	*11975*	86.7%	0.3%	*41*	*0.386*	*40*	*0.39*
6	41	-5876	*11833*	12108	11978	84.7%	0.3%	*38*	*0.52*	*37*	*0.523*

Table 3.1: Model fit statistics LCA by country Attitudes towards gender equality scale *(continued)*

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
Estonia											
1	6	*-5754*	11520	11556	11537						
2	13	-5044	10115	10192	10151	79.1%	*12.3%*	1419	0	1394	0
3	20	-5002	10045	10164	10100	80.8%	0.8%	84	0.011	83	0.012
4	**27**	**-4974**	***10001***	***10162***	***10076***	**77.7%**	**0.6%**	***57***	***0.183***	***56***	***0.189***
5	34	-4968	10004	10206	10098	78.9%	0.1%	*11*	*0.54*	*11*	*0.541*
6	41	-4965	10012	10256	10125	*81.5%*	0.1%	*7*	*0.521*	*6*	*0.522*
Finland											
1	6	*-4273*	8558	8594	8575						
2	13	-3520	7065	7144	7102	89.3%	*17.6%*	1506	0	1480	0
3	**20**	**-3477**	**6993**	***7114***	***7051***	**90.7%**	**1.2%**	**86**	**0.037**	**84**	**0.039**
4	27	-3461	6975	7139	7053	*92.3%*	0.5%	*32*	*0.57*	*31*	*0.574*
5	34	-3450	6968	7173	7065	91.3%	0.3%	*22*	*0.212*	*21*	*0.215*
6	41	-3442	*6966*	7214	7084	90.2%	0.2%	*15*	*0.417*	*15*	*0.42*
Croatia											
1	6	*-6227*	12466	12503	12484						
2	13	-5417	10860	10942	10901	84.8%	*13.0%*	1619	0	1592	0
3	**20**	**-5368**	**10777**	***10902***	***10838***	**87.6%**	**0.9%**	***98***	***0.085***	***96***	***0.088***
4	27	-5353	*10759*	10929	10843	90.8%	0.3%	*31*	*0.081*	*31*	*0.084*
5	34	-5349	10765	10978	10870	91.9%	0.1%	*8*	*0.46*	*8*	*0.464*
6	41	-5346	10774	11031	10900	*94.1%*	0.0%	*5*	*0.787*	*5*	*0.789*

Table 3.1: Model fit statistics LCA by country Attitudes towards gender equality scale *(continued)*

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
Italy											
1	6	*-5615*	11242	11279	11260						
2	13	-4903	9832	9912	9870	80.9%	*12.7%*	1424	0	1399	0
3	**20**	**-4830**	**9701**	***9824***	***9760***	**84.6%**	**1.5%**	**145**	**0**	**143**	**0**
4	27	-4821	*9695*	9861	9775	*87.5%*	0.2%	*19*	*0.246*	*19*	*0.251*
5	34	-4814	9696	9904	9796	84.6%	0.1%	*14*	*0.539*	*14*	*0.542*
6	41	-4810	9703	9955	9824	73.5%	0.1%	*7*	*0.356*	*6*	*0.358*
Lithuania											
1	6	*-8481*	16973	17011	16991						
2	13	-7571	15168	15249	15207	78.3%	*10.7%*	1819	0	1788	0
3	**20**	**-7447**	**14934**	***15058***	**14994**	***82.5%***	**1.6%**	**248**	**0**	**244**	**0**
4	27	-7421	14895	15062	*14977*	78.0%	0.4%	*53*	*0.167*	*52*	*0.172*
5	34	-7409	*14885*	15096	14988	77.3%	0.2%	*24*	*0.456*	*23*	*0.46*
6	41	-7403	14888	15142	15012	71.5%	0.1%	*11*	*0.755*	*11*	*0.755*
Latvia											
1	6	*-8765*	17542	17578	17559						
2	13	-8054	16134	16213	16172	68.4%	*8.1%*	1421	0	1397	0
3	**20**	**-7993**	**16027**	***16148***	***16085***	**72.4%**	**0.8%**	***121***	***0.052***	***119***	***0.055***
4	27	-7977	16009	16172	16086	73.7%	0.2%	*32*	*0.416*	*32*	*0.42*
5	34	-7963	15994	16200	16092	77.7%	0.2%	*29*	*0.752*	*29*	*0.754*
6	41	-7955	*15992*	16241	16110	*78.6%*	0.1%	*15*	*0.458*	*15*	*0.459*

Table 3.1: Model fit statistics LCA by country Attitudes towards gender equality scale *(continued)*

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
Malta											
1	6	*-7383*	14779	14816	14797						
2	13	-6378	12782	12862	12821	78.5%	13.6%	2011	0	1977	0
3	20	-6236	12513	12637	12573	84.2%	*2.2%*	283	0.028	278	0.029
4	**27**	**-6204**	**12462**	***12629***	***12543***	**87.2%**	**0.5%**	***65***	***0.235***	***64***	***0.238***
5	34	-6190	12449	12660	12552	*88.9%*	0.2%	*27*	*0.394*	*26*	*0.396*
6	41	-6181	*12443*	12698	12567	88.7%	0.2%	*20*	*0.481*	*19*	*0.483*
Netherlands											
1	6	*-5373*	10757	10793	10774						
2	13	-4829	9683	9760	9719	75.9%	*10.1%*	1088	0	1068	0
3	**20**	**-4759**	**9557**	***9676***	***9612***	**87.0%**	**1.5%**	***140***	***0.074***	***138***	***0.076***
4	27	-4742	9539	9699	9613	*87.1%*	0.3%	*32*	*0.435*	*32*	*0.438*
5	34	-4728	*9525*	9726	9618	77.8%	0.3%	*28*	*0.543*	*28*	*0.546*
6	41	-4723	9527	9770	9640	75.9%	0.1%	*12*	*0.556*	*11*	*0.557*
Norway											
1	6	*-7878*	15767	15807	15788						
2	13	-6289	12603	12691	12649	91.8%	*20.2%*	3178	0	3126	0
3	20	-6104	12247	12382	12318	95.3%	2.9%	370	0	364	0
4	27	-6068	12189	12371	12285	*96.0%*	0.6%	72	0.039	71	0.041
5	**34**	**-6035**	**12137**	***12365***	***12257***	**93.2%**	**0.5%**	***66***	***0.281***	***65***	***0.286***
6	41	-6024	*12130*	12406	12276	93.7%	0.2%	*21*	*0.373*	*20*	*0.376*

Table 3.1: Model fit statistics LCA by country Attitudes towards gender equality scale *(continued)*

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
Slovenia											
1	6	*-5202*	10416	10451	10432						
2	13	-4369	8764	8841	8800	84.2%	*16.0%*	1666	0	1637	0
3	20	-4308	8656	8775	8711	85.5%	1.4%	122	0.018	120	0.02
4	**27**	**-4280**	**8614**	***8774***	***8689***	***87.5%***	**0.7%**	***56***	***0.158***	***55***	***0.163***
5	34	-4271	*8610*	8812	8704	86.9%	0.2%	*18*	*0.507*	*18*	*0.51*
6	41	-4264	8611	8855	8724	86.9%	0.1%	*13*	*0.297*	*13*	*0.298*
Sweden											
1	6	*-3877*	7766	7802	7783						
2	13	-3155	6336	6415	6373	90.6%	18.6%	1444	0	1419	0
3	20	-3080	6200	6321	6258	*94.3%*	*2.4%*	150	0.004	147	0.004
4	**27**	**-3049**	**6152**	***6316***	**6230**	**89.2%**	**1.0%**	***62***	***0.398***	***61***	***0.402***
5	34	-3022	*6113*	6319	*6211*	89.7%	0.9%	*54*	*0.133*	*53*	*0.136*
6	41	-3016	6114	6362	6232	89.9%	0.2%	*13*	*0.513*	*13*	*0.515*

Note:
The best loglikelihood value was not replicated for the following models:
[1] Croatia, 6 classes model

All models selected accomplish at least one or more of the criteria established for a good fit. The bivariate residuals were also analyzed, and in all countries, the selected countries have residuals around the range of acceptable as shown in the figure 3.1. There it can be seen that just one value is outside the ranges in Malta with a 4-class model.

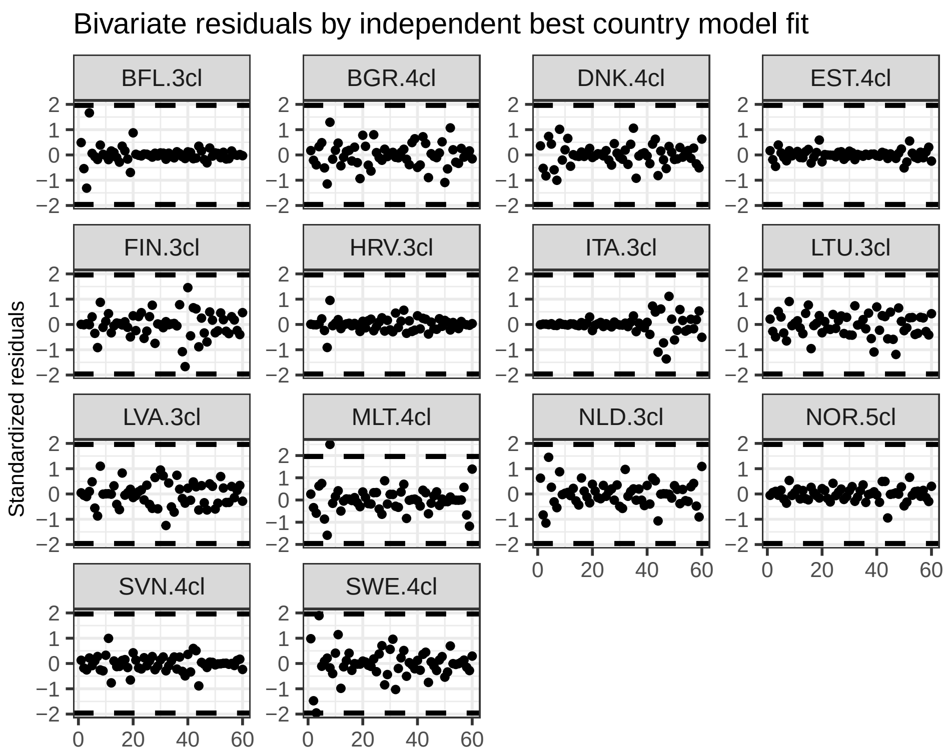


Figure 3.1: Bivariate model fit standardized residuals Gender equality scale

In figure 3.2 the classes of each independent model can be identify. In the figure, the conditional probabilities for agree to each item are shown and plotted for each of the classes modeled in each country. Here can be identified two classes that are similar in all the models, the green and purple line.

- Fully egalitarian: Most likely to agree to all items (green line)
  - Conditional probabilities greater than 0.75 to agree, class sizes around 60% (Bulgaria) and 90% (Denmark).
- Competition-driven sexism: Most likely to disagree to gender competitive items in favor of women (purple line).
  - Conditional probabilities greater than 0.75 to agree to positive views of gender equality and generally lower than 0.5 to agree to reversed negative views, class sizes around 3.6% (Denmark) and 22.5% (Bulgaria).
- Non-egalitarian: Not likely to agree to any item (orange line)

  - Conditional probabilities lower to 0.5 to agree to any item, class sizes around 0.9% (Norway) and 2.6% (Italy).

- Reverse competition-driven sexism: Most likely to agree to gender competitive items in favor of women (pink line)

  - Conditional probabilities lower than 0.25 to agree to positive views of gender equality and generally greater than 0.75 to agree to reversed negative views, class sizes around 0.6% (Norway) and 1.6% (Netherlands).

- Political egalitarian: Likely to agree to political related items (light-green line)

  - Conditional probabilities greater than 0.75 in political equality items, class sizes around 3.2% (Belgium) and 1.4% (Estonia).

- Random response: Not defined attitude (yellow line)

  - Conditional probabilities between 0.25 and 0.75 to agree all items, class sizes around 2.7% (Slovenia) and 16.8% (Bulgaria).

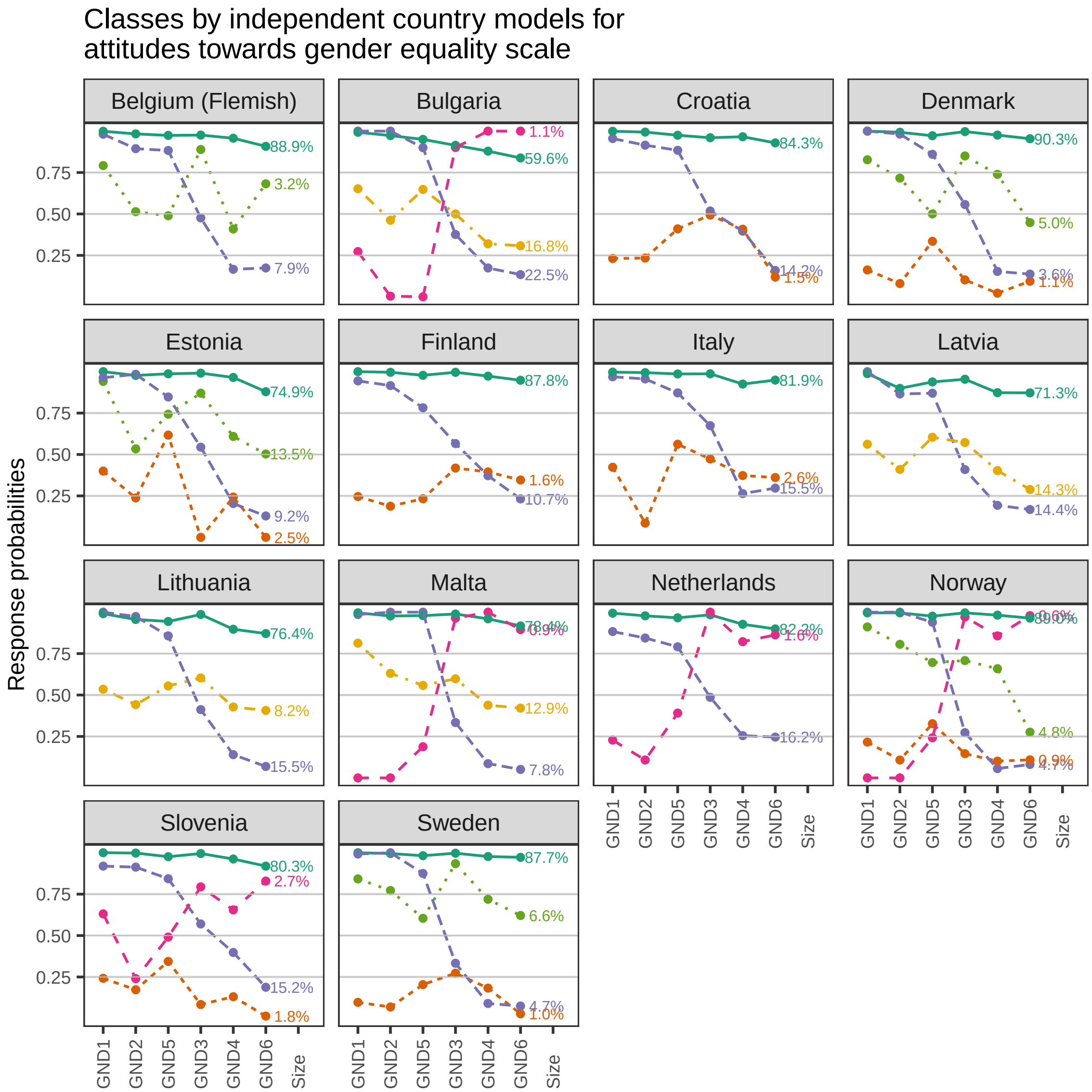


Figure 3.2: Independent country best model fit classes, Gender equality scale

3.1.2 General model

The model with a single class has the largest AIC (192.838), BIC (192.891), and ABIC (192.872) values for the European countries model, indicating that this model fits data worse than all other models. In addition, the P-values of the VLMR test, and LMR in the 2-class model are all < 0.0001; this means that both tests reject the single-class model in favor of a model with at least two latent classes. In other words, there exists heterogeneity in the target population in regard to attitudes towards gender equality. In the 6-class model, the LMR LR and VLMR are not statistically significant ($P > 0.05$). That is, the two tests are in favor of at most 5 classes.
In contrast, BIC and aBIC values are all smaller in the 5-class model than those in the 6-class model; thus consider that the models with more than 5 classes are not preferred. AIC values reach the lowest value in the 7-class model, but based on the previous results this criteria will not be considered in this case due to the tendency to overfit the data.

The relative entropy given by Mplus software, decrease when including more than 4 classes and increase again with the 6-class model, this would suggest that a model with at least 6 class or 4 classes is preferred.

Together with the percentage of reduction in the log likelihood value, that indicate that by adding two classes to the model the log-likelihood is reduced in a 13.3%, this reduction is only increased in 1.2% if the model is a 3-class model and finally this value is reduced close to 0 if more than 5 classes are included.
Now, the preferred model must be either the 5-class or the 6-class model considering the residuals of each model in figure 3.3, where all values are around -1.96 and 1.96. But based on the parsimony principle a 4-class model can be considered as well as just one value of the residuals is outside the acceptable range.

Theoretically we tend to determine that the 4-class LCA model is the preferred model. We will show later that the classes identified by the 4-class model are more interpretable and representatives than the rest of the models. And in particularly that 2-classes can be compared across countries.

Table 3.2: Model fit statistics LCA attitudes towards gender equality scale

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
All countries											
1	6	*-96413*	192838	192891	192872						
2	13	-83617	167261	167376	167334	80.5%	*13.3%*	25591	0	25258	0
3	20	-82592	165223	165400	165336	*84.5%*	1.2%	2051	0	2025	0
4	**27**	**-82327**	**164708**	**164946**	**164861**	**82.7%**	**0.3%**	**529**	**0**	**522**	**0**
5	**34**	**-82163**	**164394**	***164694***	***164586***	**81.1%**	**0.2%**	**328**	**0**	**324**	**0**
6	41	-82136	164355	164717	164586	82.5%	0.0%	*53*	*0.246*	*52*	*0.252*
7	48	-82116	*164328*	164752	164600	82.1%	0.0%	*40*	*0.244*	*40*	*0.247*

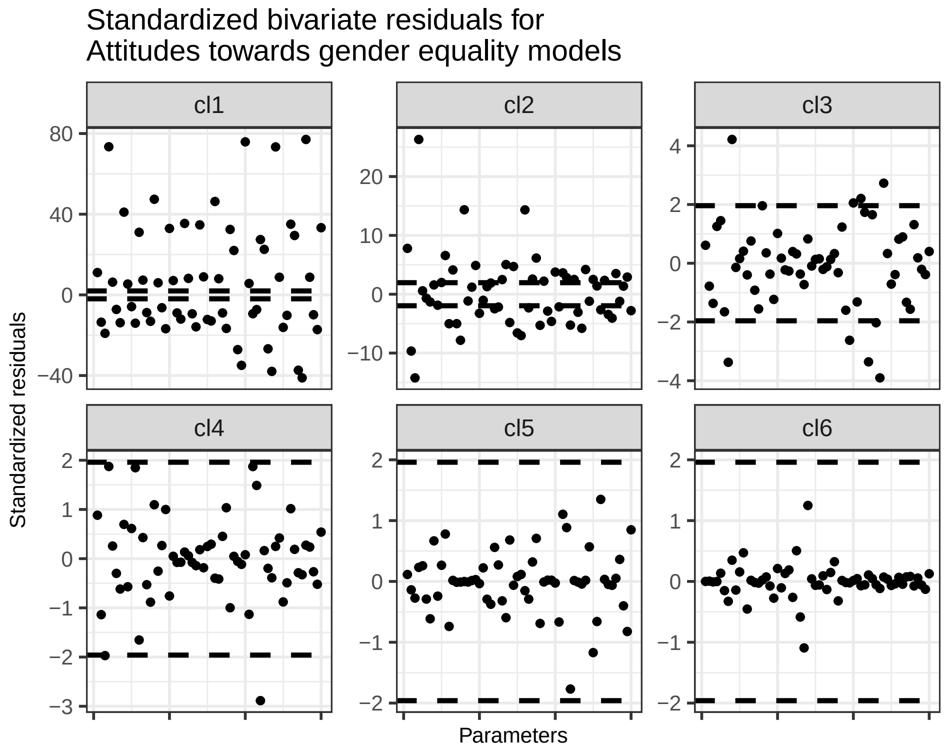


Figure 3.3: Bivariate model fit standardized residuals, Gender equality scale

3-6 class models

Three, four, five and six classes model were investigated profoundly. It is clear that is not easy to choose the best model fit without doing a full analysis. There are some pattern that can be clearly identify in all the models, Class 1 with 81%, 79.2%, 77% and 78.6% in each model respectively, the estimated probabilities to agree for this latent class, the **Fully egalitarian** group, for all six items *Men and women should have equal opportunities to take part in government*, *Men and women should have the same rights in every way*, *Men and women should get equal pay when they are doing the same job*, *Women should stay out of politics*, *Not many jobs available, men should have more right to a job than women* and *Men are better qualified to be political leaders than women* are higher than 0.92.

The second class (Class 2 in Figure 3.4) identified in all the models, called **Competition-driven sexism**. For this class, the estimated probabilities to agree to the first 3 items are close or higher than 0.9 in all models. For the last three items, the estimated probabilities to agree are not higher than 0.5 in all models. The class size differ in all four models, 11.3%, 11.5%, 12.8% and 8.6% in the 3, 4, 5, 6-class model respectively.

The third class that can seen with a similar pattern in all the models is called **Non-egalitarian**, this class appears in the 4-class model. The pattern of this class is basically showing lower estimated conditional probabilities to agree to any of these statements, no greater than 0.4, with the exception of one item *Men and women should get equal pay when they are doing the same jobs* with a estimated probability to agree no higher than 0.55. The estimated sizes for this class are 7.7%, 7% and 5.8% in each model respectively.

The four, fifth and sixth class identify in the models differ in all the models, nevertheless, one class appears to be consistent in the 5-class model, where this class called **Reverse competition-driven sexism** has opposite conditional probabilities compared to the second class identified previously.

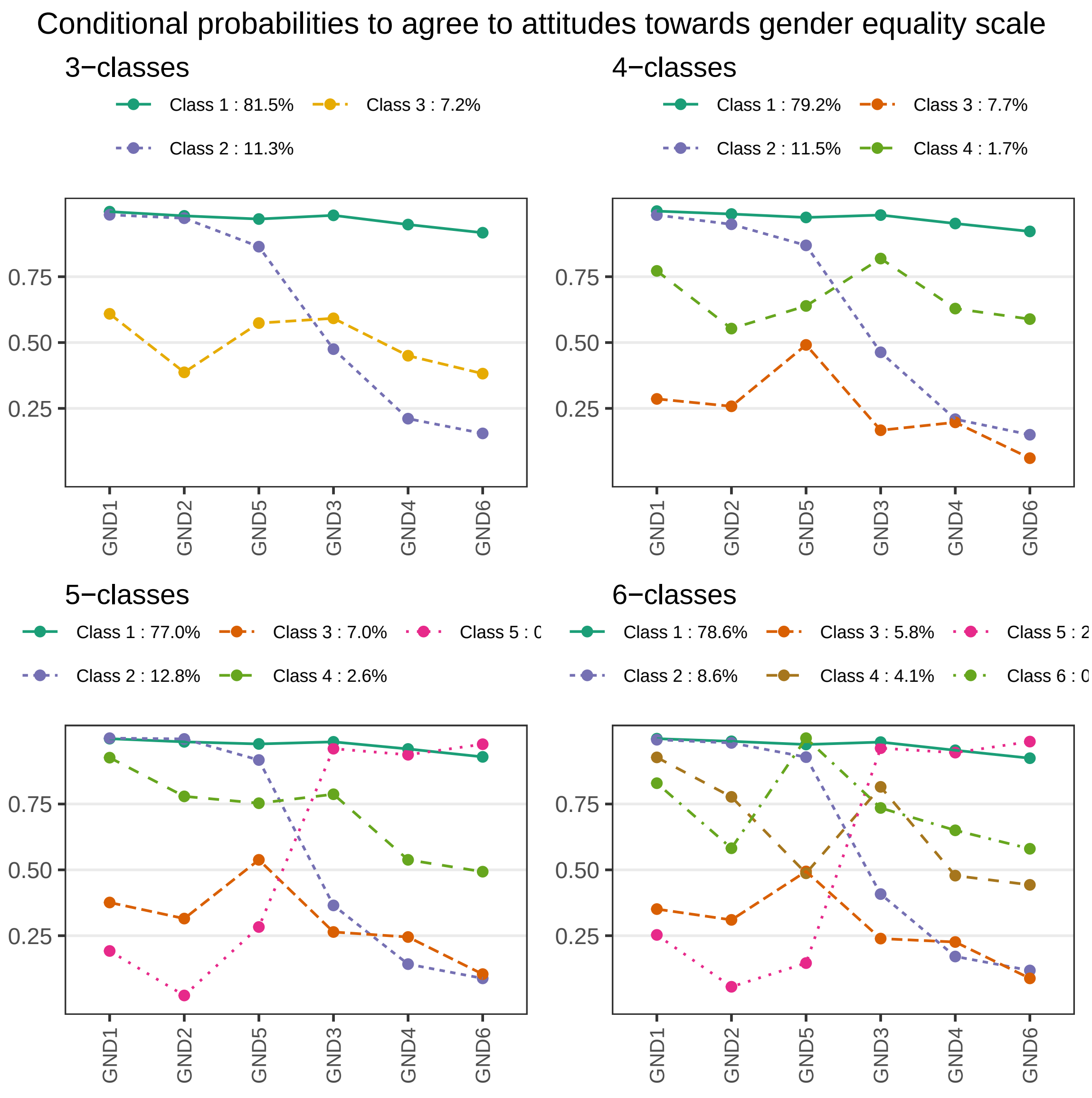


Figure 3.4: Comparative 3 to 6 latent class models, Attitudes towards gender equality scale

The main two classes in the solutions with five and six classes does not strongly differ from other models, and the remaining classes are not informative at all or very small, using this as a criteria, one can prefer a four-class solution.

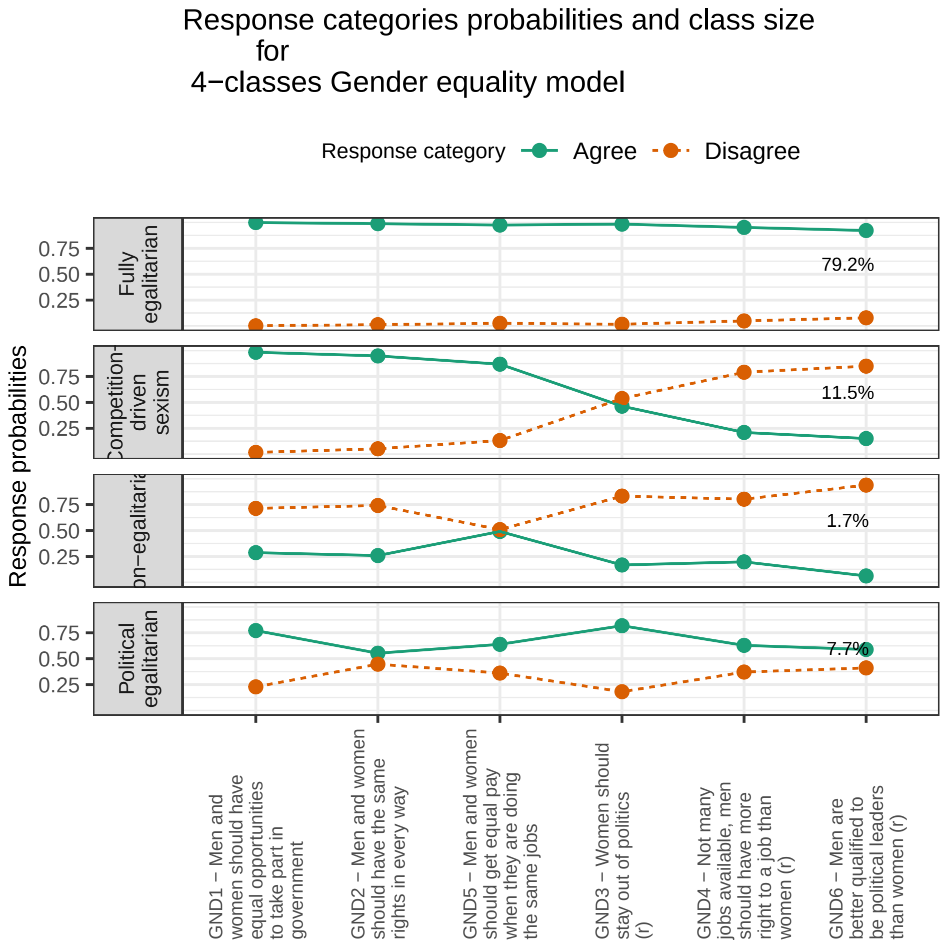
In table 3.4 the conditional probabilities to agree are shown. This values are very close to 1 in the first class, Fully egalitarian. Similar values are obtained for the positive items in the second class Competition driven-sexism, third item GND3 conditional probabilities are close to 0.5, this would mean a random response, but last two items have lower conditional probabilities close to 0.2, that would mean not likely to agree to the statements.

Table 3.3: Probabilities to agree each item 4-class Gender equality model

param	Fully egalitarian	Competition-driven sexism	Non-egalitarian	Political egalitarian
GND1 - Men and women should have equal opportunities to take part in government	0.999	0.984	0.286	0.772
GND2 - Men and women should have the same rights in every way	0.988	0.949	0.258	0.553
GND5 - Men and women should get equal pay when they are doing the same jobs	0.975	0.869	0.491	0.639
GND3 - Women should stay out of politics (r)	0.984	0.463	0.167	0.819
GND4 - Not many jobs available, men should have more right to a job than women (r)	0.952	0.209	0.197	0.629
GND6 - Men are better qualified to be political leaders than women (r)	0.922	0.15	0.061	0.589

Table 3.4: Class sizes 4-class Gender equality model

	Model estimated		Most likely	
Class	Counts	Proportion	Counts	Proportion
Fully egalitarian	39924.2	79.2%	41508	82.3%
Competition- driven sexism	5782.2	11.5%	5258	10.4%
Political egalitarian	3864.7	7.7%	2969	5.9%
Non-egalitarian	859.9	1.7%	696	1.4%



Response categories probabilities and class size for 4−classes Gender equality model
Response category
Agree
Disagree
Response probabilities
0.75
0.50
0.25
Fully egalitarian
79.2%
Competition-driven sexism
11.5%
1.7%
Political egalitarian
7.7%
GND1 – Men and women should have equal opportunities to take part in government
GND2 – Men and women should have the same rights in every way
GND5 – Men and women should get equal pay when they are doing the same jobs
GND3 – Women should stay out of politics (r)
GND4 – Not many jobs available, men should have more right to a job than women (r)
GND6 – Men are better qualified to be political leaders than women (r)

3.1.3 Country comparability

For evaluate the country comparability, the classes that were found in the independent model were identify to later check how many of them could be tested for comparability using a multigroup latent class model.

- 3-class model:

1. Fully egalitarian - ALL COUNTRIES
2. Competition-driven sexism - ALL COUNTRIES
3. Random response - BGR, LVA, LTU, MLT

- 4-class model:

1. Fully egalitarian - ALL COUNTRIES
2. Competition-driven sexism - ALL COUNTRIES
3. Non-egalitarian - HRV, DNK, EST, FIN, ITA, NOR, SLV, SWE
4. Political egalitarian - BFL, DNK, EST, NOR, SWE

- 5-class model:

1. Fully egalitarian - ALL COUNTRIES
2. Competition-driven sexism - ALL COUNTRIES
3. Non-egalitarian - HRV, DNK, EST, FIN, ITA, NOR, SLV, SWE
4. Political egalitarian - BFL, DNK, EST, NOR, SWE
5. Reverse competition-driven sexism - BGR, MLT, NLD, NOR, SLV

- 6-class model:

1. Fully egalitarian - ALL COUNTRIES
2. Competition-driven sexism - ALL COUNTRIES
3. Non-egalitarian - HRV, DNK, EST, FIN, ITA, NOR, SLV, SWE
4. Political egalitarian - BFL, DNK, EST, NOR, SWE
5. Reverse competition-driven sexism - BGR, MLT, NLD, NOR, SLV
6. Pro-women pay/job - Not defined in individual models

With 3 classes, random response class is not very interpretable. With 6 classes, a new no identified class appears, not interpretable. With 5 classes, reverse competition-driven sexism class is present in 5 countries but with class sizes lower than 1%, not representative. With 4 classes, four main classes are identified across countries. Two of them are present in all countries. Best model for comparability. Two remaining classes can be freely estimated that variates in each country and/or with a class size of 0.

Country multigroup analysis

In table 3.5 different models with multigroup analysis are tested, first the more restricted model is evaluated, complete homogeneity. In this model all conditional and unconditional probabilities are fixed to be equal across the groups.
Then, the partial homogeneity is tested where only the conditional probabilities are constrained to be equal across the groups, and the class sizes are estimated freely. A second approach of partial homogeneity is tested, where only the conditional probabilities for the two common classes identified are constrained across groups, and the remaining are freely estimated along with the unconditional probabilities. Finally, the complete heterogeneous model is tested, where not only the unconditional probabilities are estimated freely but all the conditional probabilities as well. In the last two models the best log-likelihood is not replicated, this means that the solution may not be trustworthy due to local maxima. This results can not be considered as valid.

Just by looking at the valid results, the partial homogeneity where all conditional probabilities are constrained to be equal across groups show a better fit compared to the more restricted model, the complete homogeneity. With it is valid to indicate that the 4 classes identified do not share the same unconditional probabilities (class sizes) across the groups but the conditional probabilities can be considered as equal in all groups.

Table 3.5: Multigroup model fit statistics, Attitudes towards gender equality

Type	Ngroups	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	Δ LL	Δ DF	pvalue
4-classes											
Complete homogeneity	14	40	*-215414*	430907	431260	431133	*94.0%*	-1.49%	-3158	-348	0.
Partial homogeneity all classes	**14**	**79**	**-213195**	**426549**	***427246***	**426995**	**88.1%**	**-0.44%**	**-940**	**-308**	**0.0**
Partial homogeneity 2 classes	14	223	-212710	425866	427834	427126	85.6%	-0.21%	-454	-168	0.
Partial homogeneity 2 classes	14	235	-212462	425395	427470	*426723*	93.6%	-0.10%	-207	-152	0.
Complete heterogeneity	14	391	-212256	*425293*	428745	427502	*94.0%*	*0.00%*	0	0	

Note:

The best loglikelihood value was not replicated for the following models:

[1] Partial homogeneity 2 classes with constrains;

[2] Partial homogeneity 2 classes;

[3] Complete heterogeneity;

Figure 3.5 indicates the values for the patterns with the conditional probabililities fixed in all countries, but also the unconditional probabilities are constrained to be equal in all groups. Here can be observed that the patterns are similar to the ones identified in the independent models and the global model as well. But by constraining the classes sizes the model fit is not optimal.

In the figure 3.6, partial homogeneity constrained the conditional probabilities to be equal but not the unconditional probabilities, with this the model fit improves compared to the complete homogeneous model.

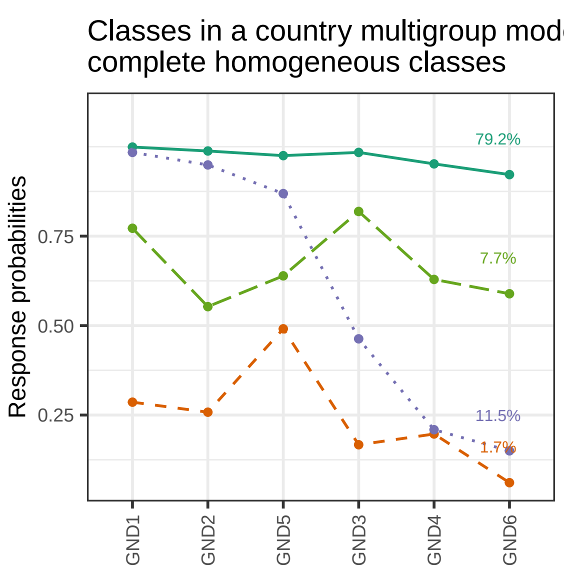


Figure 3.5: Conditional probabilities to agree in a complete homogeneous multigroup model, Gender equality scale

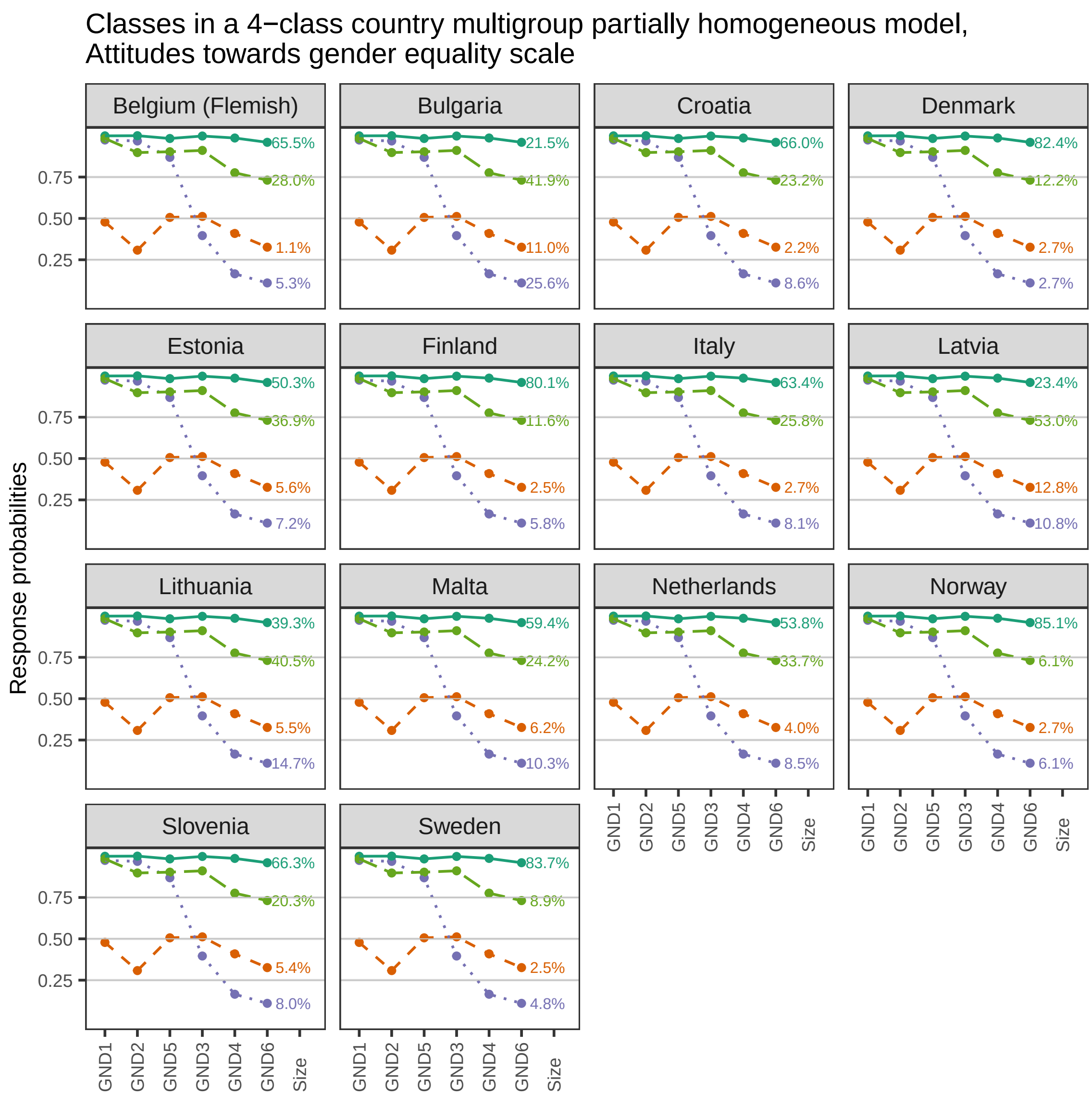


Figure 3.6: Conditional probabilities to agree in a partial homogeneous multigroup model, Gender equality scale

3.1.4 Confirmatory Latent Class Analysis

The confirmatory model was performed by establishing some constrained based on the previous research. For the attitudes towards gender equality scale the hypothesis was that the conditional probabilities for the the first item in the first class Fully egalitarian, is 1 and the probabilities to agree to the second and third items in the same class are equal to the probabilities of the first item in the second class. The third hypothesis is that the conditional probability of the third item in the second class is 0.5. The rest of the conditional probabilities were estimated freely.

In table 3.6 the model fit statistics of this model do not differ considerable from the exploratory approach analysed previously, only the AIC value is better in the exploratory model.

Table 3.6: Model fit statistics Confirmatory LCA attitudes towards gender equality scale

Type	N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction
All countries								
Exploratory LCA	4	27	-82327	*164708*	164946	164861	*82.7%*	
Confirmatory LCA	4	23	*-82340*	164726	*164929*	*164856*	82.5%	*0.0%*

Table 3.7: Thresholds 4-class Confirmatory LCA Gender equality scale

Parameter	Fully egalitarian	Competition-driven sexism	Non-egalitarian	Political egalitarian
GND1$1	15.000	4.228	-0.867	1.099
GND2$1	4.228	2.777	-0.983	0.211
GND5$1	3.668	1.852	-0.021	0.568
GND3$1	4.228	0.000	-1.507	1.494
GND4$1	3.014	-1.217	-1.419	0.595
GND6$1	2.488	-1.604	-2.806	0.442
Means	2.404	0.541	-1.390	

Table 3.8: Class sizes 4-class Gender equality model

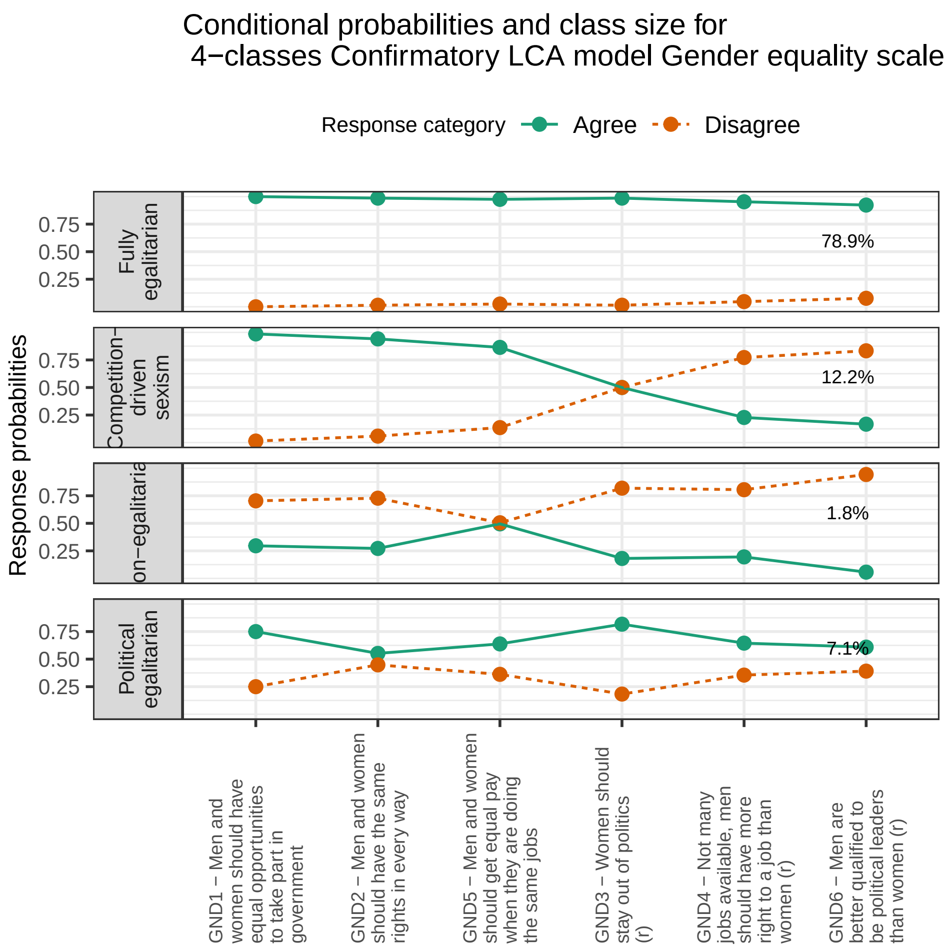
	Model estimated		Most likely	
Class	Counts	Proportion	Counts	Proportion
Fully egalitarian	39769.2	78.9%	41486	82.3%
Competition- driven sexism	6172.5	12.2%	5476	10.9%
Political egalitarian	3593.9	7.1%	2699	5.4%

Table 3.8: Class sizes 4-class Gender equality model *(continued)*

Class	Counts	Proportion	Counts	Proportion
Non-egalitarian	895.4	1.8%	770	1.5%

Table 3.9: Probabilities to agree each item 4-class Confirmatory LCA Gender equality scale

param	Fully egalitarian	Competition-driven sexism	Non-egalitarian	Political egalitarian
GND1 - Men and women should have equal opportunities to take part in government	1	0.986	0.296	0.75
GND2 - Men and women should have the same rights in every way	0.986	0.941	0.272	0.552
GND5 - Men and women should get equal pay when they are doing the same jobs	0.975	0.864	0.495	0.638
GND3 - Women should stay out of politics (r)	0.986	0.5	0.181	0.817
GND4 - Not many jobs available, men should have more right to a job than women (r)	0.953	0.228	0.195	0.645
GND6 - Men are better qualified to be political leaders than women (r)	0.923	0.167	0.057	0.609



Conditional probabilities and class size for
4−classes Confirmatory LCA model Gender equality scale
Response category
Agree
Disagree
Response probabilities
0.75
0.50
0.25
Fully egalitarian
78.9%
Competition−driven sexism
12.2%
on−egalitaria
1.8%
Political egalitarian
7.1%
GND1 − Men and women should have equal opportunities to take part in government
GND2 − Men and women should have the same rights in every way
GND5 − Men and women should get equal pay when they are doing the same jobs
GND3 − Women should stay out of politics (r)
GND4 − Not many jobs available, men should have more right to a job than women (r)
GND6 − Men are better qualified to be political leaders than women (r)

3.2 Ethnic and race scale

This scale is composed by 5 items, in the following results, this items were ordered in the output for a easier interpretation of the results. This ordering consider first ll ethnic and racial groups should have equal chance to get good education (ETH1), All ethnic and racial groups should have an equal chance to get good jobs (ETH2), All ethnic and racial groups should have same rights and responsibilities (ETH5), and All ethnic and racial groups schools should teach students to respect (ETH3), followed by All ethnic and racial groups should be encouraged to run in elections (ETH4). As mentioned before all these variables were recoded in two categories, as Agree and Disagree. All 14 countries were analysed independently and then pooled in the same dataset.

3.2.1 Analysis by country

A latent class analysis with 1 to 6-class models were performed in each country in order to evaluate the model fit of each one of them. The results are summarized in table 3.10. In most European countries, the best model fit based on the different criteria indicated previously are by including 3 or 4 latent classes.

For Belgium, Bulgaria, Estonia, Italy, Lithuania, Latvia, Slovenia, Netherlands, Norway, Slovenia and Sweden according to the statistical tests, BIC, and aBIC criteria, the best model is a 3-class model.

On the other hand, Denmark and Malta have a better model fit in a 4-class model, consistently results between statistical test and BIC criteria.

In Croatia models, tests indicate that a 2-class model is better for their data, even though BIC indicates a 3-class model to have the lowest value.

Norway is the only country from the sample that the best model fit is the one with5 latent classes according to the statistical tests and BIC and aBIC.

It is a common tendency in all the evaluated countries the AIC value is lower in the models with one more class than the indicated by the statistical tests and BIC and aBIC. Which is consistent with the indication that this criteria tends to overfit the data.Values of Entropy are higher when the tests are significant, but consistent with a better fit of the data the lower entropy found in the 3-class model is in Belgium (60.5%)and the highest value in Sweden (90.2%). The log likelihood reduction is consistent in all countries, where having more than 3 latent classes reduce the log likelihood around 0.1% and 0.6%.

Table 3.10: Model fit statistics LCA by country Attitudes towards ethnic and race equal rights scale

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
Belgium (Flemish)											
1	5	*-4321*	8653	8683	8667						
2	11	-4051	8123	8189	8154	85.1%	*6.3%*	542	0	530	0
3	**17**	**-4019**	**8072**	***8174***	***8120***	**60.5%**	**0.8%**	**63**	**0.021**	**62**	**0.023**
4	23	-4011	*8068*	8205	8132	61.8%	0.2%	*16*	*0.231*	*16*	*0.235*
5	29	-4009	8076	8249	8157	60.9%	0.1%	*4*	*0.451*	*4*	*0.453*
6	35	-4008	8086	8295	8184	*88.2%*	0.0%	*1*	*0.627*	*1*	*0.627*
Bulgaria											
1	5	*-6406*	12822	12852	12836						
2	11	-5451	10923	10989	10954	84.7%	*14.9%*	1910	0	1871	0
3	**17**	**-5354**	**10742**	***10843***	**10789**	**78.5%**	**1.8%**	**193**	**0**	**190**	**0**
4	23	-5335	10717	10854	*10781*	82.3%	0.3%	*37*	*0.192*	*36*	*0.198*
5	29	-5325	*10708*	10882	10790	*88.3%*	0.2%	*20*	*0.385*	*20*	*0.39*
6	35	-5322	10714	10923	10812	87.7%	0.1%	*6*	*0.506*	*6*	*0.508*
Denmark											
1	5	*-9787*	19585	19618	19602						
2	11	-8519	17061	17134	17099	86.9%	13.0%	2536	0	2488	0
3	17	-8309	16652	16766	16712	68.6%	*2.5%*	421	0	413	0
4	**23**	**-8282**	***16610***	***16764***	***16691***	**72.3%**	**0.3%**	***54***	***0.059***	***53***	***0.062***
5	29	-8280	16617	16811	16719	*88.2%*	0.0%	*5*	*0.583*	*5*	*0.584*
6	35	-8278	16625	16859	16748	84.8%	0.0%	*4*	*0.545*	*4*	*0.546*
Estonia											

Table 3.10: Model fit statistics LCA by country Attitudes towards ethnic and race equal rights scale *(continued)*

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
1	5	*-3577*	7165	7195	7179						
2	11	-3298	6618	6684	6649	82.8%	*7.8%*	559	0	547	0
3	**17**	**-3254**	**6543**	***6644***	***6590***	**69.8%**	**1.3%**	**87**	**0.002**	**86**	**0.002**
4	23	-3245	*6537*	6674	6601	74.9%	0.3%	*18*	*0.638*	*18*	*0.643*
5	29	-3243	6545	6717	6625	75.2%	0.1%	*4*	*0.344*	*4*	*0.345*
6	35	-3242	6553	6761	6650	*97.3%*	0.1%	*4*	*0.428*	*4*	*0.429*
Finland											
1	5	*-4186*	8382	8412	8396						
2	11	-3491	7003	7070	7035	88.9%	16.6%	1391	0	1363	0
3	**17**	**-3391**	**6815**	***6918***	**6864**	**80.8%**	***2.9%***	**200**	**0**	**196**	**0**
4	23	-3370	*6786*	6925	*6852*	87.3%	0.6%	41	0.008	40	0.009
5	29	-3365	6788	6964	6872	*93.6%*	0.1%	*9*	*0.367*	*9*	*0.372*
6	35	-3364	6797	7009	6898	88.0%	0.0%	*3*	*0.517*	*3*	*0.519*
Croatia											
1	5	*-5101*	10213	10244	10228						
2	11	-4548	9119	9188	9153	*87.6%*	*10.8%*	1106	0	1084	0
3	**17**	**-4507**	**9047**	***9153***	**9099**	**76.1%**	**0.9%**	***84***	***0.416***	***82***	***0.422***
4	23	-4491	9027	9171	*9098*	82.8%	0.4%	*32*	*0.126*	*31*	*0.128*
5	29	-4479	*9016*	9197	9105	79.0%	0.3%	*23*	*0.206*	*23*	*0.211*
6	35	-4478	9027	9246	9134	86.6%	0.0%	*1*	*0.618*	*1*	*0.618*
Italy											
1	5	*-5113*	10235	10266	10250						

Table 3.10: Model fit statistics LCA by country Attitudes towards ethnic and race equal rights scale *(continued)*

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
2	11	-4427	8876	8943	8909	85.8%	*13.4%*	1371	0	1344	0
3	**17**	**-4354**	**8742**	***8846***	**8792**	**81.1%**	**1.6%**	**146**	**0**	**143**	**0**
4	23	-4330	8706	8847	*8774*	81.6%	0.6%	*48*	*0.114*	*47*	*0.119*
5	29	-4319	*8696*	8874	8781	85.2%	0.3%	*22*	*0.082*	*22*	*0.086*
6	35	-4316	8702	8917	8806	*88.8%*	0.1%	*5*	*0.63*	*5*	*0.632*
Lithuania											
1	5	*-4822*	9654	9685	9669						
2	11	-4232	8486	8554	8519	87.9%	*12.2%*	1180	0	1156	0
3	**17**	**-4194**	**8423**	***8528***	***8474***	**84.8%**	**0.9%**	**75**	**0.016**	**74**	**0.017**
4	23	-4188	*8422*	8565	8492	88.9%	0.1%	*12*	*0.514*	*12*	*0.518*
5	29	-4183	8424	8603	8511	90.9%	0.1%	*11*	*0.498*	*10*	*0.501*
6	35	-4181	8433	8649	8538	*93.0%*	0.0%	*3*	*0.533*	*3*	*0.534*
Latvia											
1	5	*-5794*	11599	11629	11613						
2	11	-5416	10853	10920	10885	77.5%	*6.5%*	757	0	742	0
3	**17**	**-5353**	**10741**	***10844***	***10790***	**64.0%**	**1.1%**	**124**	**0.001**	**122**	**0.001**
4	23	-5341	10728	10867	10794	71.3%	0.2%	*25*	*0.357*	*24*	*0.362*
5	29	-5335	*10728*	10903	10811	78.5%	0.1%	*12*	*0.426*	*12*	*0.428*
6	35	-5333	10736	10948	10837	*87.8%*	0.0%	*3*	*0.592*	*3*	*0.593*
Malta											
1	5	*-6393*	12796	12827	12811						
2	11	-5798	11619	11687	11652	72.0%	*9.3%*	1189	0	1166	0

Table 3.10: Model fit statistics LCA by country Attitudes towards ethnic and race equal rights scale *(continued)*

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
3	17	-5730	11493	11599	11545	74.1%	1.2%	138	0.002	135	0.002
4	**23**	**-5691**	**11428**	***11570***	***11497***	**80.3%**	**0.7%**	**78**	**0.032**	**76**	**0.034**
5	29	-5684	*11425*	11605	11512	78.4%	0.1%	*15*	*0.381*	*14*	*0.385*
6	35	-5680	11429	11646	11535	*83.2%*	0.1%	*8*	*0.515*	*8*	*0.517*
Netherlands											
1	5	*-5359*	10727	10757	10741						
2	11	-4814	9650	9715	9680	*79.6%*	*10.2%*	1089	0	1067	0
3	**17**	**-4729**	**9493**	***9593***	***9539***	**69.7%**	**1.8%**	**170**	**0**	**166**	**0**
4	23	-4718	9482	9618	9545	73.8%	0.2%	*23*	*0.358*	*22*	*0.365*
5	29	-4711	*9480*	9651	9559	77.6%	0.2%	*14*	*0.548*	*14*	*0.552*
6	35	-4709	9487	9695	9583	77.7%	0.0%	*4*	*0.483*	*4*	*0.484*
Norway											
1	5	*-7290*	14590	14623	14607						
2	11	-5551	11125	11199	11164	*94.7%*	*23.8%*	3477	0	3412	0
3	**17**	**-5448**	**10930**	***11044***	**10990**	**88.1%**	**1.9%**	**207**	**0**	**203**	**0**
4	23	-5426	*10897*	11052	*10978*	90.0%	0.4%	*45*	*0.057*	*44*	*0.06*
5	29	-5421	10900	11094	11002	91.2%	0.1%	*9*	*0.773*	*9*	*0.775*
6	35	-5419	10908	11143	11031	92.2%	0.0%	*4*	*0.293*	*4*	*0.294*
Slovenia											
1	5	*-4916*	9841	9871	9855						
2	11	-4315	8652	8718	8683	*86.7%*	*12.2%*	1201	0	1176	0
3	**17**	**-4272**	**8578**	***8679***	**8625**	**77.5%**	**1.0%**	**87**	**0.027**	**85**	**0.029**

Table 3.10: Model fit statistics LCA by country Attitudes towards ethnic and race equal rights scale *(continued)*

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
4	23	-4255	8556	8693	*8620*	83.9%	0.4%	*34*	*0.101*	*33*	*0.105*
5	29	-4248	*8555*	8727	8635	81.3%	0.2%	*13*	*0.388*	*13*	*0.393*
6	35	-4246	8563	8771	8660	85.7%	0.0%	*4*	*0.541*	*4*	*0.543*
Sweden											
1	5	*-3175*	6360	6390	6374						
2	11	-2379	4780	4847	4812	*95.8%*	25.1%	1592	0	1560	0
3	**17**	**-2306**	**4646**	***4749***	***4695***	**90.2%**	***3.1%***	**147**	**0.011**	**144**	**0.012**
4	23	-2299	4643	4783	4710	92.4%	0.3%	*14*	*0.427*	*14*	*0.43*
5	29	-2292	*4642*	4818	4726	93.2%	0.3%	*13*	*0.432*	*13*	*0.434*
6	35	-2291	4651	4863	4752	95.2%	0.1%	*3*	*0.543*	*3*	*0.543*

Note:

The best loglikelihood value was not replicated for the following models

[1] Denmark - 6-classes complete heterogeneity;

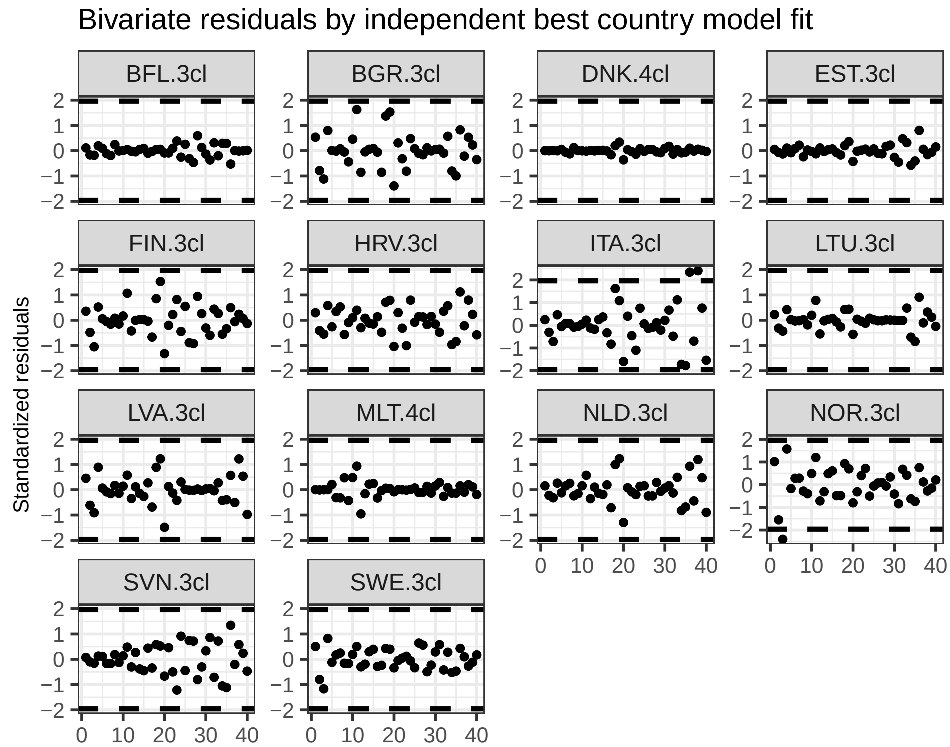


Figure 3.7: Bivariate model fit standardized residuals Ethnic and race equal rights scale

In figure 3.8 the classes of each independent model can be identify. In the figure, the conditional probabilities for agree to each item are shown and plotted for each of the classes modeled in each country. Here can be identified two classes that are similar in all the models, the green and purple line.

- Fully egalitarian: (green line)
  - Conditional probabilities greater than 0.7 to agree, class sizes around 61.8% (Latvia) and 90% (Sweden)
- Political non-egalitarian: (orange line)
  - Conditional probabilities to agree higher than 0.5 in all items but political item (< 0.5), class sizes around 7.6% (Denmark) and 36% (Latvia).
- Non-egalitarian: (purple line)
  - Conditional probabilities lower than 0.5 to agree all items, class sizes around 1.4% (Lithuania) and 5.4% (Bulgaria).
- Country specific class: (pink line)
  - Employment non-egalitarian: Class size 8.3% (Malta)
  - Strong political non-egalitarian: Class size 21.3% (Denmark).

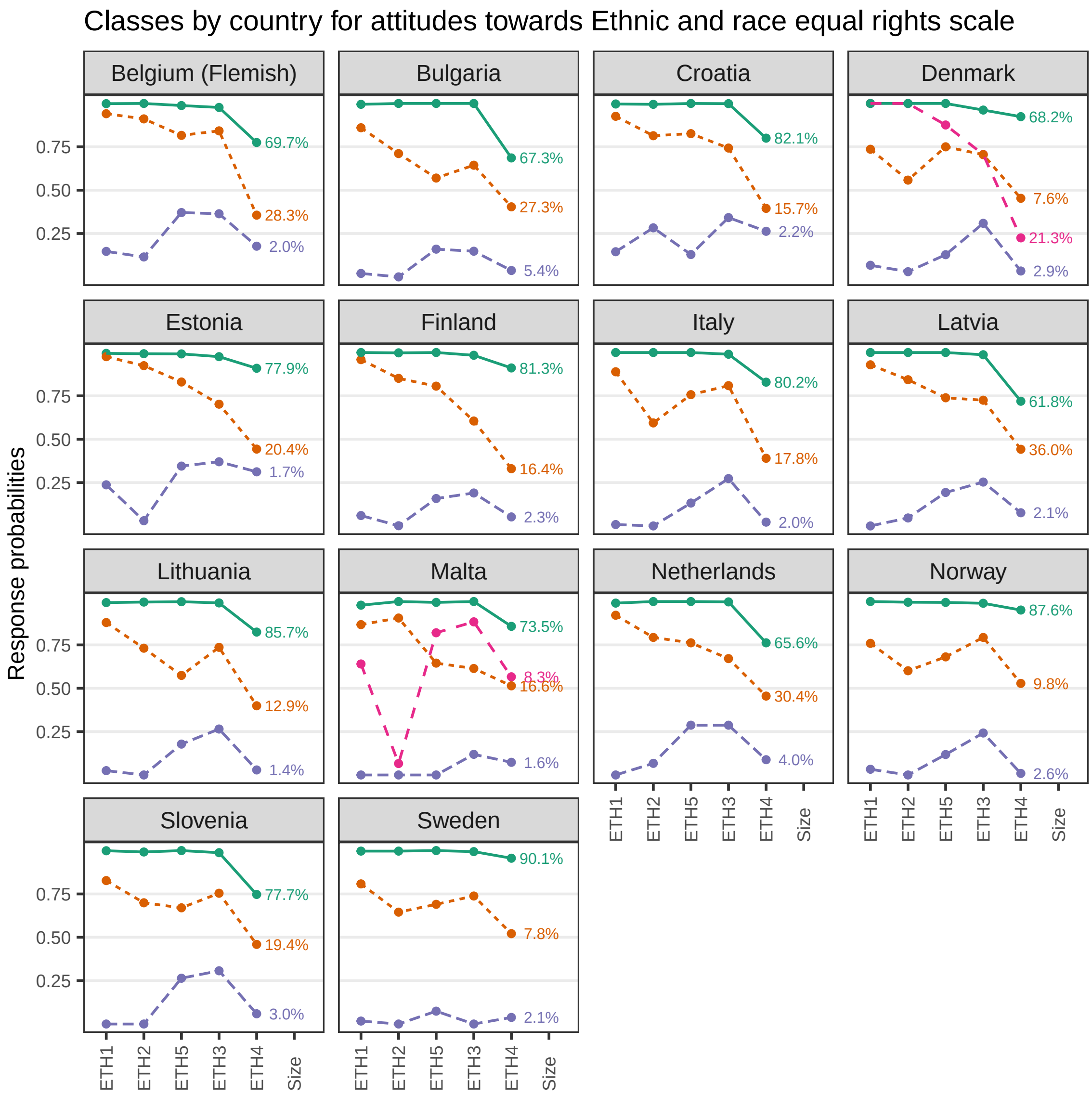


Figure 3.8: By country 3-Classes model

3.2.2 General model

The model with a single class has the largest AIC (159.379), BIC (159.423), and ABIC(159407) values for the European countries model in Table 3.11, indicating that this model fits data worse than all other models. In addition, the P-values of the VLMR test, and LMR in the 2-class model are all < 0.0001; this means that both tests reject the single-class model in favor of a model with at least two latent classes. In other words, there exists heterogeneity in the target population in regard to attitudes towards gender equality.

In the 6-class model, the LMR LR and VLMR are not statistically significant (P > 0.05). That is, the two tests are in favor of at most 5 classes. In contrast, AIC, BIC and aBIC values are all smaller in the 5-class model than those in the 6-class model; thus consider that the models with more than 5 classes are not preferred. The relative entropy given by Mplus software, decrease when including more than 4 classes and increase again with the 6-class model, this would suggest that a model with at least 6 class or 4 classes is preferred. Together with the percentage of reduction in the log likelihood value, that indicate that by adding two classes to the model the log-likelihood is reduced in a 12.1%, this reduction is only increased in 1.5% if the model is a 3-class model and finally this value is reduced close to 0 if more than 5 classes are included.

Now, the preferred model must be either the 4-class or higher model considering the residuals of each model in figure 3.9, where all values are around -1.96 and 1.96. Theoretically we tend to determine that the 4-class LCA model is the preferred model. We will show later that the classes identified by the 4-class model are more interpretable and representatives than the rest of the models. And in particularly that 3-classes can be compared across countries.

Table 3.11: Model fit statistics LCA attitudes towards ethnic and race equal rights scale

N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	VLMR 2*LL Dif	VLMR PValue	LMR Value	LMR PValue
All countries											
1	5	*-79684*	159379	159423	159407						
2	11	-70046	140115	140212	140177	*84.7%*	*12.1%*	19276	0	18984	0
3	**17**	**-68984**	**138003**	**138153**	**138099**	**75.4%**	**1.5%**	**2124**	**0**	**2091**	**0**
4	**23**	**-68807**	**137660**	**137863**	**137790**	**77.5%**	**0.3%**	**355**	**0**	**350**	**0**
5	29	-68755	*137568*	*137824*	*137732*	74.0%	0.1%	104	0	102	0
6	35	-68754	137578	137887	137775	80.8%	0.0%	*2*	*0.541*	*2*	*0.542*
7	41	-68754	137589	137951	137821	82.0%	0.0%	*1*	*0.528*	*1*	*0.528*

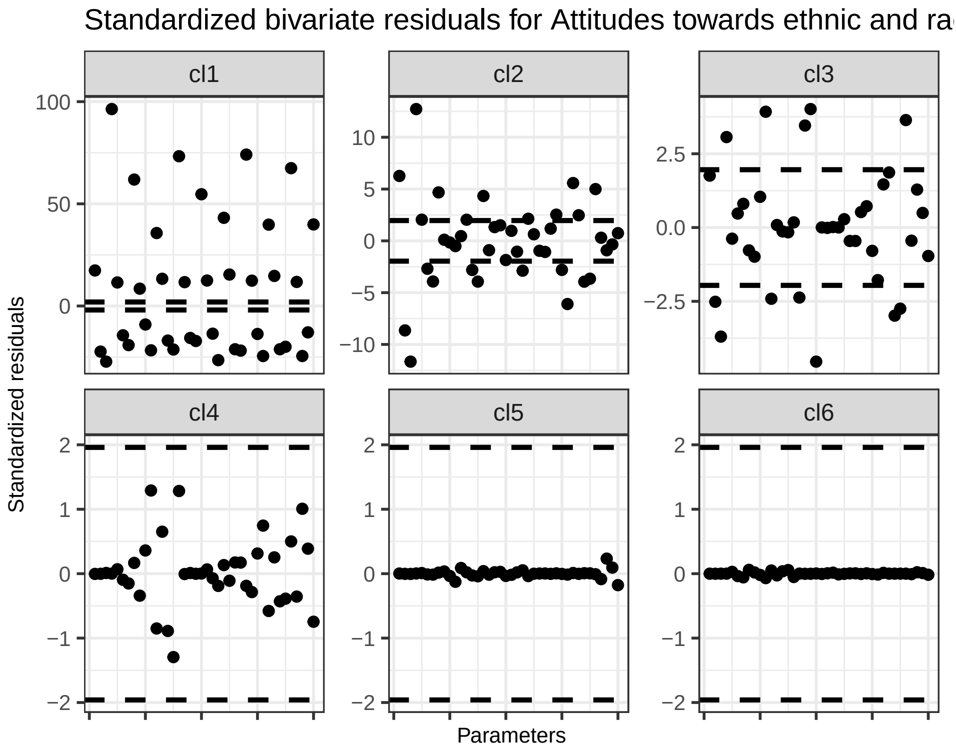


Figure 3.9: Bivariate model fit standardized residuals, ethnic and race equal rights scale

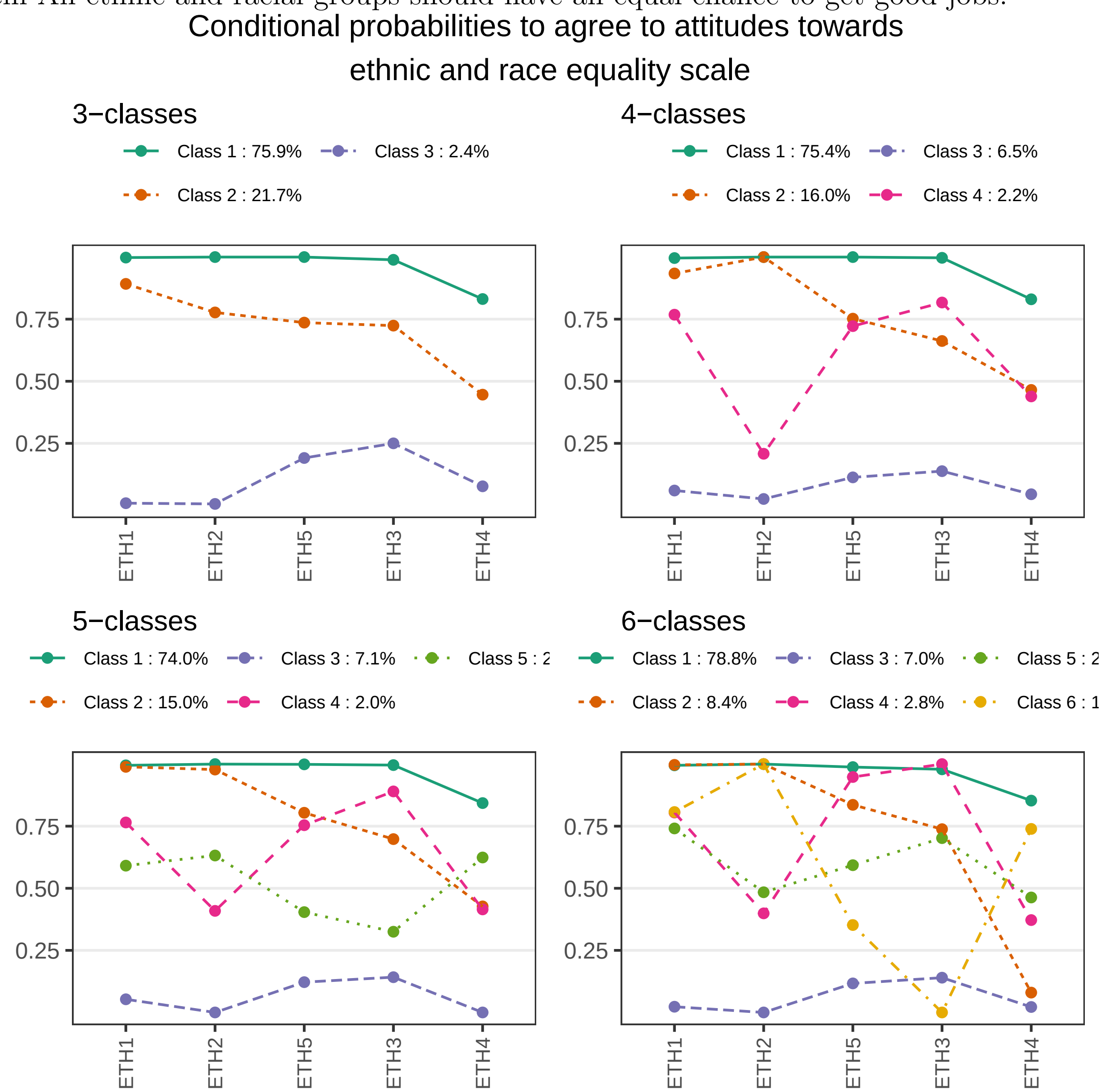
3-6 classes models

Three, four, five and six classes model were investigated profoundly. It is clear that is not easy to choose the best model fit without doing a full analysis. There are some pattern that can be clearly identify in all the models, Class 1 with 75.9%, 75.4%, 74% and 78.8% in each model respectively, the estimated probabilities to agree for this latent class, the **Fully egalitarian** group, for all four first items are higher than 0.99 and 0.83 for the item All ethnic and racial groups should be encouraged to run in elections.

The second class (Class 2 in figures in **??**) identified in all the models, called **Political non-egalitarian**. For this class, the estimated probabilities to agree to the first 2 items are higher than 0.93 in all models. For the next two items, the estimated probabilities to agree are around 0.66 and 0.75 in all models and for the last item probabilities decrease to 0.5. The class size differ in all four models, 21.7%, 16%, 15% and 8.4% in the 3, 4, 5, 6-class model respectively.

The third class that can seen with a similar pattern in all the models is called **Non-egalitarian**, this class appears from the 3-class model on. The pattern of this class is basically showing lower estimated conditional probabilities to agree to any of these statements, no greater than 0.13. The estimated sizes for this class are 2.4%, 6.5%, 7.1% and 7% in each model respectively.

The fifth and sixth class identify in the models differ in all the models, nevertheless, one class appears to be consistent in the 5-class model, where this class called Employment non-egalitarian has low conditional probabilities to agree (0.2) to the item All ethnic and racial groups should have an equal chance to get good jobs.



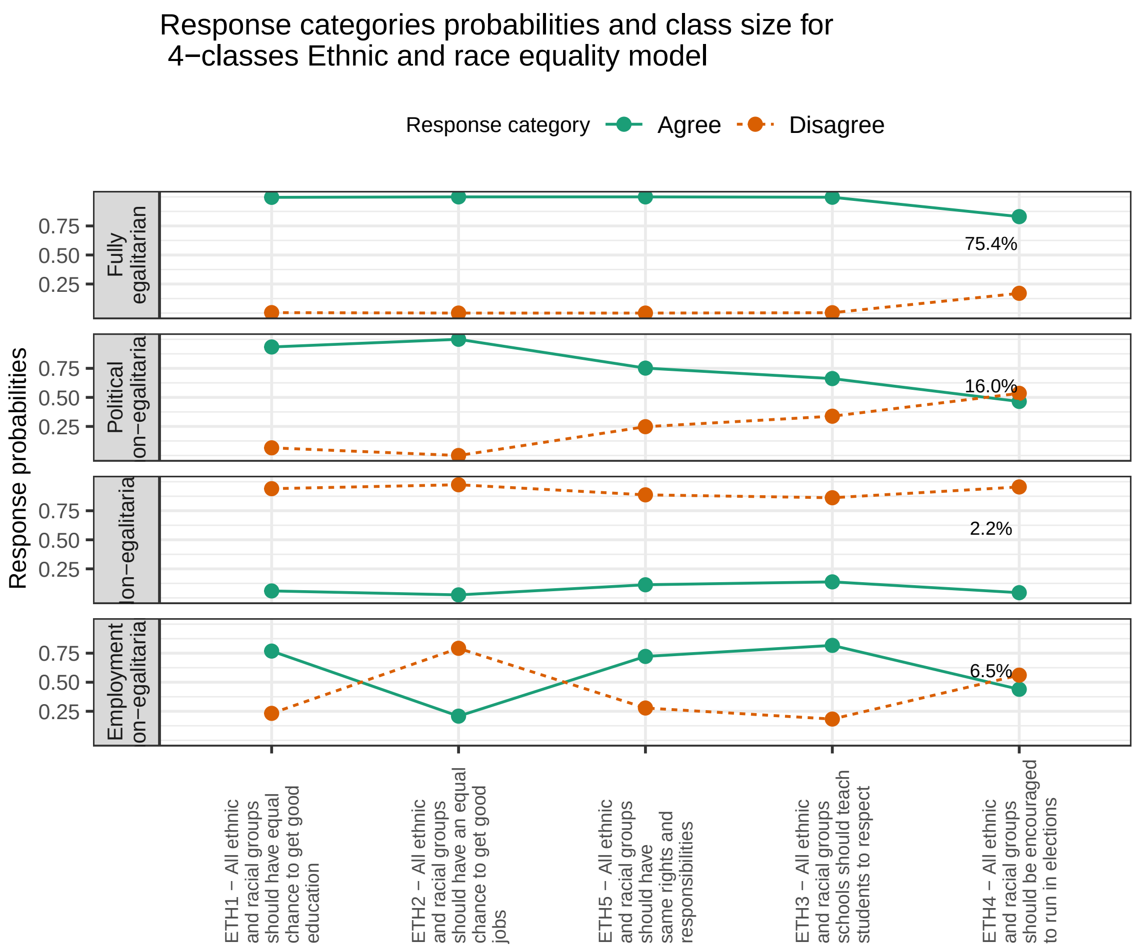
The main three classes in the solutions with three, four and five classes does not strongly differ from other models, and the remaining classes are not informative at all or very small, using this as a criteria, one can prefer a four-class solution. In table @ref(tab:bestfit2_1) the conditional probabilities to agree are shown. This values are very close to 1 in the first class, Fully egalitarian. Similar values are obtained for first two items in the second class Political non-egalitarian, next three item start decreasing the conditional probability to agree from 0.76 to 0.46. Class sizes shown in @ref(tab:bestfit2_2) indicates that proportions of unconditional probabilities even though are not exactly the same, there are similar values among the Model estimated and Most likely classification.

Table 3.12: Probabilities to agree each item 4-class Ethnic and race equality model

param	Fully egalitarian	Political non-egalitarian	Non-egalitarian	Employment non-egalitarian
ETH1 - All ethnic and racial groups should have equal chance to get good education	0.996	0.934	0.06	0.768
ETH2 - All ethnic and racial groups should have an equal chance to get good jobs	1	1	0.026	0.208
ETH5 - All ethnic and racial groups should have same rights and responsibilities	1	0.752	0.113	0.722
ETH3 - All ethnic and racial groups schools should teach students to respect	0.997	0.662	0.138	0.817
ETH4 - All ethnic and racial groups should be encouraged to run in elections	0.83	0.465	0.045	0.439

Table 3.13: Class sizes 4-class Ethnic and race equality model

	Model estimated		Most likely	
Class	Counts	Proportion	Counts	Proportion
Fully egalitarian	37774.4	75.4%	41600	83.0%
Political non-egalitarian	8014.1	16.0%	4902	9.8%
Employment non-egalitarian	3257.5	6.5%	2521	5.0%
Non-egalitarian	1080.1	2.2%	1103	2.2%


Response categories probabilities and class size for
4−classes Ethnic and race equality model
Response category
Agree
Disagree
Response probabilities
0.75
0.50
0.25
Fully egalitarian
75.4%
Political on−egalitaria
16.0%
lon−egalitaria
2.2%
Employment on−egalitaria
6.5%
ETH1 − All ethnic and racial groups should have equal chance to get good education
ETH2 − All ethnic and racial groups should have an equal chance to get good jobs
ETH5 − All ethnic and racial groups should have same rights and responsibilities
ETH3 − All ethnic and racial groups schools should teach students to respect
ETH4 − All ethnic and racial groups should be encouraged to run in elections

3.2.3 Country comparability

To evaluate the country comparability, the classes that were found in the independent models were identify to later check how many of them could be tested for comparability using a multigroup latent class model.

- 3-class model:

1. Fully egalitarian: ALL COUNTRIES
2. Political non-egalitarian: ALL COUNTRIES
3. Non-egalitarian: ALL COUNTRIES

- 4-class model:

1. Fully egalitarian: ALL COUNTRIES
2. Political non-egalitarian: ALL COUNTRIES
3. Non-egalitarian: ALL COUNTRIES
4. Employment non-egalitarian: MLT

- 5-class model:

1. Fully egalitarian: ALL COUNTRIES
2. Political non-egalitarian: ALL COUNTRIES
3. Non-egalitarian: ALL COUNTRIES
4. Employment non-egalitarian: MLT
5. Random response: Not identified in individual models

With 3 classes, all classes are very interpretable. With 5 classes, a random response class is identified, which is not interpretable. With 4 classes, Employment non-egalitarian class is present in just one country, which is not representative.

With a 4-classes model, three main classes are identified across countries. All of them are present in all countries. Best model for comparability. One remaining class can be freely estimated that variates in each country and/or with a class size of 0.

Country multigroup analysis

In table 3.14 different models with multigroup analysis are tested, first the more restricted model is evaluated, complete homogeneity. In this model all conditional and unconditional probabilities are fixed to be equal across the groups. Then, the partial homogeneity is tested where only the conditional probabilities are constrained to be equal across the groups, and the class sizes are estimated freely.

A second approach of partial homogeneity is tested, where only the conditional probabilities for the three common classes identified are constrained across groups, and the remaining are freely estimated along with the unconditional probabilities.

Finally, the complete heterogeneous model is tested, where not only the unconditional probabilities are estimated freely but all the conditional probabilities as well. In the last two models the best log-likelihood is not replicated, this means that the solution may not be trustworthy due to local maxima. This results can not be considered as valid.

Just by looking at the valid results, the partial homogeneity where all conditional probabilities are constrained to be equal across groups show a better fit compared to the more restricted model, the complete homogeneity. With it is valid to indicate that the 4 classes identified do not share the same unconditional probabilities (class sizes) across the groups but the conditional probabilities can be considered as equal in all groups.

Table 3.14: Country multigroup model Ethnic and race rights equality fit statistics

Type	Ngroups	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction	Δ LL	Δ DF	pvalue
4-classes											
Complete homogeneity	14	36	*-201088*	402248	402566	402451	92.2%	-1.20%	-2383	-299	
Partial homogeneity all classes	**14**	**75**	**-199422**	**398994**	***399656***	***399418***	**88.9%**	**-0.36%**	**-717**	**-261**	
Complete heterogeneity	14	335	-198705	*398081*	401036	399972	*93.2%*	*0.00%*	0	0	

Notes:
The best loglikelihood value was not replicated for the following models
[1] 4-classes complete heterogeneity;

Figure 3.10 indicates the values for the patterns with the conditional probabilities fixed in all countries, but also the unconditional probabilities are constrained to be equal in all groups. Here can be observed that the patterns are similar to the ones identified in the independent models and the global model as well. But by constraining the classes sizes the model fit is not optimal.

In the figure 3.11, partial homogeneity constrained the conditional probabilities to be equal but not the unconditional probabilities, with this the model fit improves compared to the complete homogeneous model and lower values for BIC and aBIC are obtained.

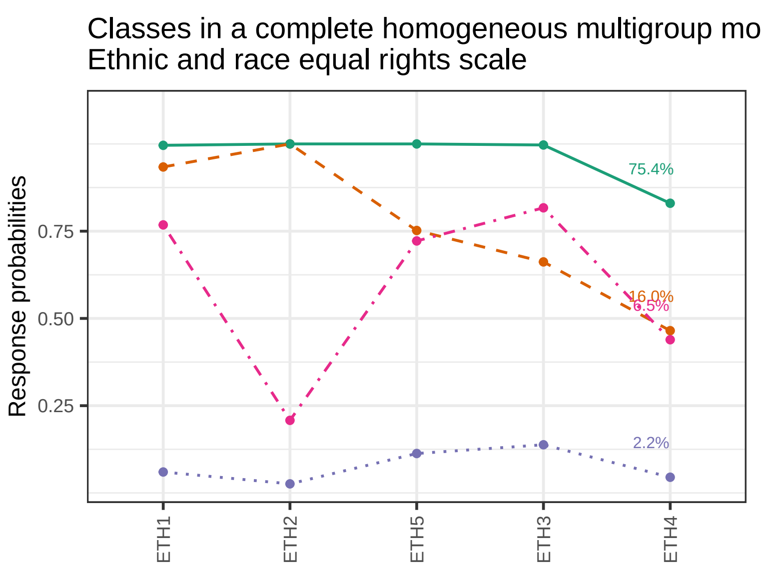


Figure 3.10: Conditional probabilities to agree in a complete homogeneous multigroup model, Ethnic and race equal rights scale

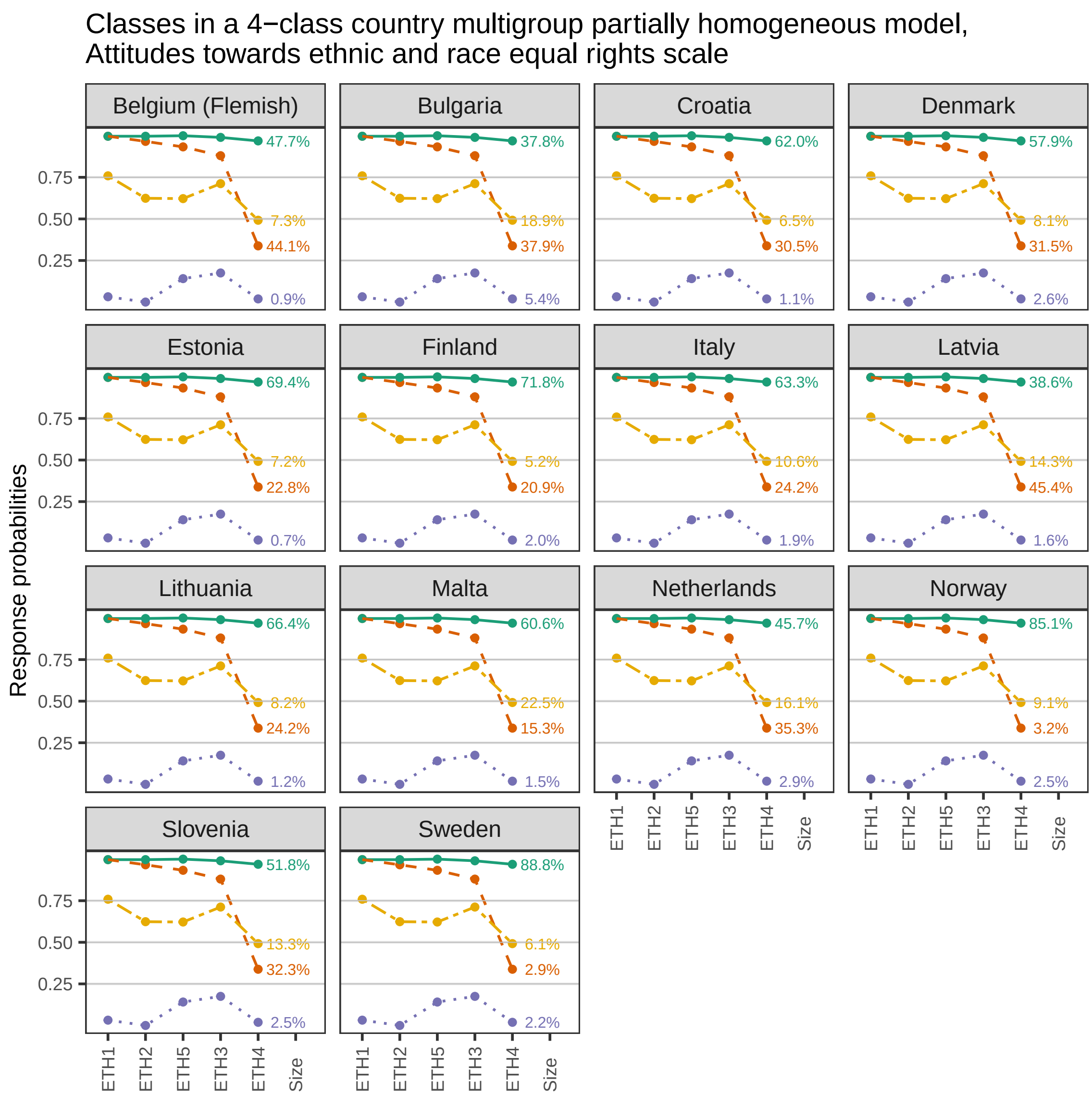


Figure 3.11: Conditional probabilities to agree in a partial homogeneous multigroup model, Ethnic and race equal rights scale

3.2.4 Confirmatory Latent Class Analysis

The confirmatory model was performed by establishing some constrained based on the previous research. For the attitudes towards ethnic and race equal rights scale, two hypothesis were tested.

First, was that the conditional probabilities for the first latent class Fully egalitarian, are the opposite to the ones in the third class Non-egalitarian. The second was that the first two conditional probabilities are equal in Class 1 and Class 2.

The rest of the conditional probabilities were estimated freely. In table 3.15 the model fit statistics of this model do not differ considerable from the exploratory approach analysed previously.

Table 3.15: Model fit statistics Confirmatory LCA attitudes towards Ethnic and race equal rights scale

Type	N Latent Classes	Param	Log-Likelihood	AIC	BIC	aBIC	Entropy	LL Reduction
All countries								
Exploratory LCA	4	23	-68807	*137660*	*137863*	*137790*	*77.5%*	
Confirmatory LCA	4	16	*-68911*	137854	137995	137945	73.0%	*-0.2%*

Table 3.16: Thresholds 4-class Confirmatory LCA Ethnic and race equal rights scale

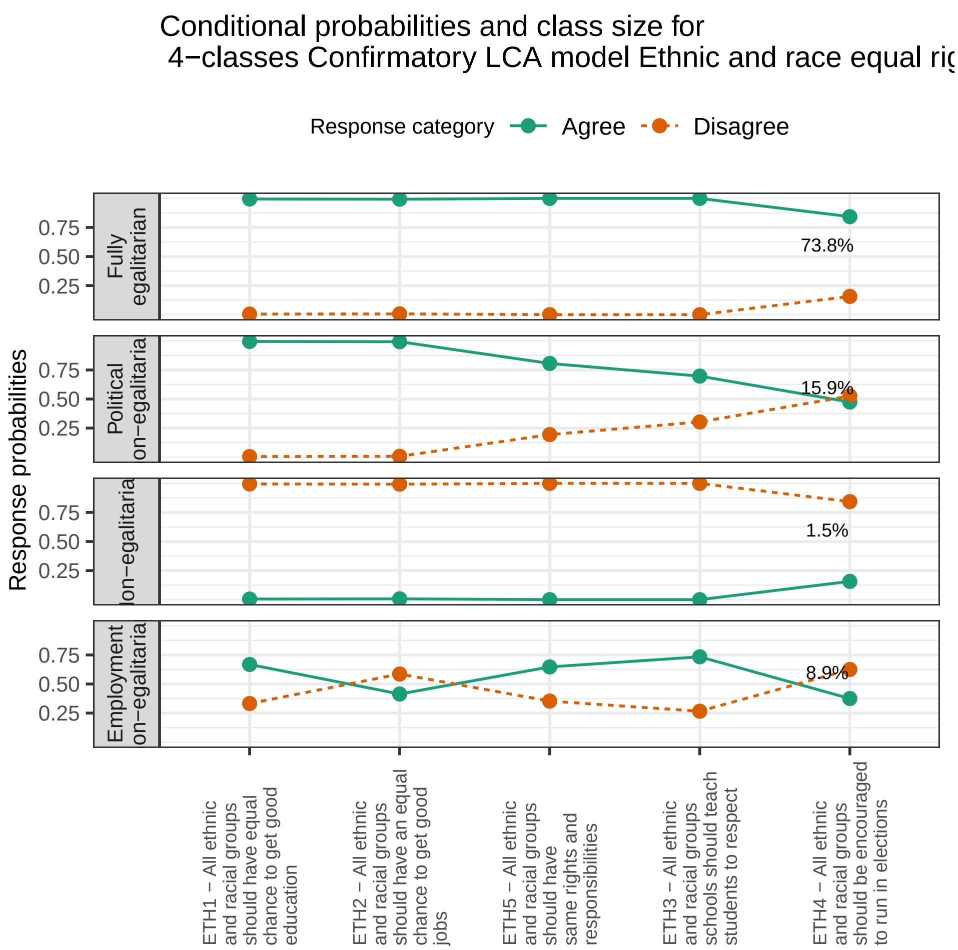
Parameter	Fully egalitarian	Political non-egalitarian	Non-egalitarian	Employment non-egalitarian
ETH1$1	5.265	5.265	-5.265	0.699
ETH2$1	5.026	5.026	-5.026	-0.346
ETH5$1	24.196	1.424	-24.196	0.606
ETH3$1	17.167	0.831	-17.167	1.016
ETH4$1	1.678	-0.102	-1.678	-0.509
Means	2.112	0.576	-1.815	

Table 3.17: Class sizes 4-class Ethnic and race equal rights model

	Model estimated		Most likely	
Class	Counts	Proportion	Counts	Proportion
Fully egalitarian	36968.5	73.8%	41874	83.5%
Political non-egalitarian	7955.2	15.9%	4053	8.1%
Employment non-egalitarian	4474.0	8.9%	3420	6.8%
Non-egalitarian	728.3	1.5%	778	1.6%

Table 3.18: Probabilities to agree each item 4-class Confirmatory LCA Ethnic and race equal rights scale

param	Fully egalitarian	Political non-egalitarian	Non-egalitarian	Employment non-egalitarian
ETH1 - All ethnic and racial groups should have equal chance to get good education	0.995	0.995	0.005	0.668
ETH2 - All ethnic and racial groups should have an equal chance to get good jobs	0.993	0.993	0.007	0.414
ETH5 - All ethnic and racial groups should have same rights and responsibilities	1	0.806	0	0.647
ETH3 - All ethnic and racial groups schools should teach students to respect	1	0.697	0	0.734
ETH4 - All ethnic and racial groups should be encouraged to run in elections	0.843	0.474	0.157	0.375



Conclusion

General

1. Comparability is not assured when we look at subpopulations patterns when analysing Large Scale Assessments.
2. A independent country analysis is the best strategy to identify common patterns in LSA scales.
3. Different country-specific subpopulations were found.
4. Some of the patterns are invariant across countries.

Attitudes towards gender equality

1. Fully egalitarian and Competition-driven sexism are the classes that can be compared across countries.

2. Neighboring countries can share some patterns.

3. Not clear if there is an impact of inverse worded items in these patterns, the relation with competition-driven sexism class could be forced by wording?.

Attitudes towards ethnic and race equal rights.

1. Fully egalitarian, Political non-egalitarian and Non-egalitarian are the classes that can be compared across countries.

2. Not many patterns are identify in every country (3-4).

Appendix A

Complementary tables

Table A.1: Countries sample sizes included in the analysis

Country	Sample size
Belgium (Flemish)	2931
Bulgaria	2966
Denmark	6254
Estonia	2857
Finland	3173
Croatia	3896
Italy	3450
Lithuania	3631
Latvia	3224
Malta	3764
Netherlands	2812
Norway	6271
Slovenia	2844
Sweden	3264

Table A.2: Items for students' endorsement of equal rights and opportunities. ICCS 2016

Item	Description
Gender equality	
IS3G24A	Men and women should have equal opportunities to take part in government
IS3G24B	Men and women should have the same rights in every way
IS3G24E	Men and women should get equal pay when they are doing the same jobs
IS3G24C	Women should stay out of politics (r)
IS3G24D	Not many jobs available, men should have more right to a job than women (r)
IS3G24F	Men are better qualified to be political leaders than women (r)
Equal rights for all ethnic and racial groups	
IS3G25A	All ethnic and racial groups should have equal chance to get good education
IS3G25B	All ethnic and racial groups should have an equal chance to get good jobs
IS3G25C	All ethnic and racial groups schools should teach students to respect
IS3G25D	All ethnic and racial groups should be encouraged to run in elections
IS3G25E	All ethnic and racial groups should have same rights and responsibilities

Appendix B

Syntax

B.1 Packages used

```
library(thesisdown)
library(plyr)
library(tidyverse)
library(knitr)
library(kableExtra)
library(MplusAutomation)
library(gridExtra)
library(grid)
library(scales)
library(RColorBrewer)
```

B.2 MplusAutomation syntax

```
library(MplusAutomation)
ds_lc <- data_model %>%
  dplyr::select(all_of(sample), all_of(Scales), IDSTUD, COUNTRY, CYCLE)

remlabclass <- function(ces){
  for (each in colnames(ces)){
    if ("labelled" %in% class(ces[[each]])){
      class(ces[[each]]) = c("numeric")
      attr(ces[[each]], "levels") <- NULL
    }
    attr(ces[[each]], "label") <- NULL
  }
  return(ces)
}
ds_lc0 <- remlabclass(ds_lc)
```

```
#----------------By country scales together by CYCLE ----------------------
for (j in 3:3) { #input file for each CYCLE 1:3
  data1 <- ds_lc0 %>%  filter(CYCLE == paste0("C",j)) %>%
    dplyr::select(all_of(sample), all_of(ScalesGND), IDSTUD, COUNTRY) %>%
    mutate_if(is.factor, ~ as.numeric(.x)) %>%
    data.frame()

  cnt <- unique(data1[,c("COUNTRY","id_k")]) %>%
    arrange(as.character(COUNTRY))

  data1 <- data1  %>% dplyr::select(-COUNTRY)
  prepareMplusData(df = data1,
           filename = paste0("data/MplusModels/ByCountry/GNDDtaC",j,".dat"),
           interactive =FALSE)

  for(c in 1:nrow(cnt)){
    data <- data1 %>%  filter(id_k == cnt$id_k[c])

    lapply(1:6, function(k) { #input file for different number of classes
      fileConn <- file(paste0("data/MplusModels/ByCountry/GNDlca_",
                              cnt$COUNTRY[c],"_C",j,"cl",
                              sprintf("%d", k),".inp"))
      writeLines(c(
        paste0("TITLE: ", cnt$COUNTRY[c], "GND LCA - C", j,
               " with ", k ," classes;"),
        "DATA: ",
        paste0("FILE = GNDDtaC",j,".dat;"),
        "",
        "VARIABLE: ",
        paste0("NAMES = ", paste(colnames(data), collapse = "\n"),";"),
        "IDVARIABLE = IDSTUD;",
        paste0("USEVARIABLES = ",
               paste(colnames(data)[grepl('^GND', colnames(data))],
                     collapse = "\n"),";"),
        paste0("USEOBSERVATIONS ARE id_k EQ ", cnt$id_k[c], ";"),
        paste0("CATEGORICAL = ",
               paste(colnames(data)[grepl('^GND', colnames(data))],
                     collapse = "\n"),";"),
        "MISSING = .;",
        paste0("CLASSES = ",sprintf("c(%d);", k)),
        "WEIGHT = ws;",
        "STRATIFICATION = id_s;",
        "CLUSTER = id_j;",
        " ",
```

```
        "ANALYSIS:",
        "TYPE = COMPLEX MIXTURE;",
        "PROCESSORS = 4;",
        "STARTS = 1000 250;",
        "STITERATIONS = 20;",
        "STSEED = 288;",
        "",
        "MODEL:",
        "%OVERALL%",
        " ",
        "OUTPUT: ",
        "TECH10",
        "TECH11",
        "SVALUES",
        ";",
        "",
        "SAVEDATA:",
        paste0("FILE = Prob_", cnt$COUNTRY[c] ,
               "_GNDlca_C", j,"cl", k,".dat;"),
        "SAVE = CPROBABILITIES;"

      ), fileConn)
      close(fileConn)
    })
  }
}

runModels(target = "data/MplusModels/ByCountry", recursive = TRUE,
          replaceOutfile = "never") #modifiedDate
ByCountry_GND <- readModels(target = "data/MplusModels/ByCountry",
                            recursive = TRUE,
                            filefilter = "GNDlca_[A-Z]{3}_C3cl")
ByCountry_ETH <- readModels(target = "data/MplusModels/ByCountry",
                            recursive = TRUE,
                            filefilter = "ETHlca_[A-Z]{3}_C3cl")

save(ByCountry_GND,
     ByCountry_ETH,
     file = "data/MplusModels_ByCountry.RData")
```

B.3 Automatized R code

```
#------Add label to variables----------
VarClass <- function(lc, orden = c(1:length(levels(factor(lc$param))))){
  b <- levels(factor(lc$param))
  b <- b[order(b)[orden]]
  labels <- NULL
  i = 0
  for (each in b){
    i = i + 1
    labels[each] <- paste0(b[i]," - ",attr(data_model[[each]], "variable.label"))
  }
  lc$param <- factor(lc$param, levels = b, labels = labels)
  return(lc)
}

#------Class barplot----------
graphclass <- function(cmodel = NULL, nclass = NULL,
                       orden = c(1:length(levels(factor(cmodel$param)))),
                       title = NULL, leg = FALSE){
  a <- levels(factor(cmodel$param))
  a <- a[order(a)[orden]]
  labels <- NULL
  for (each in a){
    labels[each] <- attr(data_model[[each]], "variable.label")
  }

  labels2 <- NULL
  n <- 0
  for (each in levels(cmodel$category)){
    n <- n + 1
    labels2[each] <- paste(each, "-", attr(data_model[[a[1]]], "levels")[n])
  }

  cmodel$paramf <- factor(cmodel$param, levels = a, labels = labels)
  cmodel$categoryf <- factor(cmodel$category, levels = levels(cmodel$category),
                             labels = labels2)

  zp1 <- ggplot(data = subset(cmodel),
         aes(x = paramf, y = value, fill = categoryf)) +
    geom_bar(stat = "identity", position = "stack") +
    ggtitle(title) +
    labs(x = "Items", y = "Response probabilities", fill ="Response category") +
    scale_fill_grey() + theme_bw() +
    theme(legend.position = "top",
```

```
        title = element_text(size=9),
        strip.text.y = element_text(size = 7),
        axis.text.x = element_text(angle = 90, vjust = 0.5, hjust = 0, size = 6),
        axis.text.y = element_text(size = 7),
        axis.title = element_text(size = 7),
        axis.ticks.y=element_blank(),
        panel.grid.major.y=element_blank(), legend.title = element_text(size = 8),
        legend.key.size = unit(0.3, "cm"),
        legend.text = element_text(size = 8)) +
    scale_x_discrete(label = function(x) str_wrap(x,25)) +
    guides(fill=guide_legend(nrow=1,byrow=TRUE)) +
    scale_y_continuous(breaks = c(0.25,0.5,0.75)) +
    geom_hline(yintercept=c(0.25,0.5,0.75), linetype = "dashed", size = 0.3,
               color = "gray") +
    facet_grid(. ~ Class, labeller = label_wrap_gen(20))

  print(zp1)
}

#------Models fit summary----------
Modelfit <- function(Modellist, title ="", fontn = 9){
  resultsbyallo <- mixtureSummaryTable(eval(parse(text=paste0(Modellist))),
                  keepCols = c("Title", "NLatentClasses", "Parameters", "LL",
                               "AIC", "BIC", "aBIC","Entropy",
                               "T11_VLMR_2xLLDiff", "T11_VLMR_PValue",
                               "T11_LMR_Value", "T11_LMR_PValue"))

  resultsbyallo <- resultsbyallo %>%
    mutate(Type = Title,
      Cycle = substr(Title,str_locate(Title, "C[0-9]+")[1],
                     str_locate(Title, "C[0-9]+")[2]+1),
      Year = ifelse(Cycle == "C1", 1999, ifelse(Cycle == "C2", 2009,
                                ifelse(Cycle == "C3", 2016, NA)))) %>%
    arrange(Year)


  resultsbyall <- resultsbyallo %>% dplyr::arrange(Year) %>%
    dplyr::group_by(Year) %>%
    dplyr::mutate(
      Reduction = scales::percent(ifelse(is.na(lag(LL)), NA,
                                  (lag(LL)-LL)/lag(LL)),accuracy = 0.1),
      LL = cell_spec(round(LL,0), italic = ifelse(LL == min(LL),
                                                  TRUE, FALSE)),
      AIC = cell_spec(round(AIC,0), italic = ifelse(AIC == min(AIC),
                                                    TRUE, FALSE)),
```

```
    BIC = cell_spec(round(BIC,0), italic = ifelse(BIC == min(BIC),
                                                  TRUE, FALSE)),
    aBIC = cell_spec(round(aBIC,0), italic = ifelse(aBIC == min(aBIC),
                                                    TRUE, FALSE)),
    Entropy = ifelse(is.na(Entropy), "",
                      cell_spec(scales::percent(Entropy,accuracy = 0.1),
                        italic = ifelse(Entropy == max(Entropy, na.rm = T),
                                               TRUE, FALSE))),
    Reduction = ifelse(is.na(Reduction),"",cell_spec(Reduction,
                      italic = ifelse(Reduction == max(Reduction, na.rm = T),
                                            TRUE, FALSE))),
    T11_VLMR_2xLLDiff = ifelse(is.na(T11_VLMR_2xLLDiff), "",
                               cell_spec(round(T11_VLMR_2xLLDiff,0),
                                italic = ifelse(T11_VLMR_PValue > 0.05,
                                                TRUE, FALSE))),
    T11_VLMR_PValue = ifelse(is.na(T11_VLMR_PValue), "",
                             cell_spec(round(T11_VLMR_PValue,3),
                                italic = ifelse(T11_VLMR_PValue > 0.05,
                                                TRUE, FALSE))),
    T11_LMR_Value = ifelse(is.na(T11_LMR_Value), "",
                           cell_spec(round(T11_LMR_Value,0),
                                italic = ifelse(T11_LMR_PValue > 0.05,
                                                TRUE, FALSE))),
    T11_LMR_PValue = ifelse(is.na(T11_LMR_PValue), "",
                            cell_spec(round(T11_LMR_PValue,3),
                                      italic = ifelse(T11_LMR_PValue > 0.05,
                                                      TRUE, FALSE)))) %>%
  ungroup()

resultsbyall <- resultsbyall[,c("Year", "NLatentClasses", "Parameters", "LL",
                              "AIC",  "BIC",  "aBIC", "Entropy", "Reduction",
                              "T11_VLMR_2xLLDiff", "T11_VLMR_PValue",
                              "T11_LMR_Value", "T11_LMR_PValue")] %>%
  setNames(c("Year", "N Latent\n Classes", "Param", "Log-Likelihood",
            "AIC",   "BIC",  "aBIC", "Entropy", "LL\n Reduction",
            "VLMR\n 2*LL Dif", "VLMR\n PValue", "LMR\n Value", "LMR\n PValue"))
tableSumm <- resultsbyall %>% select(-Year) %>%
  kbl(caption = paste0(title),
      booktabs = TRUE, longtable = TRUE, row.names = FALSE, escape = FALSE) %>%
  kable_classic_2(full_width = F) %>%
  kable_styling(latex_options = c("repeat_header", "HOLD_position"),
                font_size = fontn) %>%
  column_spec(c(1,2), width = "3em") %>%
  column_spec(c(3:12), width = "4em") %>%
```

```
  return(tableSumm)
}


#------Class highest probabilities----------
HighProb <- function(lc5, siz5, title = NULL,
                     orden = c(1:length(levels(factor(lc5$param)))),
                     longsize = 15){

  labels_x <- NULL
  for (each in levels(lc5$param)){
    labels_x[each] <- paste0(each," - ",attr(data_model[[each]], "variable.label"))
  }
  labels_x <- unlist(labels_x)

  lc5f <- lc5 %>%  mutate(Class = str_remove(Class,"\n"))
  siz5f <- siz5 %>%
    mutate(Class = str_remove(Class,"\n"),
           param = levels(lc5$param)[orden][length(levels(lc5$param))],
           category = "2")
  siz <- left_join(lc5f, siz5f, by = c("param", "category", "Class")) %>%
    arrange(Class, param) %>%
    group_by(param) %>% mutate(dif = abs(value - lag(value))) %>% ungroup() %>%
    mutate(Class = factor(Class, levels = str_remove(levels(lc5$Class),"\n")),
           param = factor(param, levels = levels(lc5$param), labels = labels_x))

  siz$paramf <- factor(siz$param, levels = levels(siz$param)[orden])
  pc5 <- siz %>%
    ggplot() +
    geom_point(aes(x = paramf, y = value, group = category, color = category),
               size = 2) +
    geom_line(aes(paramf, value, group = category, linetype = category,
                  color = category)) +
    scale_fill_grey() + theme_bw() +
    ggtitle(title)

  pc5 <- pc5 +
    geom_text(aes(x = paramf, y = 0.5, label = scales::percent(per, accuracy = 0.1)),
              size = 2.5, nudge_x = -0.15, nudge_y = 0.1) +
    facet_grid(Class ~ ., switch = "y", labeller = label_wrap_gen(10)) +
    theme(legend.position = "top", legend.box="vertical",
          strip.text.y = element_text(size = 8),
          legend.spacing.y = unit(-0.2, 'cm'),
          title = element_text(size = 9),
          axis.title.x = element_blank(),
```

```
        axis.text.y = element_text(size = 8),
        legend.title = element_text(size = 8),
        axis.text.x = element_text(angle = 90, size = 7,
                                   vjust = 0.5, hjust = 0)) +
    scale_y_continuous(breaks = c(0.25,0.5,0.75)) +
    labs(y="Response probabilities", linetype = "Response category",
         color = "Response category")  +
    scale_linetype_discrete(labels = c("Agree", "Disagree")) +
    scale_color_brewer(type = "qual", palette = "Dark2",
                       labels = c("Agree", "Disagree")) +
    scale_shape(solid = FALSE, guide = FALSE) +
    scale_x_discrete(label = function(x) str_wrap(x,20))
  print(pc5)
  cat('\n')
  cat('\n')
}

#------Comparative highest probabilities----------
ClassGraph <- function(lc5f, siz5, title = NULL,
                       orden = c(1:length(levels(factor(lc5f$param)))),
                       selected = c(1:length(levels(factor(siz5$Class))))){

  labels_x <- NULL
  for (each in levels(lc5f$param)){
    labels_x[each] <- paste0(each," - ",attr(data_model[[each]],
                                            "variable.label"))
  }
  labels_x <- unlist(labels_x)

  siz5f <- siz5 %>% arrange(desc(per)) %>% cbind(row = c(1:nrow(siz5))) %>%
    mutate(Class = factor(as.numeric(Class)),
           ClassesSizes = paste("Class", row,":",
                                scales::percent(per, accuracy = 0.1)))

  siz <- lc5f %>%
    arrange(Class, param) %>%
    group_by(param) %>% mutate(dif = abs(value - lag(value))) %>%
    ungroup()

  siz$paramf <- factor(siz$param, levels = levels(siz$param)[orden])

  pc5 <- siz %>% filter(category == 1) %>%
    ggplot() +
    geom_point(aes(x = paramf, y = value, group = Class, color = Class),
               size = 1.5) +
```

```
    geom_line(aes(paramf, value, group = Class, linetype = Class, color = Class)) +
    scale_fill_grey() + theme_bw() +
    ggtitle(title) +
    theme(legend.position = "top",
          legend.direction = "vertical",
          strip.text.y = element_text(size = 8),
          legend.spacing.x = unit(0.2, 'cm'),
          legend.spacing.y = unit(-0.2, 'cm'),
          legend.margin=margin(t = 0, unit='cm'),
          title = element_text(size = 9),
          panel.grid.minor.y = element_blank(),
          panel.grid.major.x = element_blank(),
          panel.grid.minor.x = element_blank(),
          axis.title.x = element_blank(),
          axis.title.y = element_blank(),
          legend.title = element_blank(),
          legend.text = element_text(size = 7),
          axis.text.x = element_text(angle = 90, size = 8,
                                     vjust = 0.5, hjust = 0)) +
    guides(linetype = guide_legend(nrow = 2)) +
    scale_y_continuous(breaks = c(0.25,0.5,0.75), limits = c(0,1)) +
    labs(y="Response probabilities", linetype = "Latent Classes",
         color = "Latent Classes")  +
    scale_linetype_discrete(labels = siz5f$ClassesSizes) +
    scale_colour_manual(values=cbPalette[selected],
                        labels = siz5f$ClassesSizes) +
    scale_shape(solid = FALSE, guide = FALSE) +
    scale_x_discrete(label = function(x) str_wrap(x,25))
  return(pc5)
}


#----GND 4 groups----
classes4GND <- c("Fully egalitarian",
                "Competition- driven sexism",
                "Non-egalitarian",
                "Political egalitarian")
orden4GND <- c(2,4,3,1)
lcaGND_C3cl4 <- lcaGND$GND_lca_C3cl4.out$parameters$probability.scale %>%
  rename_with(~ c("Class", "value")[which(c("LatentClass", "est") == .x)],
              .cols = c("LatentClass", "est")) %>%
  mutate_at( c("param", "category", "Class"), ~ as.factor(.x)) %>%
  mutate(Class = factor(Class, levels = orden4GND, labels = classes4GND))

counts4GND <- full_join(lcaGND$GND_lca_C3cl4.out$class_counts$modelEstimated,
```

```
                        lcaGND$GND_lca_C3cl4.out$class_counts$mostLikely,
                        by = c("class"))

lcaGND_C3cl4$orden = rep(c(1,2,4,5,3,6), each = 2)
VarClass(lcaGND_C3cl4) %>% group_by(Class, param) %>%
  filter(category == 1) %>%
  select(orden, param, Class, value) %>%
  mutate(value = cell_spec(value, color = ifelse(value >= 0.75, "Myblue",
                ifelse(value < 0.75 & value >= 0.25, "Mygreen","Myred")))) %>%
  reshape2::dcast(orden + param ~ Class) %>% arrange(orden) %>% select(-orden) %>%
  kbl(caption = "Probabilities to agree each item 4-class Gender equality model",
      booktabs = TRUE, longtable = TRUE, align = c("l", rep("r",4)),
      row.names = FALSE, digits = 3, escape = FALSE) %>%
  kable_classic_2(full_width = F) %>%
  kable_styling(latex_options = c("repeat_header", "HOLD_position"),
                font_size = 9) %>%
  column_spec(1, width = "15em") %>%
  column_spec(2:5, width = "5em") %>%
  collapse_rows(1, valign = "top") %>%
  print()

counts4GND  %>%
  mutate(class = factor(class, levels = orden4GND, labels = classes4GND),
         proportion.x = scales::percent(proportion.x,accuracy = 0.1),
         proportion.y = scales::percent(proportion.y,accuracy = 0.1)) %>%
  arrange(desc(count.y)) %>%
  kbl(col.names = c("Class", "Counts", "Proportion", "Counts", "Proportion"),
      caption = paste0("Class sizes 4-class Gender equality model"),
      booktabs = TRUE, longtable = TRUE, align = c("l", rep("r",4)),
      row.names = FALSE, digits = 1, escape = TRUE) %>%
  kable_classic_2(full_width = F) %>%
  kable_styling(latex_options = c("repeat_header", "HOLD_position"),
                font_size = 9) %>%
  add_header_above(c(" " = 1 , "Model estimated" = 2, "Most likely" = 2))

sizelca4_GND <- lcaGND$GND_lca_C3cl4.out$class_counts$modelEstimated %>%
  dplyr::select(-count) %>%
  rename_with(~ c("Gender", "Class")[which(c("proportion", "class") == .x)],
              .cols = c("proportion", "class")) %>%
  mutate(Class = factor(Class, levels = orden4GND, labels = classes4GND)) %>%
  reshape2::melt(id.vars = c("Class"), variable.name = "Group") %>%
  dplyr::arrange(Group) %>%
  dplyr::group_by(Group) %>%
  dplyr::mutate(countT= sum(value, na.rm = TRUE)) %>%
  dplyr::group_by(Class) %>%
```

```
  dplyr::mutate(per=value/countT) %>%
  dplyr::select(Group, Class, per)

HighProb(lcaGND_C3cl4, sizelca4_GND,  orden = c(1,2,5,3,4,6),
         title = "Response categories probabilities and class size
         for\n 4-classes Gender equality model")
```

B.4 Mplus syntax

B.4.1 Latent Class model with 4 classes

```
TITLE: LCA C3 GND with 4 classes;
DATA:
FILE = GND_Dta_C3.dat;

VARIABLE:
NAMES = id_i id_j id_r id_s
id_k wt ws
GND1 GND2 GND3 GND4 GND5 GND6
IDSTUD;
IDVARIABLE = IDSTUD;
USEVARIABLES = GND1
GND2 GND3 GND4 GND5 GND6;
CATEGORICAL = GND1
GND2 GND3 GND4 GND5 GND6;
MISSING = .;
CLASSES = c(4);
WEIGHT = ws;
STRATIFICATION = id_s;
CLUSTER = id_j;

ANALYSIS:
TYPE = COMPLEX MIXTURE;
PROCESSORS = 4;
STARTS = 100 50;
STITERATIONS = 5;
STSEED = 288;

OUTPUT:
TECH10
TECH11
TECH14;
SVALUES
;
```

```
SAVEDATA:
FILE = GND_Prob_C3cl4.dat;
SAVE = CPROBABILITIES;
```

B.4.2 Complete homogeneous multigroup latent class model with 4 classes

```
TITLE:C.Hom MG Country LCA GND C3 with 4 classes;
DATA:
FILE = GND_DtaC3.dat;

VARIABLE:
NAMES = id_i id_j id_r
id_s id_k wt ws
GND1 GND2 GND3 GND4 GND5 GND6
IDSTUD;
IDVARIABLE = IDSTUD;
USEVARIABLES = GND1
GND2 GND3 GND4 GND5 GND6;
CATEGORICAL = GND1
GND2 GND3 GND4 GND5 GND6;
MISSING = .;
CLASSES = g(14) c(4);
KNOWNCLASS = g(id_k =
 1    !    BFL
 2    !    BGR
 3    !    DNK
 4    !    EST
 5    !    FIN
 6    !    HRV
 7    !    ITA
 8    !    LTU
 9    !    LVA
 10   !    MLT
 11   !    NLD
 12   !    NOR
 13   !    SVN
 14   !    SWE
);
WEIGHT = ws;
STRATIFICATION = id_s;
CLUSTER = id_j;
```

```
ANALYSIS:
TYPE = COMPLEX MIXTURE;
PROCESSORS = 4;
STARTS = 1000 250;
STITERATIONS = 20;
STSEED = 288;

MODEL:
%OVERALL%
Model c:

                    %c#1%
 [GND1$1-GND6$1] (91-96);
                    %c#2%
         [GND1$1-GND6$1];
                    %c#3%
         [GND1$1-GND6$1];
                    %c#4%
         [GND1$1-GND6$1];

OUTPUT:
TECH10
SVALUES
;

SAVEDATA:
FILE = GND_Prob_MGCntry_C3cl4_3CHom.dat;
SAVE = CPROBABILITIES;
```

B.4.3 Partial homogeneous multigroup latent class model with 4 classes

```
TITLE: P.Hom MG Country LCA GND C3 with 4 classes;
DATA:
FILE = GND_DtaC3.dat;

VARIABLE:
NAMES = id_i id_j id_r id_s
id_k wt ws
GND1 GND2 GND3 GND4 GND5 GND6
IDSTUD;
IDVARIABLE = IDSTUD;
```

```
USEVARIABLES = GND1
GND2 GND3 GND4 GND5 GND6;
CATEGORICAL = GND1
GND2 GND3 GND4 GND5 GND6;
MISSING = .;
CLASSES = g(14) c(4);
KNOWNCLASS = g(id_k =
 1    !    BFL
 2    !    BGR
 3    !    DNK
 4    !    EST
 5    !    FIN
 6    !    HRV
 7    !    ITA
 8    !    LTU
 9    !    LVA
 10   !    MLT
 11   !    NLD
 12   !    NOR
 13   !    SVN
 14   !    SWE
);
WEIGHT = ws;
STRATIFICATION = id_s;
CLUSTER = id_j;

ANALYSIS:
TYPE = COMPLEX MIXTURE;
PROCESSORS = 4;
STARTS = 1000 250;
STITERATIONS = 20;
STSEED = 288;

MODEL:
%OVERALL%
c ON g;

      %g#1.c#1%
  [GND1$1] (1);
  [GND2$1] (2);
  [GND3$1] (3);
  [GND4$1] (4);
  [GND5$1] (5);
  [GND6$1] (6);
      %g#1.c#2%
```

```
 [GND1$1] (7);
 [GND2$1] (8);
 [GND3$1] (9);
[GND4$1] (10);
[GND5$1] (11);
[GND6$1] (12);
    %g#1.c#3%
[GND1$1] (13);
[GND2$1] (14);
[GND3$1] (15);
[GND4$1] (16);
[GND5$1] (17);
[GND6$1] (18);
    %g#1.c#4%
[GND1$1] (19);
[GND2$1] (20);
[GND3$1] (21);
[GND4$1] (22);
[GND5$1] (23);
[GND6$1] (24);
    %g#2.c#1%
 [GND1$1] (1);
 [GND2$1] (2);
 [GND3$1] (3);
 [GND4$1] (4);
 [GND5$1] (5);
 [GND6$1] (6);
    %g#2.c#2%
 [GND1$1] (7);
 [GND2$1] (8);
 [GND3$1] (9);
[GND4$1] (10);
[GND5$1] (11);
[GND6$1] (12);
    %g#2.c#3%
[GND1$1] (13);
[GND2$1] (14);
[GND3$1] (15);
[GND4$1] (16);
[GND5$1] (17);
[GND6$1] (18);
    %g#2.c#4%
[GND1$1] (19);
[GND2$1] (20);
[GND3$1] (21);
```

```
[GND4$1] (22);
[GND5$1] (23);
[GND6$1] (24);
     %g#3.c#1%
 [GND1$1] (1);
 [GND2$1] (2);
 [GND3$1] (3);
 [GND4$1] (4);
 [GND5$1] (5);
 [GND6$1] (6);
     %g#3.c#2%
 [GND1$1] (7);
 [GND2$1] (8);
 [GND3$1] (9);
[GND4$1] (10);
[GND5$1] (11);
[GND6$1] (12);
     %g#3.c#3%
[GND1$1] (13);
[GND2$1] (14);
[GND3$1] (15);
[GND4$1] (16);
[GND5$1] (17);
[GND6$1] (18);
     %g#3.c#4%
[GND1$1] (19);
[GND2$1] (20);
[GND3$1] (21);
[GND4$1] (22);
[GND5$1] (23);
[GND6$1] (24);
     %g#4.c#1%
 [GND1$1] (1);
 [GND2$1] (2);
 [GND3$1] (3);
 [GND4$1] (4);
 [GND5$1] (5);
 [GND6$1] (6);
     %g#4.c#2%
 [GND1$1] (7);
 [GND2$1] (8);
 [GND3$1] (9);
[GND4$1] (10);
[GND5$1] (11);
[GND6$1] (12);
```

```
    %g#4.c#3%
[GND1$1] (13);
[GND2$1] (14);
[GND3$1] (15);
[GND4$1] (16);
[GND5$1] (17);
[GND6$1] (18);
    %g#4.c#4%
[GND1$1] (19);
[GND2$1] (20);
[GND3$1] (21);
[GND4$1] (22);
[GND5$1] (23);
[GND6$1] (24);
    %g#5.c#1%
 [GND1$1] (1);
 [GND2$1] (2);
 [GND3$1] (3);
 [GND4$1] (4);
 [GND5$1] (5);
 [GND6$1] (6);
    %g#5.c#2%
 [GND1$1] (7);
 [GND2$1] (8);
 [GND3$1] (9);
[GND4$1] (10);
[GND5$1] (11);
[GND6$1] (12);
    %g#5.c#3%
[GND1$1] (13);
[GND2$1] (14);
[GND3$1] (15);
[GND4$1] (16);
[GND5$1] (17);
[GND6$1] (18);
    %g#5.c#4%
[GND1$1] (19);
[GND2$1] (20);
[GND3$1] (21);
[GND4$1] (22);
[GND5$1] (23);
[GND6$1] (24);
    %g#6.c#1%
 [GND1$1] (1);
 [GND2$1] (2);
```

```
 [GND3$1] (3);
 [GND4$1] (4);
 [GND5$1] (5);
 [GND6$1] (6);
     %g#6.c#2%
 [GND1$1] (7);
 [GND2$1] (8);
 [GND3$1] (9);
[GND4$1] (10);
[GND5$1] (11);
[GND6$1] (12);
     %g#6.c#3%
[GND1$1] (13);
[GND2$1] (14);
[GND3$1] (15);
[GND4$1] (16);
[GND5$1] (17);
[GND6$1] (18);
     %g#6.c#4%
[GND1$1] (19);
[GND2$1] (20);
[GND3$1] (21);
[GND4$1] (22);
[GND5$1] (23);
[GND6$1] (24);
     %g#7.c#1%
 [GND1$1] (1);
 [GND2$1] (2);
 [GND3$1] (3);
 [GND4$1] (4);
 [GND5$1] (5);
 [GND6$1] (6);
     %g#7.c#2%
 [GND1$1] (7);
 [GND2$1] (8);
 [GND3$1] (9);
[GND4$1] (10);
[GND5$1] (11);
[GND6$1] (12);
     %g#7.c#3%
[GND1$1] (13);
[GND2$1] (14);
[GND3$1] (15);
[GND4$1] (16);
[GND5$1] (17);
```

```
[GND6$1] (18);
     %g#7.c#4%
[GND1$1] (19);
[GND2$1] (20);
[GND3$1] (21);
[GND4$1] (22);
[GND5$1] (23);
[GND6$1] (24);
     %g#8.c#1%
 [GND1$1] (1);
 [GND2$1] (2);
 [GND3$1] (3);
 [GND4$1] (4);
 [GND5$1] (5);
 [GND6$1] (6);
     %g#8.c#2%
 [GND1$1] (7);
 [GND2$1] (8);
 [GND3$1] (9);
[GND4$1] (10);
[GND5$1] (11);
[GND6$1] (12);
     %g#8.c#3%
[GND1$1] (13);
[GND2$1] (14);
[GND3$1] (15);
[GND4$1] (16);
[GND5$1] (17);
[GND6$1] (18);
     %g#8.c#4%
[GND1$1] (19);
[GND2$1] (20);
[GND3$1] (21);
[GND4$1] (22);
[GND5$1] (23);
[GND6$1] (24);
     %g#9.c#1%
 [GND1$1] (1);
 [GND2$1] (2);
 [GND3$1] (3);
 [GND4$1] (4);
 [GND5$1] (5);
 [GND6$1] (6);
     %g#9.c#2%
 [GND1$1] (7);
```

```
 [GND2$1] (8);
 [GND3$1] (9);
[GND4$1] (10);
[GND5$1] (11);
[GND6$1] (12);
    %g#9.c#3%
[GND1$1] (13);
[GND2$1] (14);
[GND3$1] (15);
[GND4$1] (16);
[GND5$1] (17);
[GND6$1] (18);
    %g#9.c#4%
[GND1$1] (19);
[GND2$1] (20);
[GND3$1] (21);
[GND4$1] (22);
[GND5$1] (23);
[GND6$1] (24);
   %g#10.c#1%
 [GND1$1] (1);
 [GND2$1] (2);
 [GND3$1] (3);
 [GND4$1] (4);
 [GND5$1] (5);
 [GND6$1] (6);
   %g#10.c#2%
 [GND1$1] (7);
 [GND2$1] (8);
 [GND3$1] (9);
[GND4$1] (10);
[GND5$1] (11);
[GND6$1] (12);
   %g#10.c#3%
[GND1$1] (13);
[GND2$1] (14);
[GND3$1] (15);
[GND4$1] (16);
[GND5$1] (17);
[GND6$1] (18);
   %g#10.c#4%
[GND1$1] (19);
[GND2$1] (20);
[GND3$1] (21);
[GND4$1] (22);
```

```
[GND5$1] (23);
[GND6$1] (24);
    %g#11.c#1%
 [GND1$1] (1);
 [GND2$1] (2);
 [GND3$1] (3);
 [GND4$1] (4);
 [GND5$1] (5);
 [GND6$1] (6);
    %g#11.c#2%
 [GND1$1] (7);
 [GND2$1] (8);
 [GND3$1] (9);
[GND4$1] (10);
[GND5$1] (11);
[GND6$1] (12);
    %g#11.c#3%
[GND1$1] (13);
[GND2$1] (14);
[GND3$1] (15);
[GND4$1] (16);
[GND5$1] (17);
[GND6$1] (18);
    %g#11.c#4%
[GND1$1] (19);
[GND2$1] (20);
[GND3$1] (21);
[GND4$1] (22);
[GND5$1] (23);
[GND6$1] (24);
    %g#12.c#1%
 [GND1$1] (1);
 [GND2$1] (2);
 [GND3$1] (3);
 [GND4$1] (4);
 [GND5$1] (5);
 [GND6$1] (6);
    %g#12.c#2%
 [GND1$1] (7);
 [GND2$1] (8);
 [GND3$1] (9);
[GND4$1] (10);
[GND5$1] (11);
[GND6$1] (12);
    %g#12.c#3%
```

```
[GND1$1] (13);
[GND2$1] (14);
[GND3$1] (15);
[GND4$1] (16);
[GND5$1] (17);
[GND6$1] (18);
    %g#12.c#4%
[GND1$1] (19);
[GND2$1] (20);
[GND3$1] (21);
[GND4$1] (22);
[GND5$1] (23);
[GND6$1] (24);
    %g#13.c#1%
 [GND1$1] (1);
 [GND2$1] (2);
 [GND3$1] (3);
 [GND4$1] (4);
 [GND5$1] (5);
 [GND6$1] (6);
    %g#13.c#2%
 [GND1$1] (7);
 [GND2$1] (8);
 [GND3$1] (9);
[GND4$1] (10);
[GND5$1] (11);
[GND6$1] (12);
    %g#13.c#3%
[GND1$1] (13);
[GND2$1] (14);
[GND3$1] (15);
[GND4$1] (16);
[GND5$1] (17);
[GND6$1] (18);
    %g#13.c#4%
[GND1$1] (19);
[GND2$1] (20);
[GND3$1] (21);
[GND4$1] (22);
[GND5$1] (23);
[GND6$1] (24);
    %g#14.c#1%
 [GND1$1] (1);
 [GND2$1] (2);
 [GND3$1] (3);
```

```
  [GND4$1] (4);
  [GND5$1] (5);
  [GND6$1] (6);
     %g#14.c#2%
  [GND1$1] (7);
  [GND2$1] (8);
  [GND3$1] (9);
 [GND4$1] (10);
 [GND5$1] (11);
 [GND6$1] (12);
     %g#14.c#3%
 [GND1$1] (13);
 [GND2$1] (14);
 [GND3$1] (15);
 [GND4$1] (16);
 [GND5$1] (17);
 [GND6$1] (18);
     %g#14.c#4%
 [GND1$1] (19);
 [GND2$1] (20);
 [GND3$1] (21);
 [GND4$1] (22);
 [GND5$1] (23);
 [GND6$1] (24);

OUTPUT:
TECH10
SVALUES
;

SAVEDATA:
FILE = GND_Prob_MGCntry_C3cl4_2PHom.dat;
SAVE = CPROBABILITIES;
```

Complete heterogeneous multigroup latent class model with 4 classes

```
TITLE: C.Het MG Country LCA GND C3 with 4 classes;
DATA:
FILE = GND_DtaC3.dat;

VARIABLE:
NAMES = id_i id_j id_r id_s
id_k wt ws
GND1 GND2 GND3 GND4 GND5 GND6
IDSTUD;
```

```
IDVARIABLE = IDSTUD;
USEVARIABLES = GND1
GND2 GND3 GND4 GND5 GND6;
CATEGORICAL = GND1
GND2 GND3 GND4 GND5 GND6;
MISSING = .;
CLASSES = g(14) c(4);
KNOWNCLASS = g(id_k =
 1    !    BFL
 2    !    BGR
 3    !    DNK
 4    !    EST
 5    !    FIN
 6    !    HRV
 7    !    ITA
 8    !    LTU
 9    !    LVA
 10   !    MLT
 11   !    NLD
 12   !    NOR
 13   !    SVN
 14   !    SWE
);
WEIGHT = ws;
STRATIFICATION = id_s;
CLUSTER = id_j;

ANALYSIS:
TYPE = COMPLEX MIXTURE;
PROCESSORS = 4;
STARTS = 1000 250;
STITERATIONS = 20;
STSEED = 288;

MODEL:
%OVERALL%
c ON g;

      %g#1.c#1%
  [GND1$1] (1);
  [GND2$1] (2);
  [GND3$1] (3);
  [GND4$1] (4);
  [GND5$1] (5);
  [GND6$1] (6);
```

```
     %g#1.c#2%
 [GND1$1] (7);
 [GND2$1] (8);
 [GND3$1] (9);
[GND4$1] (10);
[GND5$1] (11);
[GND6$1] (12);
     %g#1.c#3%
[GND1$1] (13);
[GND2$1] (14);
[GND3$1] (15);
[GND4$1] (16);
[GND5$1] (17);
[GND6$1] (18);
     %g#1.c#4%
[GND1$1] (19);
[GND2$1] (20);
[GND3$1] (21);
[GND4$1] (22);
[GND5$1] (23);
[GND6$1] (24);
     %g#2.c#1%
[GND1$1] (25);
[GND2$1] (26);
[GND3$1] (27);
[GND4$1] (28);
[GND5$1] (29);
[GND6$1] (30);
     %g#2.c#2%
[GND1$1] (31);
[GND2$1] (32);
[GND3$1] (33);
[GND4$1] (34);
[GND5$1] (35);
[GND6$1] (36);
     %g#2.c#3%
[GND1$1] (37);
[GND2$1] (38);
[GND3$1] (39);
[GND4$1] (40);
[GND5$1] (41);
[GND6$1] (42);
     %g#2.c#4%
[GND1$1] (43);
[GND2$1] (44);
```

```
[GND3$1] (45);
[GND4$1] (46);
[GND5$1] (47);
[GND6$1] (48);
     %g#3.c#1%
[GND1$1] (49);
[GND2$1] (50);
[GND3$1] (51);
[GND4$1] (52);
[GND5$1] (53);
[GND6$1] (54);
     %g#3.c#2%
[GND1$1] (55);
[GND2$1] (56);
[GND3$1] (57);
[GND4$1] (58);
[GND5$1] (59);
[GND6$1] (60);
     %g#3.c#3%
[GND1$1] (61);
[GND2$1] (62);
[GND3$1] (63);
[GND4$1] (64);
[GND5$1] (65);
[GND6$1] (66);
     %g#3.c#4%
[GND1$1] (67);
[GND2$1] (68);
[GND3$1] (69);
[GND4$1] (70);
[GND5$1] (71);
[GND6$1] (72);
     %g#4.c#1%
[GND1$1] (73);
[GND2$1] (74);
[GND3$1] (75);
[GND4$1] (76);
[GND5$1] (77);
[GND6$1] (78);
     %g#4.c#2%
[GND1$1] (79);
[GND2$1] (80);
[GND3$1] (81);
[GND4$1] (82);
[GND5$1] (83);
```

```
 [GND6$1] (84);
      %g#4.c#3%
 [GND1$1] (85);
 [GND2$1] (86);
 [GND3$1] (87);
 [GND4$1] (88);
 [GND5$1] (89);
 [GND6$1] (90);
      %g#4.c#4%
 [GND1$1] (91);
 [GND2$1] (92);
 [GND3$1] (93);
 [GND4$1] (94);
 [GND5$1] (95);
 [GND6$1] (96);
      %g#5.c#1%
 [GND1$1] (97);
 [GND2$1] (98);
 [GND3$1] (99);
[GND4$1] (100);
[GND5$1] (101);
[GND6$1] (102);
      %g#5.c#2%
[GND1$1] (103);
[GND2$1] (104);
[GND3$1] (105);
[GND4$1] (106);
[GND5$1] (107);
[GND6$1] (108);
      %g#5.c#3%
[GND1$1] (109);
[GND2$1] (110);
[GND3$1] (111);
[GND4$1] (112);
[GND5$1] (113);
[GND6$1] (114);
      %g#5.c#4%
[GND1$1] (115);
[GND2$1] (116);
[GND3$1] (117);
[GND4$1] (118);
[GND5$1] (119);
[GND6$1] (120);
      %g#6.c#1%
[GND1$1] (121);
```

```
[GND2$1] (122);
[GND3$1] (123);
[GND4$1] (124);
[GND5$1] (125);
[GND6$1] (126);
      %g#6.c#2%
[GND1$1] (127);
[GND2$1] (128);
[GND3$1] (129);
[GND4$1] (130);
[GND5$1] (131);
[GND6$1] (132);
      %g#6.c#3%
[GND1$1] (133);
[GND2$1] (134);
[GND3$1] (135);
[GND4$1] (136);
[GND5$1] (137);
[GND6$1] (138);
      %g#6.c#4%
[GND1$1] (139);
[GND2$1] (140);
[GND3$1] (141);
[GND4$1] (142);
[GND5$1] (143);
[GND6$1] (144);
      %g#7.c#1%
[GND1$1] (145);
[GND2$1] (146);
[GND3$1] (147);
[GND4$1] (148);
[GND5$1] (149);
[GND6$1] (150);
      %g#7.c#2%
[GND1$1] (151);
[GND2$1] (152);
[GND3$1] (153);
[GND4$1] (154);
[GND5$1] (155);
[GND6$1] (156);
      %g#7.c#3%
[GND1$1] (157);
[GND2$1] (158);
[GND3$1] (159);
[GND4$1] (160);
```

```
[GND5$1] (161);
[GND6$1] (162);
      %g#7.c#4%
[GND1$1] (163);
[GND2$1] (164);
[GND3$1] (165);
[GND4$1] (166);
[GND5$1] (167);
[GND6$1] (168);
      %g#8.c#1%
[GND1$1] (169);
[GND2$1] (170);
[GND3$1] (171);
[GND4$1] (172);
[GND5$1] (173);
[GND6$1] (174);
      %g#8.c#2%
[GND1$1] (175);
[GND2$1] (176);
[GND3$1] (177);
[GND4$1] (178);
[GND5$1] (179);
[GND6$1] (180);
      %g#8.c#3%
[GND1$1] (181);
[GND2$1] (182);
[GND3$1] (183);
[GND4$1] (184);
[GND5$1] (185);
[GND6$1] (186);
      %g#8.c#4%
[GND1$1] (187);
[GND2$1] (188);
[GND3$1] (189);
[GND4$1] (190);
[GND5$1] (191);
[GND6$1] (192);
      %g#9.c#1%
[GND1$1] (193);
[GND2$1] (194);
[GND3$1] (195);
[GND4$1] (196);
[GND5$1] (197);
[GND6$1] (198);
      %g#9.c#2%
```

```
[GND1$1] (199);
[GND2$1] (200);
[GND3$1] (201);
[GND4$1] (202);
[GND5$1] (203);
[GND6$1] (204);
     %g#9.c#3%
[GND1$1] (205);
[GND2$1] (206);
[GND3$1] (207);
[GND4$1] (208);
[GND5$1] (209);
[GND6$1] (210);
     %g#9.c#4%
[GND1$1] (211);
[GND2$1] (212);
[GND3$1] (213);
[GND4$1] (214);
[GND5$1] (215);
[GND6$1] (216);
    %g#10.c#1%
[GND1$1] (217);
[GND2$1] (218);
[GND3$1] (219);
[GND4$1] (220);
[GND5$1] (221);
[GND6$1] (222);
    %g#10.c#2%
[GND1$1] (223);
[GND2$1] (224);
[GND3$1] (225);
[GND4$1] (226);
[GND5$1] (227);
[GND6$1] (228);
    %g#10.c#3%
[GND1$1] (229);
[GND2$1] (230);
[GND3$1] (231);
[GND4$1] (232);
[GND5$1] (233);
[GND6$1] (234);
    %g#10.c#4%
[GND1$1] (235);
[GND2$1] (236);
[GND3$1] (237);
```

```
[GND4$1] (238);
[GND5$1] (239);
[GND6$1] (240);
     %g#11.c#1%
[GND1$1] (241);
[GND2$1] (242);
[GND3$1] (243);
[GND4$1] (244);
[GND5$1] (245);
[GND6$1] (246);
     %g#11.c#2%
[GND1$1] (247);
[GND2$1] (248);
[GND3$1] (249);
[GND4$1] (250);
[GND5$1] (251);
[GND6$1] (252);
     %g#11.c#3%
[GND1$1] (253);
[GND2$1] (254);
[GND3$1] (255);
[GND4$1] (256);
[GND5$1] (257);
[GND6$1] (258);
     %g#11.c#4%
[GND1$1] (259);
[GND2$1] (260);
[GND3$1] (261);
[GND4$1] (262);
[GND5$1] (263);
[GND6$1] (264);
     %g#12.c#1%
[GND1$1] (265);
[GND2$1] (266);
[GND3$1] (267);
[GND4$1] (268);
[GND5$1] (269);
[GND6$1] (270);
     %g#12.c#2%
[GND1$1] (271);
[GND2$1] (272);
[GND3$1] (273);
[GND4$1] (274);
[GND5$1] (275);
[GND6$1] (276);
```

```
    %g#12.c#3%
[GND1$1] (277);
[GND2$1] (278);
[GND3$1] (279);
[GND4$1] (280);
[GND5$1] (281);
[GND6$1] (282);
    %g#12.c#4%
[GND1$1] (283);
[GND2$1] (284);
[GND3$1] (285);
[GND4$1] (286);
[GND5$1] (287);
[GND6$1] (288);
    %g#13.c#1%
[GND1$1] (289);
[GND2$1] (290);
[GND3$1] (291);
[GND4$1] (292);
[GND5$1] (293);
[GND6$1] (294);
    %g#13.c#2%
[GND1$1] (295);
[GND2$1] (296);
[GND3$1] (297);
[GND4$1] (298);
[GND5$1] (299);
[GND6$1] (300);
    %g#13.c#3%
[GND1$1] (301);
[GND2$1] (302);
[GND3$1] (303);
[GND4$1] (304);
[GND5$1] (305);
[GND6$1] (306);
    %g#13.c#4%
[GND1$1] (307);
[GND2$1] (308);
[GND3$1] (309);
[GND4$1] (310);
[GND5$1] (311);
[GND6$1] (312);
    %g#14.c#1%
[GND1$1] (313);
[GND2$1] (314);
```

```
[GND3$1] (315);
[GND4$1] (316);
[GND5$1] (317);
[GND6$1] (318);
     %g#14.c#2%
[GND1$1] (319);
[GND2$1] (320);
[GND3$1] (321);
[GND4$1] (322);
[GND5$1] (323);
[GND6$1] (324);
     %g#14.c#3%
[GND1$1] (325);
[GND2$1] (326);
[GND3$1] (327);
[GND4$1] (328);
[GND5$1] (329);
[GND6$1] (330);
     %g#14.c#4%
[GND1$1] (331);
[GND2$1] (332);
[GND3$1] (333);
[GND4$1] (334);
[GND5$1] (335);
[GND6$1] (336);

OUTPUT:
TECH10
SVALUES
;

SAVEDATA:
FILE = GND_Prob_MGCntry_C3cl4_1CHet.dat;
SAVE = CPROBABILITIES;
```

B.4.4 Confirmatory latent class model with 4 classes Attitudes towards gender equality

```
TITLE: ConfLCA C3 GND with 4 classes;
DATA:
FILE = GND_Dta_C3.dat;

VARIABLE:
```

```
NAMES = id_i id_j id_r
id_s id_k wt ws
GND1 GND2 GND3 GND4 GND5 GND6
IDSTUD;
IDVARIABLE = IDSTUD;
!subpopulation is (id_k == 1);
USEVARIABLES = GND1
GND2 GND3 GND4 GND5 GND6;
CATEGORICAL = GND1
GND2 GND3 GND4 GND5 GND6;
MISSING = .;
CLASSES = c(4);
WEIGHT = ws;
STRATIFICATION = id_s;
CLUSTER = id_j;

ANALYSIS:
TYPE = COMPLEX MIXTURE;
PROCESSORS = 4;
STARTS = 100 50;
STITERATIONS = 5;
STSEED = 288;


MODEL:
%OVERALL%
%C#1%
[GND1$1*15] (p1);
[GND2$1*4.3] (p2);
[GND3$1*4.2] (p2);
[GND4$1*3.2] (p4);
[GND5$1*3.8] (p5);
[GND6$1*2.6] (p6);

%C#2%
[GND1$1*6] (p2);
[GND2$1*6] (p8);
[GND5$1*2.4] (p9);
[GND3$1*0] (p10);
[GND4$1*-1.8] (p11);
[GND6$1*-2.3] (p12);

%C#3%
[GND1$1] (p13);
[GND2$1] (p14);
```

```
[GND5$1] (p15);
[GND3$1] (p16);
[GND4$1] (p17);
[GND6$1] (p18);

%C#4%
[GND1$1] (p19);
[GND2$1] (p20);
[GND5$1] (p21);
[GND3$1] (p22);
[GND4$1] (p23);
[GND6$1] (p24);

MODEL CONSTRAINT:
p1 = 15;
p10 = 0;


OUTPUT:
TECH10
TECH11
TECH14;
SVALUES
;

SAVEDATA:
FILE = GND_ConfProb_C3cl4.dat;
SAVE = CPROBABILITIES;
```

B.4.5 Confirmatory latent class model with 4 classes Attitudes towards ethnic and race equal rights

```
TITLE: ConfLCA C3 ETH with 4 classes;
DATA:
FILE = ETH_Dta_C3.dat;

VARIABLE:
NAMES = id_i id_j id_r
id_s id_k wt ws
ETH1 ETH2 ETH3 ETH4 ETH5
IDSTUD;
IDVARIABLE = IDSTUD;
USEVARIABLES = ETH1
```

```
ETH2 ETH3 ETH4 ETH5;
CATEGORICAL = ETH1
ETH2 ETH3 ETH4 ETH5;
MISSING = .;
CLASSES = c(4);
WEIGHT = ws;
STRATIFICATION = id_s;
CLUSTER = id_j;

ANALYSIS:
TYPE = COMPLEX MIXTURE;
PROCESSORS = 4;
STARTS = 100 50;
STITERATIONS = 5;
STSEED = 288;


MODEL:
%OVERALL%
%C#1%
[ETH1$1*5.3] (p1);
[ETH2$1*15] (p2);
[ETH3$1*5.5] (p3);
[ETH4$1*1.7] (p4);
[ETH5$1*6.7] (p5);

%C#2%
[ETH1$1*4.5] (p1);
[ETH2$1*3.7] (p2);
[ETH3$1*0.8] (p8);
[ETH4$1*-0.3] (p9);
[ETH5$1*1.4] (p10);

%C#3%
[ETH1$1*-2.9] (p11);
[ETH2$1*-15] (p12);
[ETH3$1*-1.8] (p13);
[ETH4$1*-15] (p14);
[ETH5$1*-2] (p15);

%C#4%
[ETH1$1] (p16);
[ETH2$1] (p17);
[ETH3$1] (p18);
[ETH4$1] (p19);
```

```
[ETH5$1] (p20);

MODEL CONSTRAINT:
p1=-p11;
p2=-p12;
p3=-p13;
p4=-p14;
p5=-p15;

OUTPUT:
TECH10
TECH11
TECH14;
SVALUES
;

SAVEDATA:
FILE = ETH_ConfProb_C3cl4.dat;
SAVE = CPROBABILITIES;
```

References

Agresti, A. (2013). *Categorical data analysis* (3rd ed). Hoboken, NJ: Wiley.

Białowolski, P. (2016). The influence of negative response style on survey-based household inflation expectations. *Quality & Quantity*, *50*(2), 509–528. http://doi.org/10.1007/s11135-015-0161-9

Bolzendahl, C. I., & Myers, D. J. (2004). Feminist attitudes and support for gender equality: Opinion change in women and men, 1974-1998. *Social Forces*, *83*(2), 759–789. Retrieved from http://www.jstor.org/stable/3598347

Citizenship Education Study 2016, I. I. C. {and}. (n.d.). *ICCS 2016 technical report*.

Davidov, E., Schmidt, P., & Billiet, J. (Eds.). (2011). *Cross-cultural analysis: Methods and applications*. New York: Psychology Press, Taylor & Francis Group.

Dotti Sani, G. M., & Quaranta, M. (2017). The best is yet to come? Attitudes toward gender roles among adolescents in 36 countries. *Sex Roles*, *77*(1), 30–45. http://doi.org/10.1007/s11199-016-0698-7

Hagenaars, J. A., & McCutcheon, A. L. (Eds.). (2002). *Applied latent class analysis* (1st ed.). Cambridge University Press. http://doi.org/10.1017/CBO9780511499531

Hallquist, M. N., & Wiley, J. F. (2018). MplusAutomation: An r package for facilitating large-scale latent variable analyses in mplus. *Structural Equation Modeling: A Multidisciplinary Journal*, *25*(4), 621–638. http://doi.org/10.1080/10705511.2017.1402334

Hancock, G. R., Harring, J., & Macready, G. B. (Eds.). (2019). *Advances in latent class analysis: A festschrift in honor of c. Mitchell dayton*. Charlotte, NC: Information Age Publishing, Inc.

Hooghe, M., & Oser, J. (2015). The rise of engaged citizenship: The evolution of citizenship norms among adolescents in 21 countries between 1999 and 2009. *International Journal of Comparative Sociology*, *56*(1), 29–52. http://doi.org/10.1177/0020715215578488

Hooghe, M., Oser, J., & Marien, S. (2016). A comparative analysis of 'good citizenship': A latent class analysis of adolescents' citizenship norms in 38 countries. *International Political Science Review*, *37*(1), 115–129. http://doi.org/10.1177/0192512114541562

Invariance analyses in large-scale studies. (2019). (OECD Education Working Papers No. 201). Retrieved from `https://www.oecd-ilibrary.org/education/invariance-analyses-in-large-scale-studies_254738dd-en`

Isac, M. M., Palmerio, L., & Werf, M. P. C. (Greetje). van der. (2019). Indicators of (in)tolerance toward immigrants among european youth: An assessment of measurement invariance in ICCS 2016. *Large-Scale Assessments in Education*, *7*(1), 6. http://doi.org/10.1186/s40536-019-0074-5

Kankaraš, M., Vermunt, J. K., & Moors, G. (2011). Measurement equivalence of ordinal items: A comparison of factor analytic, item response theory, and latent class approaches. *Sociological Methods & Research*, *40*(2), 279–310. http://doi.org/10.1177/0049124111405301

Kaplan, D., & Publications, S. (Eds.). (2004). *The sage handbook of quantitative methodology for the social sciences.* Thousand Oaks, Calif: Sage.

Kasumovic, M. M., & Kuznekoff, J. H. (2015). Insights into sexism: Male status and performance moderates female-directed hostile and amicable behaviour. *PLOS ONE*, *10*(7), e0131613. http://doi.org/10.1371/journal.pone.0131613

Miranda, D., & Castillo, J. C. (2018). Measurement model and invariance testing of scales measuring egalitarian values in ICCS 2009. In A. Sandoval-Hernández, M. M. Isac, & D. Miranda (Eds.), *Teaching tolerance in a globalized world* (Vol. 4, pp. 19–31). Cham: Springer International Publishing. http://doi.org/10.1007/978-3-319-78692-6_3

Mukhopadhyay, P. (2016). *Complex surveys: Analysis of categorical data* (1st ed. 2016). Singapore: Springer Singapore : Imprint: Springer. http://doi.org/10.1007/978-981-10-0871-9

Nylund-Gibson, K., & Choi, A. Y. (2018). Ten frequently asked questions about latent class analysis. *Translational Issues in Psychological Science*, *4*(4), 440–461. http://doi.org/10.1037/tps0000176

Olivera-Aguilar, M., & Rikoon, S. H. (2018). Assessing measurement invariance in multiple-group latent profile analysis. *Structural Equation Modeling: A Multidisciplinary Journal*, *25*(3), 439–452. http://doi.org/10.1080/10705511.2017.1408015

Robertson, J., & Kaptein, M. (Eds.). (2016). *Modern statistical methods for HCI.* Cham ZG: Springer.

Rutkowski, L., Davier, M. von, & Rutkowski, D. (2014). *Handbook of international large-scale assessment background, technical issues, and methods of data analysis.*

Boca Raton: CRC Press.

Vermunt, J. K. (2014). Latent class model. In A. C. Michalos (Ed.), *Encyclopedia of quality of life and well-being research* (pp. 3509–3515). Dordrecht: Springer Netherlands. http://doi.org/10.1007/978-94-007-0753-5_1604

Wang, J., & Wang, X. (2020). *Structural equation modeling: Applications using mplus* (2nd ed.). Hoboken, NJ: Wiley.