# Value Polarization in Europe: Measurement, Correlates ,and Consequences

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# Previous Results

- Weak positive correlation between average level of postmaterialism and support for radical right parties in European countries.
- Does value polarization matter for support of radical policies? (losers of modernization thesis)
- Measuring value polarization – two-step approach:
  - ✓ Use ordered latent class analysis to categorize latent scale for surviving/self-expression values
  - ✓ Use measures of diversity for categorical data to obtain polarization scores for 29 European countries
- Five-class solution  with order constraints (assuming measurement invariance) fits data sufficiently well.

# Data

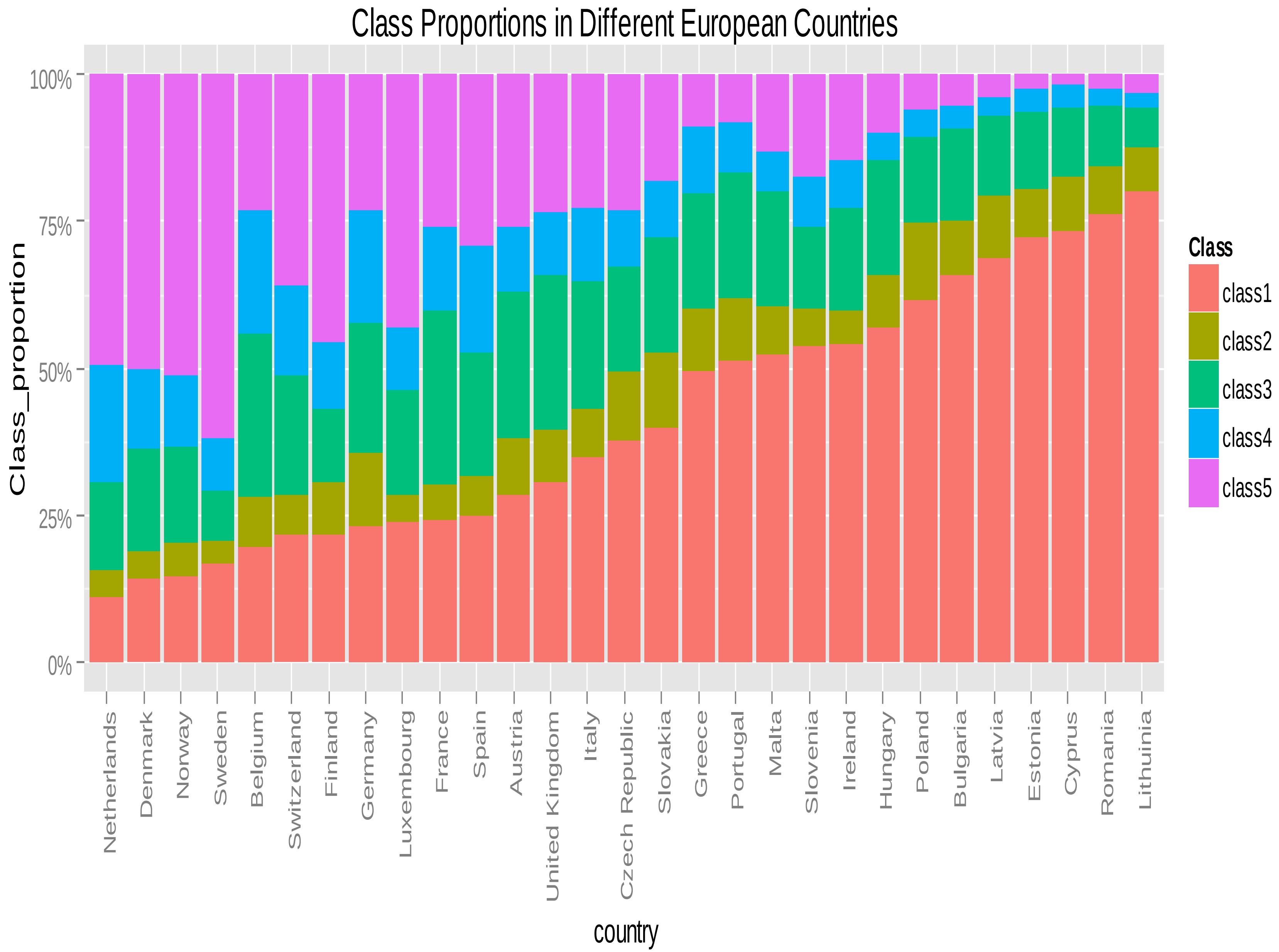
- Survival/Self-Expression Values. EVS, 2008-2009
- Manifest variables 1: Happiness, Tolerance for Homosexuality, Trust, Four-Item Postmaterialism Index (as a single variable), Signing Petition
- Manifest variables 2: Tolerance for Homosexuality. Four-Item Postmaterialism, Signing Petition
- 29 European Countries: 27 EU members, Norway, and Switzerland
- 42826 respondents
- Data were not weighted
- Data were not imputed

# Fit Statistics for Competing Models

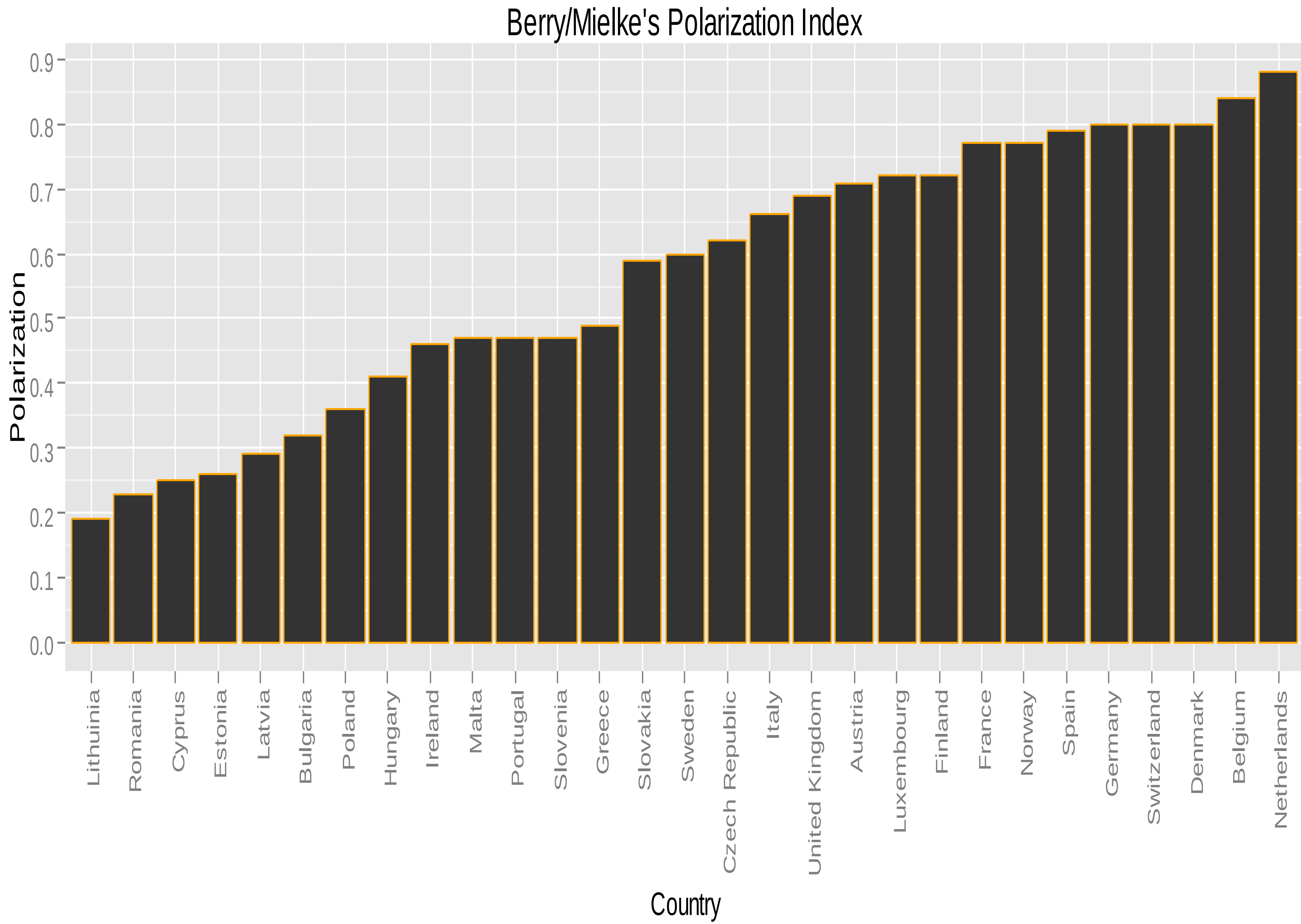
| | aBIC | LMR Test p-value | BLRT p-value | Free Parameters | Violations of Ordering |
|---|---|---|---|---|---|
| **Three Classes** | 471413.682 | 0.000 | 0.000 | 30 | 0 |
| **Four Classes** | 463097.672 | 0.000 | 0.000 | 40 | 1 |
| **Five Classes** | 448977.323 | 0.000 | 0.000 | 50 | 1 |
| **Five Classes_Ord** | 448977.441 | *** | *** | 50 | 0 |
| **Six Classes** | 446572.609 | 0.000 | 0.000 | 60 | 3 |
| **Six Classes_Ord** | 469077.511 | *** | *** | 55 | 0 |
| **Seven Classes** | 444052.829 | 0.000 | 0.000 | 70 | 6 |
| **Seven_Classes_Ord** | *** | *** | *** | 64 | 0 |

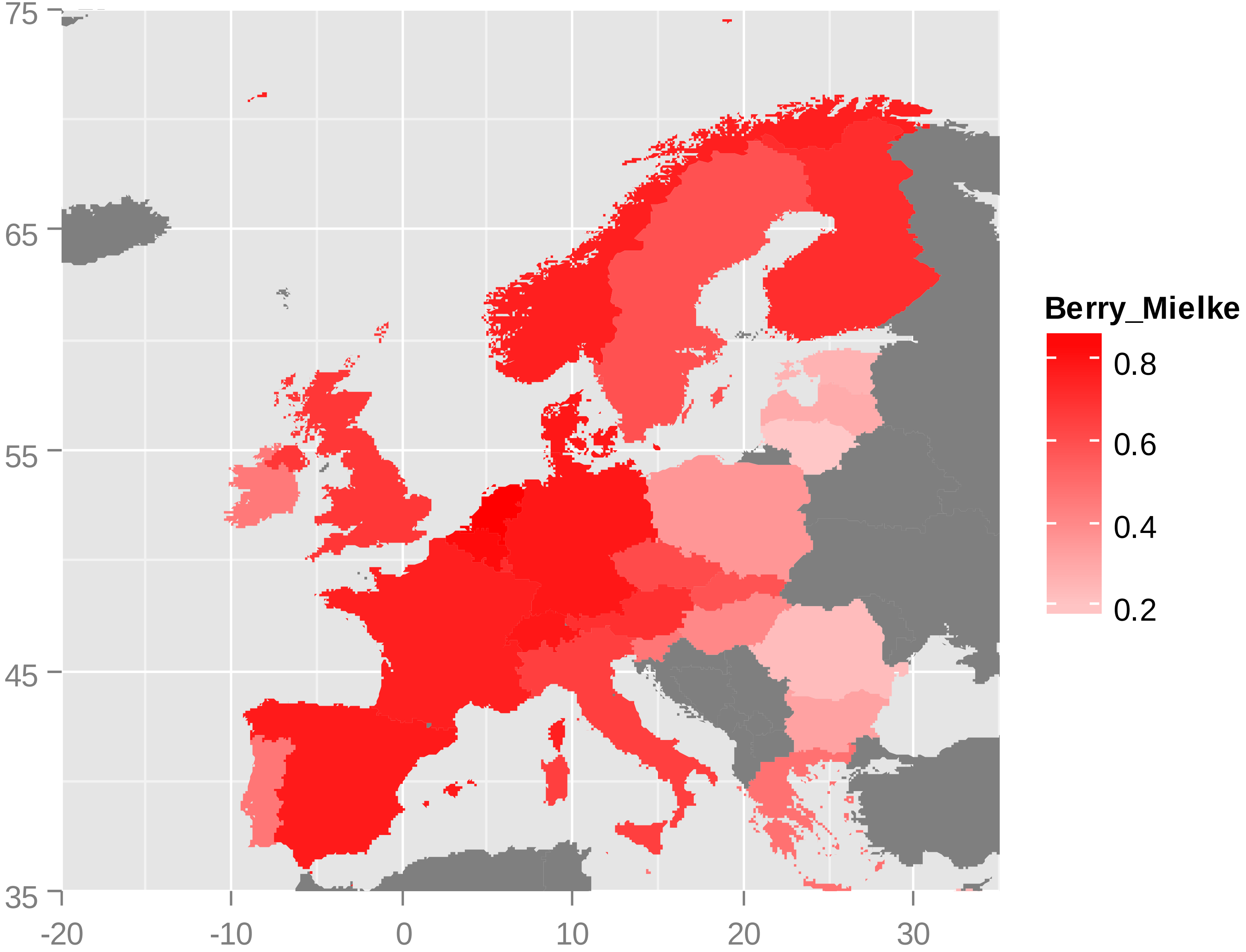
# Polarization Indices

- Standardized Van der Eijk's Agreement A measure
- Berry/Mielke Index of Ordinal Variation
- Leik's Ordinal Variation Index
- L-Squared



Class Proportions in Different European Countries
Class_proportion
100%
75%
50%
25%
0%
Netherlands
Denmark
Norway
Sweden
Belgium
Switzerland
Finland
Germany
Luxembourg
France
Spain
Austria
United Kingdom
Italy
Czech Republic
Slovakia
Greece
Portugal
Malta
Slovenia
Ireland
Hungary
Poland
Bulgaria
Latvia
Estonia
Cyprus
Romania
Lithuinia
country
Class
class1
class2
class3
class4
class5


Berry/Mielke's Polarization Index
Polarization
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
Lithuinia
Romania
Cyprus
Estonia
Latvia
Bulgaria
Poland
Hungary
Ireland
Malta
Portugal
Slovenia
Greece
Slovakia
Sweden
Czech Republic
Italy
United Kingdom
Austria
Luxembourg
Finland
France
Norway
Spain
Germany
Switzerland
Denmark
Belgium
Netherlands
Country


75
65
55
45
35
-20
-10
0
10
20
30
Berry_Mielke
0.8
0.6
0.4
0.2

# Investigating the latent trait underlying the survival/self-expression values

- For five-item models, strict unidimensionality (class ordering) holds only for models with no more than five classes. For three-item models even nine-class solution is plausible.
- When the number of classes is relatively large (to approximate continuous distribution), the distribution of latent trait is trimodal, which indicates non-normality of the self-expression index.
- Country-by-country analysis shows that the class ordering identified in five-class five-tem solution is not robust across countries. Therefore, it is likely that configural measurement invariance does not hold for categorical representation of self-expression values index.
- Surprisingly, class ordering is more frequently violated in Western European countries, rather than in less developed post-communist or southern European societies.

# Polarization Patterns for Five-Class Five-Item Model

- Class proportions vary in a large amount between countries
- There is a clear pattern: Eastern European countries shows larger proportions of survival classes (that is, less “modernized” classes)
- The less polarized countries are at the same time the less modernized while many developed countries are highly polarized
- Modernization and spread of self-expression values lead to the growth of value polarization?

# Country-Level Correlates of Value Polarization Indices

| | Berry_Mielke | L-squared | Polarization | Leik |
|---|---|---|---|---|
| Gini Index | -0.28 | -0.28 | -0.2 | -0.28 |
| Share of Migrants | 0.28 | 0.28 | 0.35‘ | 0.27 |
| GDP | 0.58** | 0.58** | 0.56** | 0.58*** |
| GDP growth rate | -0.28 | -0.28 | -0.28 | -0.25 |
| Unemployment | 0.14 | 0.14 | 0.2 | 0.1 |
| Murder | -0.64*** | -0.64*** | -0.53** | -0.64*** |
| Emancipative Values Index | 0.49*** | 0.49*** | 0.45* | 0.46** |
| Note: | ‘p<0.1 *p<0.05 **p<0.01 ***p<0.001 | | | |

# Value Polarization and Xenophobic Attitudes. Hypotheses

- (H1) Individual value class is positively associated with higher tolerance
- (H2) Country-level value polarization is positively associated with higher level of xenophobic attitudes
- (H3) In countries with higher level of polarization, the effect of individual values on polarization should be stronger.

- Dependent variables: *people that you would not like to have as neighbors* (homosexuals; people of different race; immigrants). Mentioned – 0. Not mentioned – 1.

# Value Polarization and Xenophobic Attitudes. Multilevel Models

| | Immigrants | Homosexuals | Different Race | Immigrants | Homosexuals | Different Race |
|---|---|---|---|---|---|---|
| Value Class | 0.024** | 0.078*** | 0.051*** | -0.009 | 0.132*** | -0.120** |
| Year of Completing Education | 0.128*** | 0.257*** | 0.231*** | 0.128*** | 0.257*** | 0.231*** |
| Age | -0.065*** | -0.218*** | -0.106*** | -0.066*** | -0.218*** | -0.107*** |
| Sex | 0.128*** | 0.321*** | 0.121*** | 0.128*** | 0.322*** | 0.119*** |
| Unemployment | -0.014 | -0.214*** | -0.021 | -0.014 | -0.213*** | -0.021 |
| Immigrant Status | 0.635*** | -0.058 | 0.418*** | 0.634*** | -0.057 | 0.414*** |
| Polarization * Value Class | | | | 0.045 | -0.073 | 0.229*** |
| Value Polarization | 1.779** | 4.555*** | 1.639** | 1.696** | 4.692*** | 1.222* |
| Constant | -0.257 | -2.018*** | 0.344 | -0.197 | -2.116*** | 0.646 |
| Observations | 38,945 | 39,150 | 39,031 | 38,945 | 39,150 | 39,031 |
| Groups | 29 | 29 | 29 | 29 | 29 | 29 |
| LL | -16,106.230 | -18,605.080 | -13,608.630 | -16,106.020 | -18,604.390 | -13,604.440 |
| AIC | 32,230.460 | 37,228.150 | 27,235.260 | 32,232.040 | 37,228.780 | 27,228.870 |
| BIC | 32,307.590 | 37,305.330 | 27,312.410 | 32,317.740 | 37,314.540 | 27,314.600 |
| Note: | *p<0.05 **p<0.01 ***p<0.001 | | | | | |
| Note2: | Dependent variable coding : 0 – mentioned, 1 – not mentioned | | | | | |

# Brief Summary of Multilevel Models

- Individual position on the ordered value scale is positively associated with higher level of individual tolerance (as emancipative values do)
- Value polarization is likely to affect negatively the level of xenophobia (contrary to expectations).
- *After the control for GDP the effect of polarization becomes insignificant (too less groups to include controls)*
- There is no significant interaction effect between value polarization and individual value attitudes (the only exception is the attitude toward people of different race)
- Bayesian approach provides slightly different, but still significant, coefficient estimates for value polarization.

- Modernization leads to polarization; but whether polarization leads to radicalization?

# Shortcomings and limitations

- Sample is restricted only to Europe and only to one time point
- Trade-off between efficiency and computational time might lead to biased parameter estimates
- Measurement invariance was not tested in a formal way
- LCA model selection may seem quite arbitrary
- Low number of clusters in multilevel modelling
- Endogeneity of value polarization to GDP

# Further development

- Bayesian tests for LCA measurement invariants
- Extending sample to include more second-level units in regressions
- Testing interactions of polarization with social class indicators.
- Any advice is highly welcomed!!

Thank you very much

for your attention!

# Why polarization?

- Polarization refers to level of diversity in society on some specific dimension.
- Polarization also reflects a conflict potential caused by diversity.
- Attitudinal polarization is an evidence of cultural cleavage (e.g. so called ‘modernization’ cleavage assumed by ‘losers of modernization’ thesis)
- Attitudinal polarization may be used as a second-level predictor for analyses of many social processes, especially related to politics and ethnic relations.
- Polarization (and related cleavages) may be interesting to model as well.

# Measurement of Polarization
# Previous developments

- Variance (or Standard Deviation)
- Kurtosis
- Foster-Wolfson Index
- Duclos-Esteban-Ray family of indices
- Ethno-Linguistic Fractionalization Index
- Reynal-Querol Index of polarization
- Various measures of ordinal variation
- Visual distribution comparisons
- *Ad hoc* methods (like Mouw and Sobel 2001)

# Polarization in Survey Data

- The main objects of interest are latent constructs (measured through multiple manifest variables).
- Information about distributional parameters of latent variables provided by relevant statistical software is limited.
- Measuring polarization for aggregated factor scores seems to be an inaccurate approach due to possible non-normality, multidimensionality, and measurement non-equivalence of latent scale.

# Why (Ordinal) Latent Classes?

- LCA may easily **handle non-normality** of latent variable
- LCA **allows for multidimensionality**: when the latent categorical variable is nominal rather than ordinal, it is impossible to order all individuals on all items in the same direction.
- LCA allows for testing **measurement Invariance**
- LCA **provides unique observed indicator for latent variable** by classifying respondents according to their value patterns. Several existing ordinal measures of polarization are easily applicable to the resulting classification

# Latent Class Model

- X1, X2, X3, and X4 are observed variables
- Y a latent categorical variable which accounts for the relationships among these four observed variables
- $\pi_{ijklt}^{X1X2X3X4Y} = \pi_t^Y \pi_{it}^{X1|Y} \pi_{jt}^{X2|Y} \pi_{kt}^{X3|Y} \pi_{lt}^{X4|Y}$
- $\pi_t^Y$ is a probability that a randomly selected individual will be in latent class $t$ of latent variable $Y$
- $\pi_{it}^{X1|Y}$ is a probability that a member of latent class $t$ will choose a response category $i$ for observed item $X1$
- $\pi_{jt}^{X2|Y}$ is a probability that a member of latent class $t$ will choose a response category $j$ for observed item $X2$
- $\pi_{kt}^{X3|Y}$ is a probability that a member of latent class $t$ will choose a response category $k$ for observed item $X3$
- $\pi_{lt}^{X4|Y}$ is a probability that a member of latent class $t$ will choose a response category $l$ for observed item $X4$

# Ordinal Latent Classes

- Ordering of the categories of the latent variable is provided by imposing inequality constraints on model parameters: means for continuous manifest variables and thresholds for binary and ordinal manifest variables.
- In MPLUS, thresholds $\tau_{it}$ are used instead probabilities $\pi_{it}^{Xn|Y}$ (logistic parameterization of LCA model)
- Large positive thresholds indicate that (cumulative) probability of a specific response value is relatively low, whereas large negative values suggest that the probability of the response is relatively high.
- Inequality constraint $\tau_{i1} < \tau_{i2} < \tau_{i3} < \tau_{i4}$ assumes the following ordering of classes for threshold $\tau$ for variable $i$ : Class 1 > Class 2 > Class 3 > Class4

# Approach to the Measurement of Polarization

**Step 1.** Selecting a model with an optimal number of latent classes. Best model must satisfy three following requirements

- 1) be parsimonious:  model with K classes should not include classes which are subgroups of classes  identified in a model with K - 1 latent categories.
- 2) be almost ordinal: include very few parameters violating class-ordering
- 3) show the best fit (aBIC and BLRT) comparing to all other models which satisfy 1) and 2)

**Step 2.** Testing for ordinality (*unidimensionality, or strict monotonicity*) of  latent trait: comparing unconstrained and strictly ordered models. Order-constrained hypothesis is tested directly by using Bayes factor approach

**Step 3.** Applying relevant index of nominal or ordinal polarization (depending on the results  from the Step 2) to class proportions for each country obtained at the first stage.

**Bonus.** Exploring measurement invariance and cross-country differences in class proportions

# Thresholds and Means Estimates for the Five-Class Unconstrained Model

| | Happy1 | Happy2 | Happy3 | Pmat1 | Pmat2 | Trust | Petition 1 | Petition 2 | Homosex | Order |
|---|---|---|---|---|---|---|---|---|---|---|
| **Class1** | -3.84 | -1.692 | 1.348 | -0.836 | 2.365 | 0.859 | -0.798 | 0.735 | 3.452 | 2 |
| **Class2** | -3.495 | -1.278 | 1.357 | -0.598 | 2.631 | 1.174 | -0.231 | 1.068 | 1.118 | 1 |
| **Class3** | ***-4.492*** | -2.433 | 0.604 | -1.706 | 1.291 | -0.208 | -2.322 | -0.723 | 9.819 | 5 |
| **Class4** | -4.3 | -1.931 | 0.998 | -1.038 | 1.991 | 0.69 | -1.189 | 0.263 | 5.256 | 3 |
| **Class5** | ***-4.555*** | -2.084 | 0.865 | -1.294 | 1.661 | 0.394 | -1.637 | -0.134 | 7.557 | 4 |

# Thresholds and Means Estimates for the Five-Class Model with Inequality Constraints

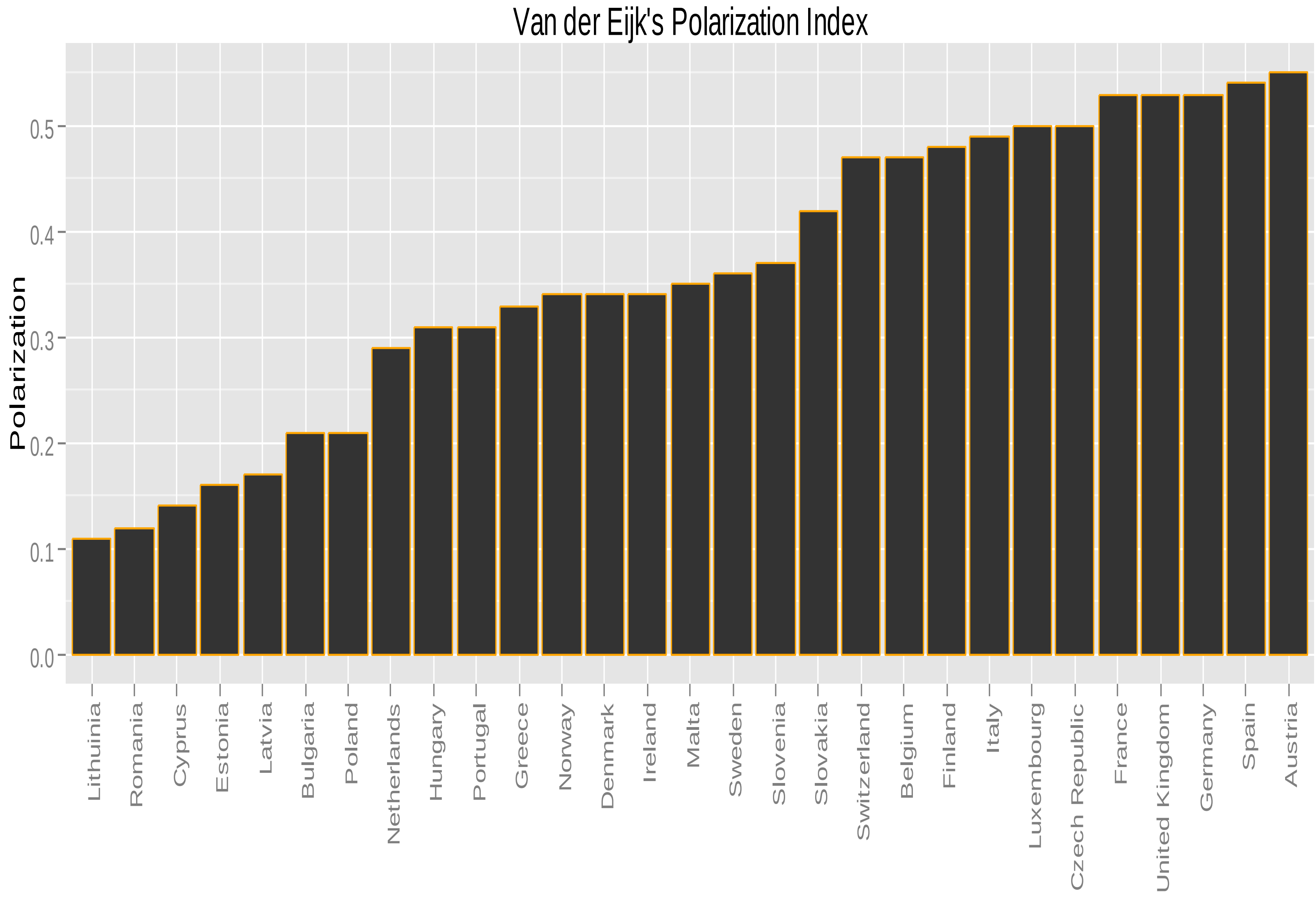
| | Happy1 | Happy2 | Happy3 | Pmat1 | Pmat2 | Trust | Petition 1 | Petition 2 | Homosex | Order |
|---|---|---|---|---|---|---|---|---|---|---|
| Class1 | -3.84 | -1.692 | 1.348 | -0.836 | 2.365 | 0.859 | -0.798 | 0.735 | 3.452 | 2 |
| Class2 | -3.495 | -1.278 | 1.357 | -0.598 | 2.631 | 1.174 | -0.231 | 1.068 | 1.118 | 1 |
| Class3 | ***-4.513*** | -2.433 | 0.604 | -1.706 | 1.291 | -0.208 | -2.322 | -0.723 | 9.819 | 5 |
| Class4 | -4.3 | -1.931 | 0.998 | -1.038 | 1.991 | 0.69 | -1.189 | 0.263 | 5.256 | 3 |
| Class5 | ***-4.512*** | -2.084 | 0.865 | -1.294 | 1.661 | 0.394 | -1.637 | -0.134 | 7.557 | 4 |

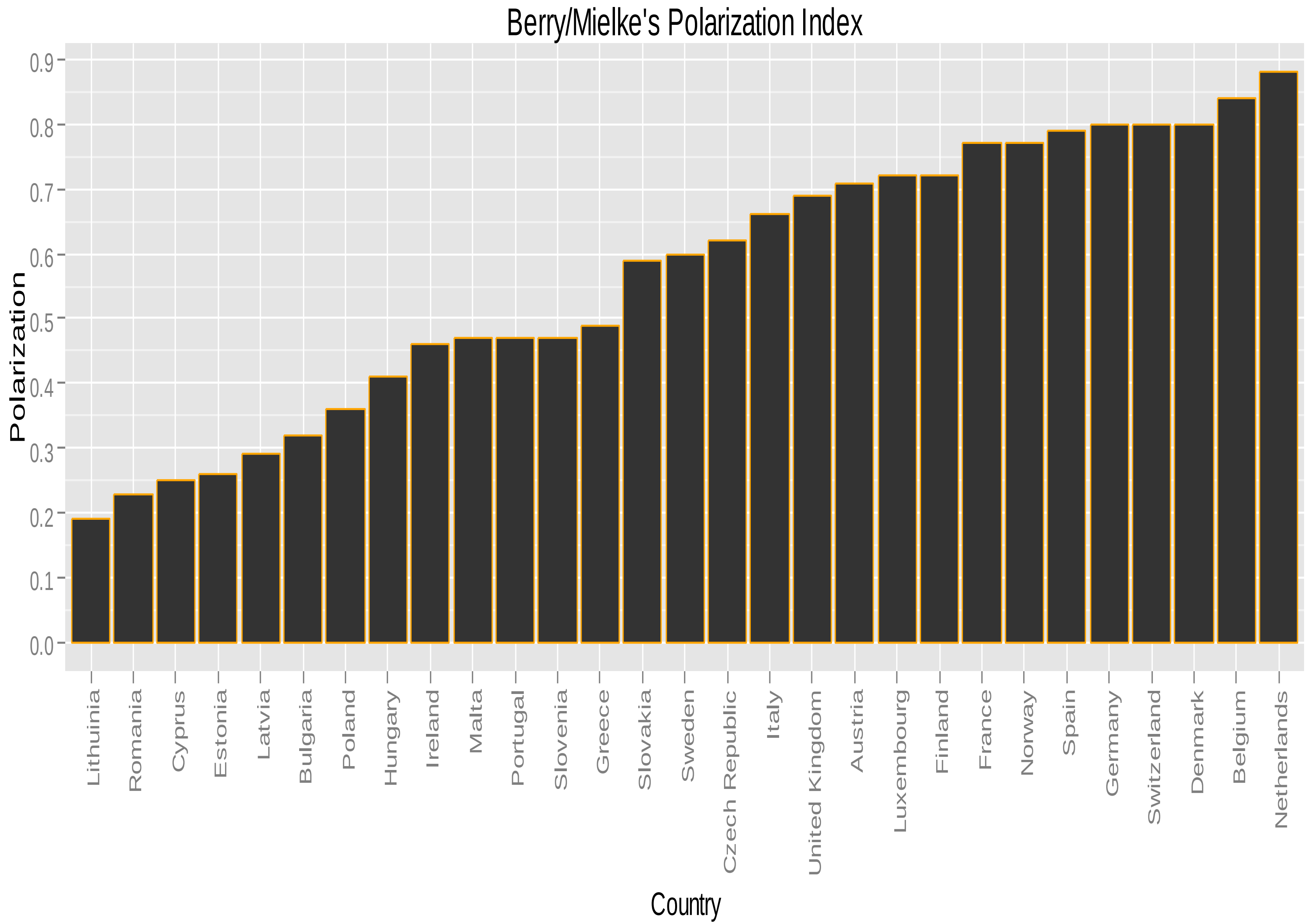
# Thresholds and Means Estimates for the Six-Class Unconstrained Model

| | Happy1 | Happy2 | Happy3 | pmat1 | pmat2 | trust | petition 1 | petition 2 | homosex | Order |
|---|---|---|---|---|---|---|---|---|---|---|
| **Class1** | -3.83 | -1.682 | 1.375 | -0.825 | 2.393 | 0.865 | -0.778 | 0.763 | 3.426 | 2 |
| **Class2** | ***-4.492*** | -2.43 | 0.605 | -1.705 | 1.292 | -0.207 | -2.321 | -0.722 | 9.819 | 6 |
| **Class3** | -4.57 | -1.969 | ***1.038*** | -1.082 | 1.847 | 0.519 | -1.216 | 0.228 | 6.023 | 4 |
| **Class4** | ***-3.495*** | -1.278 | 1.357 | -0.598 | 2.631 | 1.174 | -0.232 | 1.067 | 1.118 | 1 |
| **Class5** | ***-4.556*** | -2.092 | 0.86 | -1.303 | 1.652 | 0.387 | -1.655 | -0.147 | 7.567 | 5 |
| **Class6** | -4.215 | -1.915 | ***0.982*** | -1.022 | 2.044 | 0.754 | -1.178 | 0.277 | 4.978 | 3 |

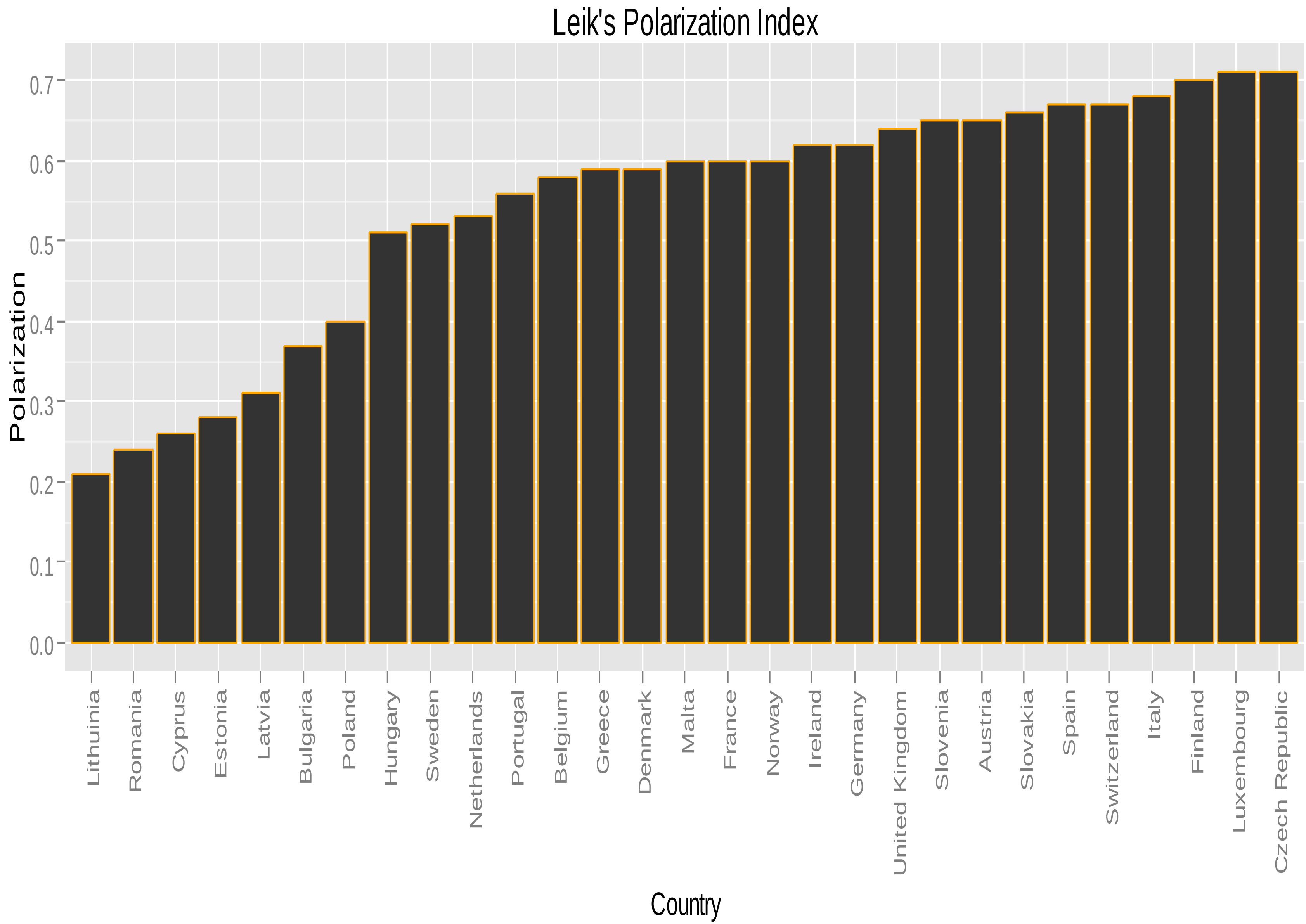
# Thresholds and Means Estimates for the Seven-Class Unconstrained Model

| | Happy1 | Happy2 | Happy3 | pmat1 | pmat2 | Trust | petition1 | petition2 | Homosex | Order |
|---|---|---|---|---|---|---|---|---|---|---|
| Class1 | ***-4.164*** | -1.46 | ***1.490*** | -0.711 | ***2.696*** | 1.028 | -0.53 | 0.803 | 2.003 | 2 |
| Class2 | ***-3.844*** | -2.698 | 1.335 | -0.841 | 2.349 | 0.854 | -0.808 | 0.722 | 3.466 | 3 |
| Class3 | ***-4.555*** | -2.083 | 0.865 | -1.294 | 1.661 | 0.394 | -1.637 | -0.133 | 7.553 | 5 |
| Class4 | ***4.476*** | ***-2.424*** | 0.573 | -1.759 | 1.249 | -0.26 | -2.401 | -0.789 | 9.996 | 7 |
| Class5 | ***-4.566*** | ***-2.454*** | 0.752 | -1.482 | 1.501 | 0.044 | -2.003 | -0.428 | 8.997 | 6 |
| Class6 | -3.433 | -1.256 | ***1.341*** | -0.583 | ***2.623*** | 1.193 | -0.194 | 1.104 | 1.004 | 1 |
| Class7 | -4.301 | -1.931 | 1 | -1.038 | 1.993 | 0.69 | -1.188 | 0.265 | 5.267 | 4 |


Van der Eijk's Polarization Index
Polarization
0.0
0.1
0.2
0.3
0.4
0.5
Lithuinia
Romania
Cyprus
Estonia
Latvia
Bulgaria
Poland
Netherlands
Hungary
Portugal
Greece
Norway
Denmark
Ireland
Malta
Sweden
Slovenia
Slovakia
Switzerland
Belgium
Finland
Italy
Luxembourg
Czech Republic
France
United Kingdom
Germany
Spain
Austria
Country



Berry/Mielke's Polarization Index
Polarization
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
Lithuinia
Romania
Cyprus
Estonia
Latvia
Bulgaria
Poland
Hungary
Ireland
Malta
Portugal
Slovenia
Greece
Slovakia
Sweden
Czech Republic
Italy
United Kingdom
Austria
Luxembourg
Finland
France
Norway
Spain
Germany
Switzerland
Denmark
Belgium
Netherlands
Country


Leik's Polarization Index
Polarization
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Lithuinia
Romania
Cyprus
Estonia
Latvia
Bulgaria
Poland
Hungary
Sweden
Netherlands
Portugal
Belgium
Greece
Denmark
Malta
France
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United Kingdom
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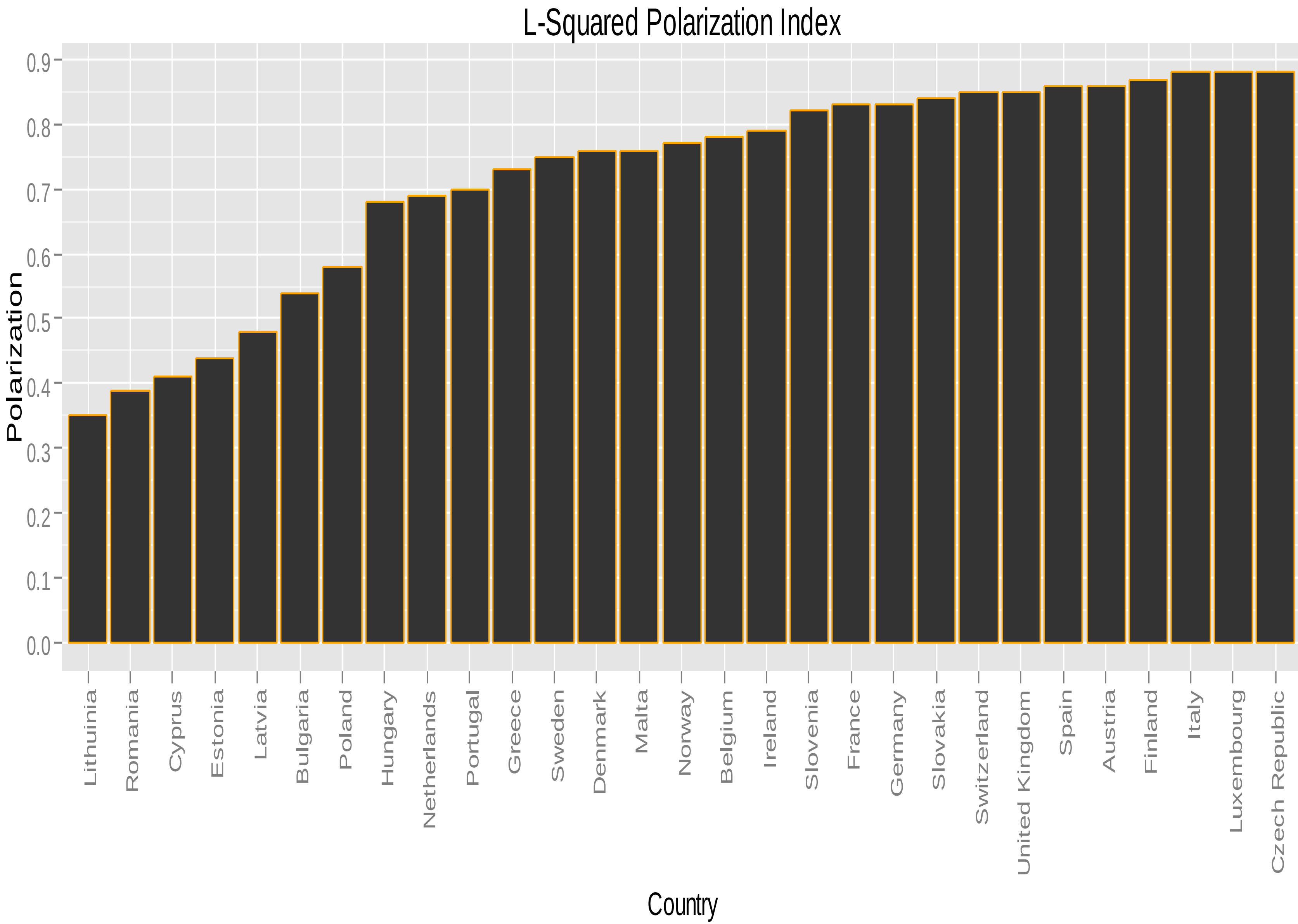
Austria
Slovakia
Spain
Switzerland
Italy
Finland
Luxembourg
Czech Republic
Country


L-Squared Polarization Index
Polarization
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
Lithuinia
Romania
Cyprus
Estonia
Latvia
Bulgaria
Poland
Hungary
Netherlands
Portugal
Greece
Sweden
Denmark
Malta
Norway
Belgium
Ireland
Slovenia
France
Germany
Slovakia
Switzerland
United Kingdom
Spain
Austria
Finland
Italy
Luxembourg
Czech Republic
Country

# Pairwise Correlations between Polarization Measures

| | RQ Index | Berry-Mielke | Lsquared | Polarization | Leik |
|---|---|---|---|---|---|
| **RQ Index** | 1 | 0.35 | 0.52 | 0.28 | 0.55 |
| **Berry_Mielke** | 0.35 | 1 | 0.82 | 0.83 | 0.79 |
| **Lsquared** | 0.52 | 0.82 | 1 | 0.94 | 0.99 |
| **Polarization** | 0.28 | 0.83 | 0.94 | 1 | 0.91 |
| **Leik** | 0.55 | 0.79 | 0.99 | 0.91 | 1 |