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**ATTITUDINAL POLARIZATION
MEASUREMENT THROUGH
(ORDERED) LATENT CLASS
ANALYSIS**

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ATTITUDINAL POLARIZATION MEASUREMENT THROUGH (ORDERED) LATENT CLASS ANALYSIS²³

This paper presents a new approach to the measurement of attitudinal polarization for cross-national or repeated cross-sectional studies. The proposed approach is a two-stage one. At the first step, order-constrained Latent Class Analysis (LCA) is used to identify a categorical latent construct underlying a set of observed items. Basing on the best LCA solution, class membership is assigned for each individual in the sample. At the second step, a broad family of categorical polarization indices may be computed for that categorical latent scale in respect to any grouping variable of interest (e.g., country of living, or wave of study). The data from the 4th wave of the European Values Study are used, and polarization between survival and self-expression values in 28 European countries is measured. The resulting polarization scores are used to test a hypothesis assuming positive aggregate-level association between values polarization and support for radical right parties and ideologies.

JEL classification: C38, Z00, Z13

Keywords: values, polarization measurement, latent class analysis, order-constrained LCA, losers of modernization

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Introduction

Attitudinal polarization has become an important research field in social sciences during recent decades (Fiorina and Abrams 2008; Hetherington 2009). Most research on polarization in sociology and political science, however, focuses mostly on the USA, with rare exceptions (see for review Munzert and Bauer 2013). Focus on any specific country (not necessary the USA) significantly reduces the sample and do not allow for proper quantitative analyses and broad generalizations. So if one is interested in investigation of causes and consequences of changes in the level of attitudinal polarization, then bringing attitudinal polarization into comparative perspective seems to be an evident next step in polarization research. This enterprise is not very problematic, since the data from large-N comparative social surveys, like the Eurobarometer, the World Values Surveys, the European Values Study, or the European Social Survey, covering a large number of countries, are widely available for scholars nowadays. These surveys are designed in order to measure not only public opinion, but also more fundamental types of attitudes, like human values (Schwartz 1992) or specific postmaterialist/emancipative values orientations (Inglehart 1990; Welzel 2013), and provide multiple opportunities for exploration of polarization trends, patterns and correlates across the world. It is nevertheless important to note that many important attitudinal concepts, implemented in cross-national social survey projects mentioned above, are latent constructs in their nature, and defined and measured accordingly, yet existing methods of polarization measurement are primarily intended to deal with polarization on observed scales and do not fit some important assumptions common in latent variable modelling.

This paper contributes to the methodology of quantitative social sciences by proposing a method for measurement of attitudinal polarization, especially suitable for dealing with polarization on latent scales. The method is a two-stage approach, which combines

categorization of the latent variable, corresponding to observed attitudinal indicators, by the means of latent class analysis, or LCA, (Stage 1), and subsequent computation of aggregated polarization score with the use of some existing measures of categorical dispersion (Stage 2). The suggested procedure of polarization measurement is illustrated by computation of polarization scores on survival/self-expression value orientations for 28 European countries. The computed scores are used to test the “losers of modernization” thesis, stating that the growing support for the radical right ideology among Europeans is a consequence of the shift from industrial to postindustrial society. The rest of the paper is organized as follows. Section 2 highlights some previous developments in polarization measurement in various fields, from sociology to political economy to organizational research, and discusses their shortcomings for the purposes of cross-cultural research. Section 3 introduces a two-stage method for the measurement of country-level value polarization. Section 4 gives an empirical illustration of how the method works, and presents polarization scores on survival versus self-expression value orientations for 28 European countries. Section 5 describes the “losers of modernization” thesis, reports correlations between values polarization and various social, economic and political aggregate-level indicators of modernization, and also studies a relationship between polarization and country-level support for anti-immigrant attitudes and political movements. Section 6 concludes.

Measurement of Attitudinal Polarization: Previous Developments

The interest towards the issue of attitudinal polarization was initially inspired in American sociology and political science by debates on so called ‘cultural wars’ (Ellison and Musick 1993; Hunter 1994). In a path-breaking paper, Di Maggio et al. (1996) introduced four different measures of polarization, namely, variance, kurtosis, Cronbach’s alpha, and differences in mean responses for the members of different social strata (like gender, birth

cohort, or social class). They applied those measures to the study of attitudes of the U.S. population towards some “hot” topics of the American politics. They explored NES and GSS data and found that only the opinion towards the abortion issue became polarized among Americans during 1970s-1990s. Di Maggio et al. provoked a great empirical debate on whether the United States really becomes more polarized (see reviews in Fiorina and Abrams 2008; Hetherington 2009; Fischer and Mattson 2009), but their particular measures of polarization were criticized by many subsequent authors. Thus, it was stressed by critics that variance and kurtosis are ineffective measures of polarization when the distribution of the dependent variable has more than two modes (Downey and Hoffman 2001; Mouw and Sobel 2001).

An important contribution to the methodology of polarization measurement was made by Mouw and Sobel (2001). They suggested a cumulative probit model with heteroscedasticity and variable cutpoints for detecting growth of polarization over time. They applied that model to the data Di Maggio et al. used, and found no evidence of polarization in attitudes towards abortion. Despite the many advantages of their sophisticated model, it is rather difficult to apply that model in cross-national research. It allows for checking whether the log-odds of being in the highest class depends on any grouping variable (like time), but does not provide any value which may be used to decide about the absolute level of polarization in a given group. It also does not provide any score which may be used as an independent variable in the further analysis of the relationships between polarization and any societal variable or attitude of interest, and therefore is of little interest for the purposes of comparative research. Baldassarri and Gelman (2008; see also Munzert and Bauer 2013) suggest another relative measure of polarization in multivariate data, based on pairwise correlations between different issue attitudes. The debate on public opinion polarization in the USA and, recently, in Europe (Munzert and Bauer 2013; Down and Wilson 2010; Adams, Vries and Leiter 2011; Adams,

Green and Milazzo. 2012a, b), is also accompanied by the research on elite polarization, which also contributes to measurement of polarization, e.g. by introducing NOMINATE-family measures (Poole and Rosenthal 1985; McCarty, Poole and Rosenthal 2006).

Another discipline where polarization is of great interest is economics, especially political economy. Empirical research on economic inequality stimulated development of several measures of heterogeneity, from the well-known Gini index (and, more broadly, all statistics based on Lorenz-curve) to recent developments by Foster and Wolfson (1992), Esteban and Ray (1994), and Duclos, Esteban, and Ray (2004). Since the work of Easterly and Levine (1997) ethnic (and then linguistic and religious) heterogeneity is considered as an important predictor in studies of economic growth as well as civil wars and political conflicts. Among the most important methodological contributions in the field are the index of ethno-linguistic fractionalization (or Herfindahl index) and its various refinements (Alesina et al. 2003; Posner 2004; Alesina and La Ferrara 2005), and the RQ index (Reynal-Querol 2002; Reynal-Querol and Montalvo 2005). Yet, several algorithms for measuring heterogeneity were proposed in health and segregation studies, organizational research, and psychology (Berry and Mielke 1992). To sum up, nowadays researcher can choose between various tools allowing for careful measurement of the level of diversity or polarization for continuous, nominal and ordinal variables.

However, existing approaches to polarization measurement are of limited utility for the purposes of cross-national sociology and political science. One of the main reasons for that is because the most important concepts in cross-cultural studies have an essentially latent, or unobserved, nature and are usually measured by multiple indicators, which often may be of different scales (e.g., nominal, ordinal, count, continuous, or both). In such cases researcher should aggregate observed scores on all indicators (as it is usually done for means comparisons) and then measure polarization in respect to the resulting composite scores. It

may involve bias due to the non-normality or undetected multidimensionality of the latent variable underlying the artificial composite score.

The reverse approach when one measures polarization for each observed indicator and then combine partial scores into a general polarization score seems to be even worse, because it assumes the possibility of combination of indices computed by different methods and for different scales. Interpretation and the exact numeric value of each polarization index strongly depends on the scale to which it is applied; but it is doubtful that the score averaged over nominal, ordinal and continuous polarization measures have any reasonable interpretation. Even if one aggregate polarization scores for the set of items of the same scale (like in Klasing and Beugelsdijk 2014), it should be noted that the validity of polarization scores, either computed for composited indices or averaged over a set of partial polarization indices, still remains sensitive to violations of the basic assumptions of the approaches used for creation of the indices, typically confirmatory or exploratory factor analyses. In addition to issues of dimensionality and normality of underlying latent construct, mentioned above, aggregated scores based on typical CFA models do not reflect possible differences in response styles or different understanding of survey questions by the respondents due to the impact of unobserved unit-specific effects. These issues are crucial for the methodology of cross-national social surveys; therefore, they are highly relevant to the issue of measurement of attitudinal polarization in cross-cultural research.

Method

The present study develops a two-stage approach to the measurement of attitudinal polarization, which is well-suited for dealing with latent scales. At the first stage, latent class analysis (LCA) is used to identify the latent construct related to the observed indicators and to represent this construct as the observed categorical variable. Then an order-constrained latent

class analysis, or OLCA (Croon 1990, 2002; Hoijsink 1998, Hoijsink and Molenaar 1997; Vermunt 2001; Van Onna 2002; Laude et al. 2004; Finch and Bronk 2011), is used to determine whether the discrete latent scale is ordinal or nominal. At the second stage, several existing indices of categorical dispersion, ordinal or nominal (depending on the best LCA-solution from the previous step), may be applied to the resulting classification of individuals within each category of some grouping variable (country, social strata, or time period) to compute polarization scores.

LCA Model

In social sciences, LCA is a common approach to the study of latent typologies and structures. It differs from a more popular factor analysis in that the LCA assumes a latent variable underlying observed items to be categorical rather than continuous, as in the factor analysis (for a summary of basic concepts behind LCA, see Vermunt and Magidson 2004; Hagenaars and McCutcheon 2002). In a formal way, a LC model can be described as follows. Let one observes J categorical items, or *manifest variables*, with index $j = 1, 2, \dots, J$, each with the number of (ordered) response categories A_j , $A_j \geq 2$ for each j , for N individuals with the index $i = 1, 2, \dots, N$. Then assume that there exists a latent categorical variable U with a number of categories equal to K . The two key parameters to be estimated in a latent class model are the class specific response probabilities π_{jak} , which represents the probabilities (cumulative probabilities, when item j is ordinal and $A_j > 2$) that a respondent from latent class k gives response a to item j , and the class weights p_k , or the probabilities that a randomly selected individual i will belong to latent class k .

The likelihood function for the model, assuming conditional independence of the outcomes Y given class memberships, is given by

$$(1) \quad P(Y|\pi, p) = \prod_{i=1}^N \sum_{k=1}^K p_k \prod_{j=1}^J \prod_{a=1}^{A_j} (\pi_{jak})^{Y_{ija}}$$

in which $Y_{ija} = 1$ if respondent i gives response a to item j and 0 otherwise (Van Onna 2002; Linzer and Lewis 2011). The model may be estimated via maximum likelihood (e.g. using some version of the EM algorithm) or via various MCMC sampling methods (Hojtink 1998, Hoijtink and Molenaar 1997; Van Onna 2002). It also may be easily extended to deal with continuous manifest variables or any combination of nominal, ordinal and continuous outcomes. For continuous manifest variables, class-specific item means and variances are estimated instead of response probabilities.

Typically, latent categorical variable U is assumed to be nominal. However, many latent constructs in cross-cultural research are supposed to be monotonically increased continuous scales. In the LCA framework, one may obtain flexible discrete approximations for such scales by imposing inequality constraints on cumulative⁴ class-specific response probabilities π_{jaK}^* of a following type (Croon 2002):

$$(2) \quad \pi_{ja1}^* \leq \pi_{ja2}^* \leq \dots \leq \pi_{ja,K-1}^* \leq \pi_{jaK}^*$$

This inequality assumes that, for given item j and response category a , the cumulative response probabilities are non-decreasing with the latent class number $k = 1, 2, \dots, K$. LC model for which such restrictions on cumulative class-specific response probabilities hold for each class, each item and each item category, or, to put it in a more generalized form,

$$(3) \quad \pi_{jak}^* \leq \pi_{ja,k+1}^*$$

for each j, a , and k , is called the Monotone Homogenous (MH) ordered latent class model

⁴ To the obvious reasons, nominal manifest variables are incompatible with ordinal latent scales.

(Van Onna 2002)⁵. For MH-model, individuals belonging to higher latent categories score higher on all observed items. One can interpret the ordinal latent variable measured with such order-constrained model as a direct counterpart of commonly used ordinal scales, say, Likert scale. If ordering constraints do not hold for one or more items, (i.e. when the assumption of monotonicity given by Equations 2.1 and 2.2. does not hold) it may indicate that 1) nominal classification fits the data better than the order-restricted model, or 2) some additional latent traits (or dimensions) are necessary to correctly represent respective latent structure.

It is important to note that some popular statistical packages for latent variable modelling use different parameterizations of LC models, rather than described here. In particular, MPLUS software, which is used in this paper, reports variable thresholds τ instead of class-specific cumulative response probabilities π_{jak}^* . The relationship between these two quantities takes the form

$$(4) \quad \pi_{jak}^* = \frac{1}{1 + e^{-\tau}}$$

Large positive thresholds indicate the probability of a specific response value is relatively low, whereas large negative values suggest that the probability of the response is relatively high. Thus, $\tau = +3$ indicates a response probability of 0.047, while $\tau = -3$ indicates a response probability of 0.953 (Finch and Bronk 2011: 136). When thresholds are used instead probabilities, order constraints expressed in (2) and (3) therefore may easily be re-specified in the following form:

$$(5) \quad \tau_{ja,1} \leq \tau_{ja,2} \leq \dots \leq \tau_{ja,K-1} \leq \tau_{ja,K}$$

Given estimates p'_k and π'_{jak} of p_k and π_{jak} , respectively, the posterior probability that each

⁵ It should be noted that similar constraints may be imposed not only on class-specific response probabilities, but if some manifest variables are continuous, also on means of continuous variables.

individual belongs to each class, conditional on the observed values of the manifest variables, can be calculated using Bayes' formula (Linzer and Lewis 2011):

$$(6) \quad P(u_k|Y_i) = \frac{p'_k \prod_{j=1}^J \prod_{a=1}^{A_j} (\pi'_{jak})^{Y_{ija}}}{\sum_{q=1}^K p'_q \prod_{j=1}^J \prod_{a=1}^{A_j} (\pi'_{jaq})^{Y_{ija}'}}$$

where $u_k \in (1, \dots, K)$. These estimates may be used to assign each individual to an estimated class. Usually, each unit is simply assigned the class label with the largest (modal) estimated posterior probability from Equation 4 (Bakk et al. 2014; Collins and Lanza 2010: 72), but some other methods, such as proportional assignment, may be used.

Some Advantages of LCA

While less popular than factor analysis, LCA has some valuable features for many research contexts. Thus, introducing of order-constrained latent class analysis allows for detecting non-normality of the latent scale (Van Onna 2002). The normality assumption is a crucial prerequisite for the use of composite indices in cross-national comparisons; however, it is almost never tested in practice. Schmitt et al's (2006) technique⁶ provides a reliable method for detecting non-normality of latent traits and furthermore allows for describing the shape of latent variable distribution. However, it is just a tool of diagnostics; it does not say us what to do, if non-normality is actually the case. OLCA solution with a moderate number of categories, nevertheless, provides a plausible way to handle non-normality of the latent trait, by replacing continuous scale by ordinal discrete one (which should not necessary be normally distributed).

Another important concern in latent variable modelling is the issue of dimensionality. In the

⁶The idea behind this method is to compare a model in which probabilities of class membership were estimated to a restricted submodel in which class memberships were fixed to normal Gauss–Hermite quadrature values (which used for approximating normal distribution).

context of LCA, the assumption of unidimensionality states that only one latent variable is needed to explain the observed individual response patterns for a given set of outcomes. Similarly, in factor analysis it is assumed that the observed variation in manifest variables corresponding to some latent factor is explained solely by this factor. When it is not the case, some further corrections of CFA measurement model are needed, like additional latent variables, cross-loadings, or residual covariances between some observed items. Within (order-restricted) LCA framework, one may detect multidimensionality by comparing the fit of a model with one [latent variable] and a model with two or more latent discrete scales (Vermunt 2001; Van Onna 2002; Ligtvoet and Vermunt 2012) or by using latent class factor analysis (Magidson and Vermunt 2001). Another plausible alternative is to model unexplained residual covariance between manifest variables explicitly.

Latent class approach is also suitable for testing measurement invariance, an important assumption in cross-cultural research. Measurement invariance (MI) implies that, for some latent variable model, conditional on the latent trait scores, the model parameters are equal across groups (cf. Mellenbergh 1989 and Van de Shoot et al. 2013). For instance, for confirmatory factor analysis (CFA) model upon a set of continuous variables tested in two or more countries, MI requires that all factor loadings and all intercepts should be the same in each country. Similarly, LCA allows for testing measurement invariance (Kankaras et al. 2011; see also Oberski et al. 2015) by forcing class-specific response probabilities to be equal across countries and comparing the fit of such constrained model to the fit of a less restricted model (which is similar to the testing for equivalence in multi-group factor analysis). It should be noted, however, that, for order-restricted LC models, testing for invariance may be a bit more complicated procedure. Kankaras et al. (2010) suggest an algorithm for checking MI in the context of LC factor model, which is slightly different from the MH-model. Probably, adoption of the approximate measurement invariance approach for CFA (Muthén and

Asparouhov 2012, 2013; Van de Shoot et al. 2013) in the LCA framework may provide a good solution.

Finally, LCA model may be adjusted for an individual response style driving a person to use a certain part of the rating scale by adding a so called method factor that loaded on all the value items (Schwartz et al. 2012, Magun et al. 2015). To sum up, LCA and its extensions provide flexible tools for constructing latent scales and checking their measurement validity. In particular, OLCA allows for constructing ordered latent scales which may be interpreted in a similar way to more popular continuous latent scales, but more flexible in handling various violations of the assumptions of normality, monotonicity, or unidimensionality of latent constructs.

Model Selection in LCA

The extensive simulation study by Nylund et al. (2007) revealed that Bayesian Information Criterion adjusted to the sample size (aBIC) was superior to such popular alternatives, as the Akaike information criterion (AIC) and the standard BIC, as well as several modifications of those, for the assessment of the fit of LCA models. Another plausible alternative to the aBIC are the Lo-Mendell-Rubin test (LMRT) and the bootstrap likelihood ratio test (BLRT), but these tests do not allow for comparisons between models with the same number of latent classes (Finch and Bronk 2011), and therefore are of less importance to the specific purposes of this study, which is aimed to comparison between nominal and ordinal LC models with the same K . Unlike LMRT and BLRT, aBIC can be used to compare models with the same number of latent classes, so this measure is used as a primary measure of model fit in the analysis below. Nevertheless, LMRT and BLRT are quite useful to determine an optimal number of latent classes before testing for plausibility of order constraints. For the AIC, BIC and aBIC, lower values indicate better model fit. For the LMRT and BLRT, significant results

suggest that the model with k classes fits the data better than the simpler $k - 1$ model. An auxiliary fit statistics that might be used for the assessment of LCA models is entropy, a standardized measure of the quality of classification of individuals into classes, based upon the posterior class probabilities. Entropy values range from 0 to 1, with values of .70 or higher indicating good classification accuracy (Reinecke, 2006; Meeus et al. 2010).

Another way to assess the fit of order-constrained LCA models is a so called informative hypothesis testing (Hojtink and Boom 2008; Van de Schoot et al. 2012). This approach is based on Bayesian framework and allows for comparing order-constraint LCA model and freely-estimated LCA models directly, by calculating so called Bayes factor for the constrained solution. To compute Bayes factor one should proceed in the following sequence. First, one needs to sample a posterior distribution of model parameters for the unconstrained LCA model with the predefined number of classes⁷. Then, proportion of the posterior distribution (call it F) in agreement with the inequality-constrained hypothesis is calculated. Another component of Bayes factor is complexity (C) of the model, or the proportion of the prior distribution of the model in agreement with the constraints imposed on model parameters, assumed by order-constrained hypothesis. The resulting statistics is computed as

$$(7) \quad BF = \frac{F/C}{(1 - F)/(1 - C)}$$

The resulting Bayes factor can be interpreted as a relative measure of support for the research questions “Is the hypothesis correct” and “Is the hypothesis incorrect?” If $BF > 1$, than the constrained model is more supported by the data than unconstrained. If $BF \approx 1$, neither of the two hypotheses is preferred by the data. For $BF < 1$, the unconstrained model should be preferred (Van de Schoot et al. 2010; van der Shoot et al. 2012)

⁷The number of classes is determined in advance, according to conventional LCA model selection criteria, like aBIC, BLRT and/or theoretical considerations.

It should be stressed that the model selection in LCA is a less formal procedure than, say, in confirmatory factor analysis. A choice of the best model depends not only on the values of the aBIC, or any other goodness-of-fit statistics, but also on non-statistical considerations. It is a common practice in applied LCA, when theory comes into collision with data, to support substantive theory (if it is a good theory, of course), rather than a senseless model which fits data slightly better. To partly control for the possibility of senseless solution, one may follow the approach of Meeus et al. (2010; p. 1571; see also Moors and Vermunt 2007) and evaluate the content of the classes from different solutions. If an additional class from a solution with k classes is a slight variation of a class already found from a solution with $k - 1$ classes⁸, then the most parsimonious solution should be preferred. Finally, if the latent categorical scale assumed to be ordered rather than nominal, according to some theoretical considerations, the relevant criterion for model selection is the requirement of minimal strict ordering, which states that the model with K classes should be preferred to the model with the $K + 1$ classes if and only if it satisfies the assumption of monotonicity, while the more complex model does not.

Measuring polarization on latent discrete scales

On the second stage of the suggested approach to polarization measurement, the resulting LCA classification is treated as a categorical observed variable, so one may compute one or several indices of variation, specified for categorical outcomes, for that scale. If the LCA favor a choice of a nominal latent scale, than the obvious choice for polarization measure is the Reynal-Querol index (Reynal-Querol 2002; Reynal-Querol and Montalvo 2005). If the LC solution is an ordinal latent scale, then one of the following alternative polarization indices may be considered: Index of Ordinal Variation (Berry and Mielke 1992; see also Blair and

⁸ Term “slight variation” refers to situation, when a model with k classes has the same class weights for all but two classes as the same classes in the model with $k - 1$ classes, and the sum of class weights for two remaining classes is equal to the class weight of some class from a simpler model.

Lacy 2000), Leik's Index of Ordinal Dispersion (Leik 1966), and polarization index based on Agreement A measure (Van Der Eijk 2001).

The **Reynal-Querol index** of polarization was initially developed for measuring ethnic heterogeneity and represents a modification of well-known index of ethno-linguistic fractionalization. It is given by

$$(8) \quad RQ = 4 \sum_{i=1}^N n_i^2 (1 - n_i),$$

where n_i is a sample proportion for the category i and N is a number of observations. It should be noted that RQ index is suitable for measuring polarization of nominal rather than ordinal variables, i.e. it is only differences in proportions between different categories of dependent variable it takes into account, not the relative distance between them. Therefore, choice between ordered and nominal LC model is of substantial importance for measuring polarization.

There is a broad family of related indexes for measuring ordinal polarization, or ordinal dispersion. Leik (1966) proposed a measure of ordinal dispersion based on the notion of *cumulative relative frequencies*. His index D may be represented in a formal way as follows.

Let

$$(9) \quad d_i = \begin{cases} F_i & \text{if } F_i \leq 0.5 \\ 1 - F_i & \text{otherwise} \end{cases},$$

where F_i is a cumulative proportion for categories $1, \dots, i$. Then

$$(10) \quad D = \frac{\sum d_i}{k-1}.$$

If all observations are in the same category, ordinal dispersion is 0. With half the observations in one extreme category, and half the observations in the other extreme, ordinal dispersion is 1. The dispersion measure is a percentage, and can be interpreted accordingly (Ruedin 2013).

Berry-Mielke's Index of Ordinal Variation (IOV) is a measure of dispersion based on squared Euclidean distances.

$$(11) \quad IOV = \frac{T}{T_{max}},$$

where $T = \sum_{i < j} n_i n_j (j - i)$. When N is odd, then $T_{max} = \frac{(N^2 - 1)(k - 1)}{4}$. When N is even, then $T_{max} = \frac{N^2(k - 1)}{4}$. N is a number of observations; k is a number of response categories; n_i is a sample proportion for the category i , $1 \leq i \leq j \leq k$.⁹

The final polarization measure that is used in this paper grounds on Van der Eijk's Agreement A index (Van der Eijk 2001)¹⁰. All indices except RQ may be easily computed using R package "Agrmt" (Ruedin 2013)¹¹.

Application 1: Polarization on Survival/Self-Expression Values in 28 European Countries

Data

For an empirical illustration of the proposed method, the data from the fourth wave of the European Values Study are used to compute polarization scores on survival/self-expression value orientations for 28 European countries, including 26 countries-members of the

⁹ In most cases, IOV is equivalent to $1 - L^2$ statistics proposed by Blair and Lacy. The latter may be interpreted as the proportion of the maximum possible sum of cumulative binomial variances exhibited by observed distribution (Blair and Lacy 2000: 259). More formally, this index is given by (notation is as for the IOV):

$$(12) \quad 1 - l^2 = \sum_{i=1}^{k-1} \frac{n_i(1 - n_i)}{(k - 1)/4}$$

¹⁰ The algorithm for computation of this index is somewhat extensive, so it is not presented in the paper to save space. Anyone interested in the algorithm can look at the original Van der Eijk's article or user manual for the R package "Agrmt".

¹¹ The R code for the computation of all indices is available from the author upon request.

European Union¹² at the time when national surveys of the wave were conducting (2008), and also Norway and Switzerland¹³. The total number of observations in the dataset is 40808. Data are weighted. The main variables of interest, which are used in the first-stage LC model are the five items defining the index of survival/self-expression values (Inglehart and Baker 2000; Inglehart and Welzel 2005: 49): *self-reported happiness* (four-category item), *generalized trust* (binary variable), *four-item postmaterialism index*, *readiness to sign petitions* (three-category item), and *tolerance to homosexuality* (1 to 10-points scale; treated as continuous).

Identification of latent typology for self-expression values

At the first step, a set of models with consequently increasing numbers of classes without any restrictions on parameters is estimated using MPLUS software (Muthén and Muthén 2012). The analysis starts from a three-class model and find that adding more classes improves fit statistics. Table 1 provides the AIC, BIC and aBIC for unconstrained models with three, four, five, six classes.

Table 1 about here

The LMRT¹⁴ also favors models with higher number of classes. Moreover, exploratory tests demonstrate that models with 7, 8, 9, and even 10 classes have an increasingly better fit (results are not shown). Nevertheless, further analysis focuses only on the models with no more than six classes. There are two reasons for that. First, when the sample is large, LCA models with higher number of classes typically have a better fit due to numerical reasons, but

¹² Italy is excluded due to the fact that the item “whether homosexuality can be justified” was not asked in Italy in the 2008 EVS round.

¹³ While not being EU-members, these two countries are highly modernized and also have established radical right parties. So it is interesting to consider them in the context of hypothetical link between values polarization and population’s reaction to immigrant issue, which is tested in the next section of the paper.

¹⁴ In MPLUS software, bootstrap-based tests are not compatible with the use of weighting scores, so BLRT was not used in model selection.

may not have a meaningful interpretation. The best classification is one that enlists all possible combinations of the observed response categories, but such classification may be very unparsimonious and have little to do with the goals of scientific study. As Nylund et al. (2007) put that, the researcher should have a good theory when deciding on the exact number of classes in LCA models. From this point of view, models with the number of classes which exceeds six are very difficult to interpret while the models with three to six classes could be easily represented as an ordered survey item.

Another reason why not use more than six classes is the fact that in models with more than six classes the number of violations of ordering of thresholds is growing rapidly. Four and five-class models present only one and two violations of the strict ordering, while the six-class model has three violations, and the seven-class model has six violations (see Tables 2.1 – 2.3)¹⁵. Thus, the higher number of parameter constrains is required, and therefore model fit for order-constrained model becomes worse (comparing to unconstrained model with the same number of classes). Furthermore, difference in aBIC values between order-constrained (MH-) model and unrestricted model with five classes is less than 6, but the difference in aBIC between the six-class MH- and unconstrained model cannot be computed because the best likelihood for the MH-solution has not been replicated even after the large number of iterations, and therefore aBIC for that solution is unreliable (see Table 1). It indicates that for the relatively large number of classes the assumption of monotonicity does obviously not hold, and nominal solution is more appropriate. In fact, analysis reveals that only for models with no more than five classes monotonicity is a quite reasonable assumption.

Tables 2.1 – 2.3 about here

¹⁵ In addition, in the unconstrained model with seven classes, classes 4 and 5, are nothing but subclasses of the class 4 in the unconstrained model with six classes. Further division of one of the smallest class in sample is not of great substantial interest, and so a more parsimonious model should be preferred, as was noted in Section 3.3.

Informative hypothesis testing approach also favors the five-class order-constrained model. Bayes factor for the five-class-ordered-model vs. five-class-unconstrained model is equal approximately to 1.77, which indicates that for the five-class constrained solution fit the data slightly better than unconstrained one, while for the four-class MH model vs. four-class unconstrained model BF is 0.615, and for the six-class MH-model vs. unconstrained six-class model BF is 0.43¹⁶. Therefore, the five-class model may be considered as the best trade-off between purely empirical selection criteria and the concept of survival/self-expression value orientations, which assumes monotonic scale. So the five-class order-constrained is used for further analysis.

It nonetheless should be noted that unless the classification is not perfect, the assigned class belongings do not correspond exactly to the true values. Thus, classification error is introduced. As a consequence, further inferences based on that classification may be biased. However, Bakk et al. (2014) reveal that the amount of measurement error in LCA model is negligibly small when classes are well-separated, i.e. when a level of entropy for that model is high (> 0.9). Entropy for the five-class MH-model is .947, so the issue of classification error is of less relevance for this model.

Measuring polarization on categorical version of self-expression values

LCA shows that the five-class order-constrained model is a reasonable compromise between

¹⁶ To sample model parameters from the joint posterior distribution for unconstrained four-, five-, and six-class LC models, I use MPLUS software (Muthén and Muthén 2012). I exploit default MPLUS prior distributions for Bayesian estimation of parameters of interest in LCA models. In MPLUS, the default prior for thresholds, as well as for means of observed variables has the normal distribution $N(0; \infty)$. The default prior for all class proportions is the Dirichlet prior $D(10; 10; \dots; 10)$ (Asparouhov and Muthen 2010a: 58). The MPLUS default for the number of iterations is 10,000, but I set that number to 105000 (by setting `FBITERATIONS = 100000`), from which number the first 5000 iterations served as a burn-in period and were discarded. To prevent label switching, which is one of the major problems in the estimation of latent class models by the tools of Bayesian statistics, I follow recommendations by Asparouhov and Muthen (2010b: 26-27) and run only one MCMC chain. In models, estimated with Bayes MPLUS estimator, trace plots for parameters show good convergence; and PSR (Potential Scale Reduction), a formal criterion developed for diagnosis of convergence for Bayesian models, reaches its critical value of 1.05. Autocorrelation in MCMC chains does not exceed 0.1 for lags from 1 to 25, which seems to be a satisfactory result. Annotated R and MPLUS code used for the analysis is available from the author upon request.

the data and theory of self-expression values¹⁷. According to this model, 40.9% of respondents in the pooled sample belong to Class 1 (which consists of people with the lowest scores on self-expression values). Class 3, including people with mixed values, represents 18% of the sample. Class 5 consists of people who score high on self-expression values (22.5% of respondents). Classes 2 and 4 are intermediate categories including people with values somewhere in between survival and mixed values and mixed and self-expression values respectively. These classes contain 8.5% and 10.2% of the sample. In general, almost the half of European population has still shared survival or close-to-survival values in 2008. However, country-specific class proportions vary significantly across Europe (see Figure 1), and in seven countries the absolute majority of population shares self-expression values. The highest proportion of people in Classes 4 and 5 is in Sweden (71.4%) and the lowest proportions of people in those classes are in Estonia, Cyprus and Latvia (about 5%).

Figure 1 about here

Now three indices of ordinal polarization are computed for the five-class MH-model. To assess potential bias due to incorrect choice between nominal and ordinal LC models, it might be useful also to compute the RQ index. Respective polarization scores for each country are presented in Table 3. Pairwise correlations between different indices of polarization and country-specific standard deviations and kurtoses for the standard index of self-expression values¹⁸ are shown in Table 4. All measures of ordinal variation are highly correlated (respective Pearson's ρ s are all higher than 0.945), while RQ index, which is designed to

¹⁷ Several recent studies indicate that some important assumptions, such as measurement invariance, may not hold for self-expression values, as well for the short post-materialism index, which is treated here as a categorical indicator variable in the measurement model for self-expression values (Dülmer 2012; Alemán and Woods 2015; Ippel et al. 2014; Mackintosh 1998; Moors 2007; Moors and Vermunt 2007). While the focus of the paper is on polarization measurement rather than on complete test for the measurement validity of self-expression values, some model corrections were omitted for the sake of simplicity. However, the method proposed here is flexible enough to handle the issue of [configural] measurement non-invariance by simply assuming that some latent classes are not presented in some countries (Kankaras et al. 2011: 16).

¹⁸ The index is computed as the weighted average of the five manifest items

assess nominal polarization, demonstrates only moderate correlations with other indices. Therefore, assumption, whether latent variable is a nominal or ordinal one, directly affects the resulting polarization score and is of a great importance for the practical application of the proposed approach.

Tables 3 and 4 about here

Furthermore, though pairwise correlations between ordinal polarization scores are very high, particular indices provide slightly different orderings of countries in respect to their polarization level. Because there is no solid theoretical justification for preferring any one of these four indices, it may be reasonable to obtain average polarization score across all three ordinal indices. In the rest of the paper, the average polarization score (APS) is used (last column in Table 3; see also Figure 2). According to that score, the most polarized European society is the UK (APS = 0.702), and the least polarized country is Lithuania (APS = 0.222). Finally, it should be mentioned that country-specific kurtoses and especially standard deviations (which are frequently used as naïve polarization measures for continuous scales) for the standard version of the index of self-expression values correlate with the measures of ordinal polarization at the exceptionally high rate (Pearson's ρ s > 0.9), despite the fact that LCA-based representation for self-expression values suggests that the respective latent trait is obviously non-normal.

Figure 2 about here

Application 2: Modernization and Values Polarization

Though the distribution of country-specific polarization scores on survival/self-expression values across Europe is itself an interesting subject to be measured and analyzed, the value of any polarization measure raises significantly when that measure provides not only descriptive

information, but also information that is useful for empirical testing of hypotheses derived from substantial theories. One important advantage of the method developed in this paper over other approaches to polarization measurement in multi-item domains is that the method allows not only for delineating polarization trends (as in Baldassarri and Gelman 2008 or Munzert and Bauer 2013) or cross-national differences in the level of polarization. The method also provides polarization scores that can be easily incorporated in statistical analyses (e.g. regression modeling) as either dependent or independent variable. The current section illustrates this advantage by using polarization scores on survival/self-expression values for operationalization and testing of so called “losers of modernization” thesis.

The “Losers of Modernization” Thesis

In their pioneer work, Seymour Lipset and Stein Rokkan supposed that the structure of political competition in developed Western societies was shaped by long-standing social cleavages (Lipset and Rokkan 1967). By cleavage, they meant a presence of two groups in society, whose interests clash over some important socioeconomic issue. In particular, they defined four main cleavages: Center – Periphery (reflected in rhetoric of various regionalist parties), State – Church (capturing divide between secular and religious voters), Owner – Worker (i.e., classic Marxist class conflict between workers and capitalists, reflected in left-right division of party space), and Land – Industry. Subsequent research found that the role of traditional cleavages in electoral competition in Western countries decreased significantly over 1970s and 1980s (Dalton 1996). One of the main causes for that was a postmaterialist change occurred in the most developed societies. Instead of old socio-cultural cleavages, several new controversies, such as environmental protection, women’s right, or tolerance to homosexuality, became politically significant in those societies (Inglehart 1990, 1997). Such new important phenomena in European party politics as the rise of green parties on the one hand and radical right parties on the other hand were attributed by some scholars to that

change (Ignazi 1992, 2003; McGann and Kitschelt 1995; Ennser 2012).

In particular, so called ‘losers of modernization’ thesis was proposed. According to the thesis, an increase in support for radical right parties was a form of reaction to modernization and rapid societal change destructing traditional social roles and environments (Betz 1994; Betz and Immerfall 1998; Minkenberg 2003), for example, such as ethno-nationalistically defined community (Rydgren 2007). That thesis received solid empirical support (Rydgren 2007: 249). However, previous research on the topic was based on a socio-economic definition of the “losers” and focused on the effects of such stratification variables as education, social status, or individual unemployment. In fact, common operationalization of the “losers of modernization” thesis represents a modification of the well-known class-conflict theory which replaces traditional opposition “capitalists-workers” by more actual opposition “immigrants-workers”, rather than refers to modernization as such. The problem is that one cannot distinguish empirically between predictions of the “losers of modernization” thesis and those of several rational-choice theories (for instance, ethnic competition theory), basing solely on this operationalization.

This paper uses an alternative operationalization of the “losers of modernization” thesis, which relies on the concept of survival/self-expression value orientations (Inglehart and Baker 2000; Inglehart and Welzel 2005). An important advantage of this operationalization is that value orientations directly reflect cultural dimension of social conflict. In the same time, value orientations are also an informative proxy for the status of the “loser” of modernization. It is known that individual values are closely related to one’s feeling of existential security (Inglehart 1997; Inglehart and Baker 2000; Inglehart and Welzel 2005). So it is reasonable to admit that people, who may be considered as the “losers” of modernization, should worry more about the satisfaction of their basic needs and their life perspectives (that is, feel themselves less secured) than people who tolerate new aspects of society emerging during

modernization and are able to utilize those aspects for their own good. If this assumption is correct, it inevitably leads to the conclusion that the majority of “losers” of modernization should share survival value orientations.

If then the hypothesis about the positive link between the status of the “loser” and probability of voting for the radical right is correct, one may expect that in countries where the fraction of the “losers” is high, radical right parties gain more votes. It is worth noting however that in societies, where survival values are prevalent, there should be no “losers” of modernization as a distinct social group, because there are no obvious “winners”. In addition, in countries where self-expression values are strongly prevalent, the proportion of “losers” should be small, and political forces intending to represent the “losers” should not gain broad electoral support. Conflict potential caused by the modernization cleavage should be the highest in countries where significant fractions of population with opposite values exist, that is, where polarization between adherents of survival values and those who share self-expression value orientations is high. This implies a simple aggregate-level hypothesis: the higher values polarization in country the higher support for the radical right in that country.¹⁹

Empirical Evidence

Table 5 about here

Before direct testing of the hypothesis stated above, it is useful first to understand whether values polarization is actually related to the process of modernization. Table 5 report correlations between the average polarization score and various country-level socio-economic

¹⁹ This hypothesis may be also formulated in a more sophisticated way, by assuming the existence of cross-level interaction effect between value polarization and individual attitudes: in countries where the gap between the least and the most modernized groups is bigger, less modernized people should be frustrated to a greater extent (because their ‘losership’ is more obvious both for themselves and for more successful people) and therefore be more supportive for conservative political forces, such as radical right parties. Since the proper testing of that hypothesis involves a need in the use of multilevel analysis, the individual class membership indicator, based on the LCA classification from the first stage of the proposed method of polarization measurement, might be used in the analysis along with the country-level polarization scores.

indicators for 28 European countries. At the country-level, value polarization positively correlates with the Human Development Index, GDP per capita (in 2008 USD), and mean score on the standard index of self-expression values, and negatively correlates with Gini coefficient. The associations between polarization and the last year GDP per capita growth rate, between polarization and political regime (measured as Polity IV score) and between polarization and unemployment are statistically insignificant. It means that long-standing economic development entails not only the increase in mean level of self-expression values, but also the increase in values polarization. At the same time, values polarization is not very sensitive to short-time economic fluctuations. These findings are in line with predictions of the revised modernization theory, according to which transition from industrial to postindustrial (or knowledge) society leads to the formation of a group of individuals with values distinct from the rest of country's population (Inglehart and Welzel 2005; Welzel 2013), that in turn increases values polarization.

It is important, however, that the most postmaterialist societies (those of Northern Europe; also with the highest GDPs per capita and HDIs) exhibit only moderate level of polarization (Figure 2). It is not surprising because the vast majority of population in those countries belongs to "postmaterialist" classes, and the fraction of "losers" is relatively small. The least modernized societies in Europe (the republics of the former Soviet Union and other post-socialist countries) are also the less polarized. The most polarized countries are Central and West European countries, where significant fractions of both "winners" and "losers" of modernization exist. Thus, modernization (defined as the shift from industrial to postindustrial society) does actually lead to formation of the cleavage in value orientations of European population (yet the further modernization goes the more diminishing cleavage is). Whether this modernization cleavage is reflected in European politics and provides additional electoral opportunities for radical right parties?

Tables 6 and 7 about here

Table 6 reports the results of regressions of different aggregate indicators of how xenophobic is population of some country on the average polarization score. Value polarization has a significant (and negative) effect only on the proportion of people in country who don't like to see Jews as their neighbors. Polarization affects neither the percentage of votes for the radical right²⁰, nor the average position of all political parties in specific country on the left-right scale²¹, nor the percentage of people with prejudice against other ethnic/racial/religious minorities. However, country-mean score on the standard version of the index of self-expression values does. The average level of self-expression values has a significant or marginally significant effect on all dependent variables presented in Table 7. Interestingly, higher country-mean scores on self-expression values are associated *positively* with the vote for the radical right and the average position of country's party system on the left-right scale, but *negatively* with the share of people with prejudices against various cultural minorities. These results indicate that successful radical right parties are actually a feature of postindustrial societies, rather than industrial ones, but the level of polarization in self-expression values appears not to be the reason for that, at least at the aggregate level. Moreover, the increase in support for the radical right does not necessarily involve the spread of prejudices against ethnic or religious minorities. Deep investigation of that interesting puzzle, however, goes beyond the scope of the current paper.

²⁰ Data on the share of votes for the radical rights are taken for the election closest in time to the country EVS surveys conducted within the 4th round (2008 for the most countries). Complete list of parties treated as "radical right" is given in the Appendix II.

²¹ It is a composite score based on the Comparative Manifesto Project data. More concrete, it is an average score over four CMP issues, "multiculturalism", "internationalism", the "national way of life", and "law and order". This measure was originated by Arzheimer and Carter (2006). They, however, computed differences between the position of the most radical party and the position of mainstream right party on the issues mentioned. My preliminary computations show that the original version of their index does not provide a reasonable ordering of political parties along the left-right axis, and a simple mean score may better reflect the average level of electoral support for the radical right rhetoric in country (measured on the "supply" side). Country-mean scores are computed using CMP data for the election closest in time to the country EVS surveys conducted during the 4th round

Conclusion

This paper presents a method for measurement of polarization on latent scales, which is based on combination of the (order-restricted) latent class analysis and variety of categorical dispersion measures, and applies it to the assessment of polarization on self-expression values in 28 European countries. Country polarization scores obtained using that procedure are then used to test a hypothesis based on the “losers of modernization” thesis, which states that the recent growth in support for radical right parties is related to the transition of European countries to the postmaterialist society. Regressions of different country-level indicators of how xenophobic is one country’s population on value polarization scores does not reveal significant relationships between value heterogeneity and aggregate support for the radical right parties in general and for different anti-immigrant attitudes in particular.

These findings nevertheless do not mean that the “losers of modernization” thesis is generally wrong. Presented analysis is conducted in an exploratory (illustrative) mode and involves only aggregate cross-sectional data for 28 countries. It does not reflect potential lagged effect of increase in value polarization on support for anti-immigrant ideology and movement, or cross-level interactions between values polarization and individual social positions. Selection of the radical right parties used in the paper also may affect the results. The analysis, however, may be easily extended in future research to overcome these limitations. For instance, one can obtain country-specific polarization scores from different waves of WVS/EVS, using the same procedure as described here, and then test the same hypothesis, but on a reasonably larger sample. Alternatively, one may use multilevel analysis and explore how country-level values polarization interacts with the individual values and socio-economic indicators in respect to individual voting preferences and attitudes towards ethnic minorities.

In any case, the method of polarization measurement proposed here is not an *ad hoc* approach,

and might be useful in many practical applications involving the notion of attitudinal polarization/heterogeneity, beyond the concept of self-expression values and EVS/WVS data. In addition, the first part of the approach, the (order-constrained) LCA may be considered by researchers as a flexible tool for measuring latent attitudinal constructs in large-N cross-national surveys.

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Appendix I: Computation of Bayes Factors

As Tables 2.1-2.3 show, in the freely estimated four-class model, only one order constraint

does not hold: $\tau_{Happy1,3} > \tau_{Happy1,4}$. In the freely estimated five-class model, the number of violated restrictions is two: $\tau_{Happy1,4} > \tau_{Happy1,5}$ and $\tau_{Happy3,1} > \tau_{Happy3,2}$. Finally, the freely estimated six-class model has three violated constraints: $\tau_{Happy1,4} > \tau_{Happy1,6}$, $\tau_{Happy1,5} > \tau_{Happy1,6}$, and $\tau_{Happy3,1} > \tau_{Happy3,2}$. In informative hypothesis testing, we compare freely estimated LCA model with the same-number-of-classes model imposing order constraints on some parameters. Because original unconstrained models with four, five, and six classes seems to approach the strict MH-model well (number of violations of monotonicity assumption for these model is small, from 1 to 3), it seems not necessary to impose inequality constraints on all model parameters²². So I place restrictions only on those parameters that violate monotonicity assumption in respective models. To give an illustration of computing BF for order-constrained LCA model, let me use the most complex example, the six-class model. To compute complexity (C), we should estimate the proportion of the prior distribution of the model in agreement with the constraints imposed on model parameters, or to put it simply, determine the number of all possible orderings of the involved parameters, and then determine how much of these orderings are in line with the desired model. Because we impose three constraints, which involve three class-specific thresholds for Happy1 and two class-specific thresholds for Happy 3, the total number of all possible prior models is $3! * 2! = 12$, or:

$$M1: \tau_{1,4} > \tau_{1,5} > \tau_{1,6} \ \& \ \tau_{3,1} > \tau_{3,2};$$

$$M2: \tau_{1,4} > \tau_{1,6} > \tau_{1,5} \ \& \ \tau_{3,1} > \tau_{3,2};$$

$$M3: \tau_{1,5} > \tau_{1,6} > \tau_{1,4} \ \& \ \tau_{3,1} > \tau_{3,2};$$

²² It should be noticed that the fully constrained four-class MH-model has the complexity equal to $(\frac{1}{24})^{10}$. As Van de Shoot et al. (2012) reported, even a model with complexity about .000025, requires more than 20000000 iterations after burn-in to estimate BF accurately. Because ML estimates demonstrate that the inequality constraints assumed by the full MH-model hold for the most pairs of parameter in four-, five-, and six-class models, I use this evidence as strong prior reasons to consider freely estimated models as partially MH-models, and therefore imply constraints only on violating parameters.

$$\text{M4: } \tau_{1,5} > \tau_{1,4} > \tau_{1,6} \text{ \& } \tau_{3,1} > \tau_{3,2};$$

$$\text{M5: } \tau_{1,6} > \tau_{1,4} > \tau_{1,5} \text{ \& } \tau_{3,1} > \tau_{3,2};$$

$$\text{M6: } \tau_{1,6} > \tau_{1,5} > \tau_{1,4} \text{ \& } \tau_{3,1} > \tau_{3,2},$$

and also six similar models with $\tau_{3,1} < \tau_{3,2}$. From this set only one prior model, M1, agrees with the actually imposed constraints. Because there are no strict reasons to favour any prior model, we can say that each of them has the same prior probability of 1/12, so $C_6 = 1/12$

To estimate the proportion of the posterior distribution (F) in agreement with the inequality-constrained hypothesis, we should compute the proportion of draws from the joint posterior sample, provided by MPLUS for the five parameters of interest, which satisfy $(\tau_{1,4} > \tau_{1,5} > \tau_{1,6}) \text{ \& } (\tau_{3,1} > \tau_{3,2})$. For the six-class model, $F_6 = 0.0378$. After substituting C_6 and F_6 in (7), one obtains $BF_6 \approx 0.43$. This implies that the six-class MH-model receives slightly less support from the data, than the unconstrained six-class model does.

The five-class MH-model requires only two additional parameters constraint, compare to the unconstrained model, each involving only two parameters, so the complexity for this model is $C_5 = 1/(2! * 2!) = 1/4$, a posteriori computed F_5 is 0.37126, which gives $BF_6 \approx 1.77$. Finally, the four-class MH-model involves only one constraint, so $C_5 = 1/2$, which, with $F_4 = 0.38084$, gives $BF_6 \approx 0.62$. The annotated R code used for computation of BFs is provided in the replication archive (available from the author upon request).

Appendix II: List of Radical Right Parties²³

Austria: Freedom Party

Belgium: Flemish Interest, National Front

Bulgaria: Attack

Cyprus: *none*

Czech Republic: *none*

Denmark: Danish People's Party

Estonia: *none*

Finland: True Finns

France: National Front, Miscellaneous Right

Germany: The Republicans, National Democratic Party

Greece: Popular/People's Orthodox Rally

Hungary: Justice and Life Party, Jobbic

Ireland: *none*

Latvia: National Alliance

Lithuania: Order and Justice

Luxembourg: *None*

Malta: *None*

Netherlands: Centre Democrats, Reformed Political Party, Party For Freedom

Norway: Progress Party

Poland: League of Polish Families

Portugal: *None*

Romania: Greater Romania

Slovakia: National Party

Slovenia: National Party

Spain: *none*

Sweden: Sweden Democrats

Switzerland: Federal Democratic Union, Motorist Party / Freedom Party (FPS), Swiss Democrats, Swiss People's Party, Tessinian League

United Kingdom: British National Party, United Kingdom Independence Party

²³ The list is based on some recent articles attempting at classification and/or definition of European radical right parties. Since there is still no consensus among scholars about which parties are the radical right and which are the mainstream right, the list may be considered as somewhat arbitrary, and criticized for being too much *inclusive* by some researchers.

Tables and Figures

Table 1: Fit Criteria for Different Model Specifications

Model	Parameters	LL	AIC	BIC	aBIC	Entropy	VLMR p-value
2 classes	20	-234,879.1	469,798.2	469,970.5	469,907.0	0.792	0.000
3 classes	30	-224,994.7	450,049.5	450,308.0	450,212.6	0.914	0.000
4 classes	40	-221,073.0	442,226.1	442,570.7	442,443.6	0.916	0.000
5 classes	50	-214,386.8	428,873.5	429,304.4	429,145.5	0.947	0.000
6 classes	60	-212,968.7	426,057.4	426,574.3	426,383.7	0.927	0.000
7 classes	70	-211,144.4	422,428.7	423,031.9	422,809.4	0.943	0.000
4 classes (order-restricted)	40	-221,073.0	442,226.1	442,570.7	442,443.6	0.916	NA
5 classes (order-restricted)	50	-214,389.6	428,879.2	429,310.0	429,151.1	0.947	NA
6 classes (order-restricted)	60	The best likelihood was not replicated					

Notes: Parameters = number of model parameters; LL = $-2 \log$ -likelihood; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; aBIC = Bayesian Information Criterion adjusted to the sample size; Entropy is a classification entropy, VLMR p-value = the p-value of Vuong-Lo-Mendell-Rubin likelihood ratio test for $k - 1$ (H_0) versus k classes (not available for models with order constraints on parameters). All models were estimated using MPLUS 6.12 for Windows.

Table 2.1: Latent Class Solution for Four-Class Unconstrained Model

	Homosex	Postmat 1	Postmat 2	Happiness 1	Happiness 2	Happiness 3	Trust	Petition 1	Petition 2
Class 1	1.311	-0.637	2.616	-3.619	-1.378	1.319	1.127	-0.278	1.083
Class 2	4.967	-1.011	2.033	-4.270	-1.976	1.022	0.714	-1.135	0.370
Class 3	7.526	-1.313	1.662	-4.653	-2.154	0.872	0.416	-1.593	-0.074
Class 4	9.810	-1.723	1.294	-4.609	-2.491	0.556	-0.224	-2.334	-0.715

Table 2.2: Latent Class Solution for Five-Class Unconstrained Model

	Homosex	Postmat 1	Postmat 2	Happiness 1	Happiness 2	Happiness 3	Trust	Petition 1	Petition 2
Class 1	1.123	-0.616	2.622	-3.582	-1.344	1.307	1.161	-0.234	1.105
Class 2	3.444	-0.879	2.322	-3.977	-1.747	1.317	0.831	-0.805	0.741
Class 3	5.253	-1.045	1.990	-4.385	-2.039	0.971	0.675	-1.205	0.299
Class 4	7.556	-1.320	1.653	-4.648	-2.157	0.864	0.402	-1.606	-0.090
Class 5	9.818	-1.710	1.305	-4.605	-2.481	0.562	-0.209	-2.310	-0.699

Table 2.3: Latent Class Solution for Six-Class Unconstrained Model

	Homosex	Postmat 1	Postmat 2	Happiness 1	Happiness 2	Happiness 3	Trust	Petition 1	Petition 2
Class 1	1.124	-0.616	2.622	-3.583	-1.345	1.307	1.160	-0.234	1.105
Class 2	3.426	-0.873	2.336	-3.970	-1.738	1.335	0.834	-0.791	0.760
Class 3	4.992	-1.014	2.052	-4.315	-2.019	0.962	0.735	-1.182	0.314
Class 4	6.509	-1.142	1.835	-4.643	-2.050	0.938	0.499	-1.298	0.210
Class 5	8.315	-1.459	1.555	-4.701	-2.334	0.839	0.318	-1.870	-0.282
Class 6	9.935	-1.758	1.258	-4.573	-2.490	0.527	-0.283	-2.392	-0.768

Notes: Entries are class-specific means for the item “Homosex” and class-specific thresholds for the other items. All estimates are significant at the 0.01 level. Parameters in bold are those violating order restrictions imposed by the MH-model.

Table 3: Polarization Scores on Self-Expression vs. Survival Values (measured on categorical latent scale) for 28 European Countries (data from the 4th round of EVS).

	Reynal-Querol's Index of Polarization	Leik's Index of Polarization	Berry-Mielke's Index of Ordinal Variation	Agreement A based Index of Polarization	Average Polarization Score
Austria	0.695	0.647	0.865	0.558	0.690
Belgium	0.676	0.576	0.785	0.473	0.611
Bulgaria	0.723	0.367	0.544	0.210	0.373
Cyprus	0.659	0.257	0.409	0.138	0.268
Czech Republic	0.704	0.713	0.881	0.504	0.700
Denmark	0.744	0.593	0.754	0.340	0.563
Estonia	0.672	0.279	0.439	0.158	0.292
Finland	0.727	0.701	0.873	0.475	0.683
France	0.706	0.601	0.825	0.525	0.651
Germany	0.656	0.621	0.829	0.527	0.659
Greece	0.734	0.592	0.732	0.326	0.550
Hungary	0.755	0.511	0.686	0.307	0.501
Ireland	0.703	0.679	0.876	0.495	0.683
Latvia	0.705	0.314	0.480	0.167	0.320
Lithuania	0.557	0.206	0.353	0.106	0.222
Luxembourg	0.748	0.709	0.879	0.498	0.695
Malta	0.748	0.599	0.760	0.347	0.569
Netherlands	0.750	0.534	0.693	0.292	0.506
Norway	0.738	0.602	0.769	0.339	0.570
Poland	0.738	0.401	0.577	0.210	0.396
Portugal	0.746	0.561	0.701	0.314	0.526
Romania	0.624	0.237	0.388	0.125	0.250
Slovakia	0.703	0.664	0.837	0.421	0.640
Slovenia	0.742	0.647	0.824	0.375	0.615
Spain	0.693	0.666	0.859	0.535	0.687
Sweden	0.735	0.511	0.734	0.345	0.530
Switzerland	0.706	0.673	0.852	0.466	0.664
United Kingdom	0.699	0.655	0.871	0.581	0.702

Notes: Average Polarization Score is a polarization score averaged over three particular polarization indices: Leik's Index of Polarization, Berry-Mielke's Index of Ordinal Variation and Van Der Eijk's Agreement A – based Index of Polarization.

Table 4: Pairwise correlations between different measures of value heterogeneity in 28 European Countries (data from the 4th round of EVS).

	Reynal-Querol's Index of Polarization	Leik's Index of Polarization	Berry-Mielke's Index of Ordinal Variation	Agreement A based Index of Polarization	Average Polarization Score	Self-Expression Values, country standard deviation	Self-Expression Values, country kurtosis
Reynal-Querol's Index of Polarization		0.535	0.503	0.267	0.448	0.538	-0.600
Leik's Index of Polarization	0.535		0.991	0.909	0.985	0.977	-0.937
Berry-Mielke's Index of Ordinal Variation	0.503	0.991		0.945	0.997	0.978	-0.931
Agreement A based Index of Polarization	0.267	0.909	0.945		0.966	0.902	-0.866
Average Polarization Score	0.448	0.985	0.997	0.966		0.970	-0.928
Self-Expression Values, country standard deviation	0.538	0.977	0.978	0.902	0.970		-0.922
Self-Expression Values, country kurtosis	-0.600	-0.937	-0.931	-0.866	-0.928	-0.922	

Notes: Entries are pairwise Pearson correlation coefficients. All correlations, except those in bold, are significant at the 0.05 level. Self-Expression Values are an aggregate index computed as a weighted average over five observed indicators. Weights are factor loadings for the respective items from the CFA model for the self-expression values from the 4th round of WVS. Weights are 0.532 for *postmaterialism*, 0.727 for *tolerance to homosexuality*, 0.459 for *happiness*, 0.586 for *generalized trust*, and 0.688 for *signing petition*. Average Polarization Score is a polarization score averaged over three particular polarization indices: Leik's Index of Polarization, Berry-Mielke's Index of Ordinal Variation and Van Der Eijk's Agreement A – based Index of Polarization

Table 5: Pairwise correlations between the average polarization score and different economic and political indicators for 28 European Countries

	Gini Coefficient	Human Development Index	GDP PPP in 2008 USD	GDP PPP growth (last year)	Self-Expression Values, mean score	Polity IV	Unemployment
Average Polarization Score	-0.500**	0.627***	0.540***	-0.150	0.703***	-0.301	0.071

Notes: Entries are pairwise Pearson correlation coefficients. All country-level indicators are for 2008. Average Polarization Score is a polarization score averaged over three particular polarization indices: Leik's Index of Polarization, Berry-Mielke's Index of Ordinal Variation and Van Der Eijk's Agreement A – based Index of Polarization
* p < .05; ** p < .01; *** p < .005

Table 6: Average Polarization Score as a Predictor of the Different Aggregate Indicators of How Xenophobic is the Population of a Given Country

	Percentage of Votes for the Radical Right Tobit	Arzheimer- Carter Index OLS	Muslims as Neighbors OLS	Migrants as Neighbors OLS	Jews as Neighbors OLS	Gypsy as Neighbors OLS	People of Different Race as Neighbors OLS
Average Polarization Score	2.684 (13.564)	9.366 (12.617)	-0.151 (0.108)	-0.088 (0.105)	-0.214* (0.087)	-0.221 (0.151)	-0.108 (0.087)
Constant	4.090 (7.597)	12.119 (7.076)	0.297*** (0.061)	0.210*** (0.059)	0.233*** (0.049)	0.509*** (0.085)	0.184*** (0.049)
N	28	28	28	28	28	28	28
R ²		0.021	0.070	0.026	0.189	0.076	0.056
Adjusted R ²		-0.017	0.034	-0.011	0.158	0.041	0.020
Log Likelihood	-82.411						

Notes: Entries are Tobit regression coefficients for the first column and non-standardized OLS regression coefficients for the rest of the table. Average Polarization Score is a polarization score averaged over three particular polarization indices: Leik’s Index of Polarization, Berry-Mielke’s Index of Ordinal Variation and Van Der Eijk’s Agreement A – based Index of Polarization.

The dependent variable in Column 1 is the percentage of votes for all radical right parties competing during the election closest to the moment of the EVS data collection (2007 or 2008) in respective country. The dependent variable in Column 2 is an average score over four indicators from the *Comparative Manifesto Project* dataset measuring average ideological position of all political parties in country on the left-right scale (higher values indicate positions closer to the right) during the election closest to the moment of the EVS data collection in that country. The dependent variables in Columns 3-7 are the country-specific percentages of people said that they didn’t like to see representatives of the respective out-group as their neighbors in the 4th round of the EVS. Test statistics of heteroskedasticity (Breush-Pagan test) and influential cases (Bonferroni p-values for Studentized residuals) reveal no violation of ordinary least squares (OLS) assumptions.

* p < .05; ** p < .01; *** p < .005

Table 7: Mean Score on Self-Expression Values (Standard Index) as a Predictor of the Different Aggregate Indicators of How Xenophobic is the Population of a Given Country

	Percentage of Votes for the Radical Right Tobit	Arzheimer- Carter Index OLS	Muslims as Neighbors OLS	Migrants as Neighbors OLS	Jews as Neighbors OLS	Gypsy as Neighbors OLS	People of Different Race as Neighbors OLS
Mean Self-Expression Score	5.515 (3.128)	7.170* (2.868)	-0.051 (0.026)	-0.049 (0.025)	-0.062** (0.021)	-0.093* (0.035)	-0.056** (0.020)
Constant	7.091*** (2.097)	19.113*** (1.904)	0.202*** (0.017)	0.148*** (0.017)	0.101*** (0.014)	0.365*** (0.023)	0.111*** (0.013)
N	28	28	28	28	28	28	28
R ²		0.021	0.070	0.026	0.189	0.076	0.056
Adjusted R ²		-0.017	0.034	-0.011	0.158	0.041	0.020
Log Likelihood	-82.411						

Notes: Entries are Tobit regression coefficients for the first column and non-standardized OLS regression coefficients for the rest of the table. The dependent variable in Column 1 is the percentage of votes for all radical right parties competing during the election closest to the moment of the EVS data collection (2007 or 2008) in respective country. The dependent variable in Column 2 is an average score over four indicators from the *Comparative Manifesto Project* dataset measuring average ideological position of all political parties in country on the left-right scale (higher values indicate positions closer to the right) during the election closest to the moment of the EVS data collection in that country. The dependent variables in Columns 3-7 are the country-specific percentages of people said that they didn't like to see representatives of the respective out-group as their neighbors in the 4th round of the EVS. Test statistics of heteroskedasticity (Breusch-Pagan test) and influential cases (Bonferroni p-values for Studentized residuals) reveal no violation of ordinary least squares (OLS) assumptions.

* p < .05; ** p < .01; *** p < .005

Figure 1: Class Proportions for Five-Class Order-Constrained Model of Self-Expression Values in 28 European Countries (data from the 4th round of EVS)

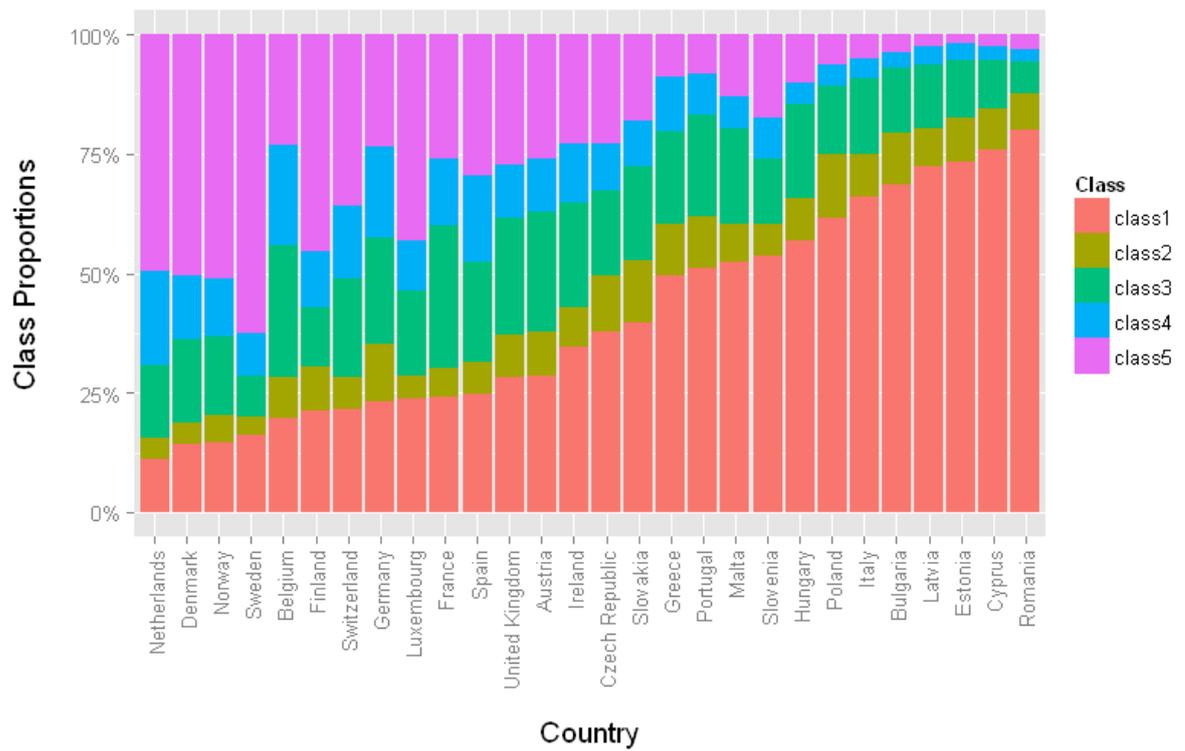
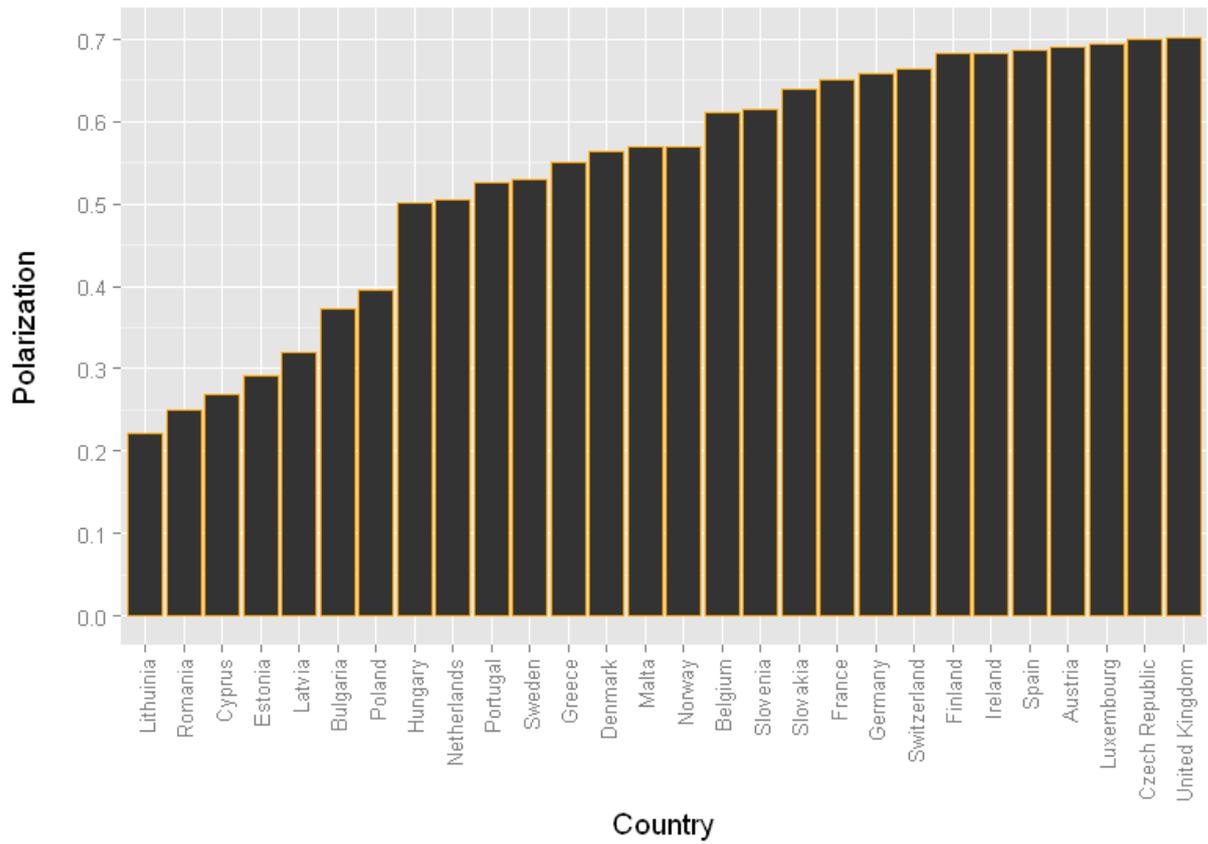


Figure 2: Average Polarization Scores on Self-Expression vs. Survival Values (measured on

categorical latent scale) for 28 European Countries (data from the 4th round of EVS)



Note: Average Polarization Score is a polarization score averaged over three particular polarization indices: Leik's Index of Polarization, Berry-Mielke's Index of Ordinal Variation and Van Der Eijk's Agreement A – based Index of Polarization

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