Electronic Supplementary Material for Decomposing Attitude Distributions to Characterize Attitude Polarization in Europe

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Appendix 1: Data Details

Table 1 shows the wording of the questions and the corresponding acronym. Figure 1 gives an overview of how often a topic occurred per country in the ESS data set.

Table 2 shows the response rates in the surveys of the ESS rounds in different countries from the documentation reports. If response rates decrease over time the error in the distributions could increase and the validation of our model would be increasingly less informative about the general population. However, Koen Beullens (2018) and Table 2 show no systematic decrease in response rates.

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Table 1 ID-string, abbreviated wording, and answering scale of all questions used from the European Social Survey (ESS).

ID	Desciption
ATCHCTR	How emotionally attached to [country] (0=Not at all, 10=Very)
ATCHERP	How emotionally attached to Europe (0=Not at all, 10=Very)
CCGDBD	Climate change good or bad impact across world (0=Extremely bad, 10=Extremely good)
EUFTF	European unification go further or gone too far (0=Already gone too far, 10=Go further)
EVFREDU	Everyone in country fair chance achieve level of education they seek (0=Not at all, 10=Completely)
EVFRJOB	Everyone in country fair chance get job they seek (0=Not at all, 10=Completely)
GVSRDCC	How likely, governments in enough countries take action to reduce climate change (0=Not at all, 10=Extremely)
HAPPY	How happy are you (0=Extremely unhappy, 10=Extremely happy)
IFREDU	Compared other people in country, fair chance achieve level of education I seek (0=Not at all, 10=Completely)
IFRJOB	Compared other people in country, fair chance get job I seek (0=Not at all, 10=Completely)
IMBGECO	Immigration bad or good for country's economy (0=Bad, 10=Good)
IMUECLT	Country's cultural life undermined or enriched by immigrants (0=Undermined, 10=Enriched)
IMWBCNT	Immigrants make country worse or better place to live (0=Worse, 10=Better)
LKLMTEN	How likely, large numbers of people limit energy use (0=Not at all, 10=Extremely)
LKREDCC	Imagine large numbers of people limit energy use, how likely reduce climate change (0=Not at all, 10=Extremely)
LRSCALE	Placement on left right scale (0=Left, 10=Right)
OWNRDCC	How likely, limiting own energy use reduce climate change (0=Not at all, 10=Extremely)
PPLFAIR	Most people try to take advantage of you, or try to be fair (0=Take advantage, 10=Try to be fair)
PPLHLP	Most of the time people helpful or mostly looking out for themselves (0=Look out for themselves, 10=Try to be helpful)
PPLTRST	Most people can be trusted or you can't be too careful (0=Can't be too careful, 10=Can be trusted)
STFDEM	How satisfied with the way democracy works in country (0=Extremely dissatisfied, 10=Extremely satisfied)
STFECO	How satisfied with present state of economy in country (0=Extremely dissatisfied, 10=Extremely satisfied)
STFEDU	State of education in country nowadays (0=Extremely bad, 10=Extremely good)
STFGOV	How satisfied with the national government (0=Extremely dissatisfied, 10=Extremely satisfied)
STFHLTH	State of health services in country nowadays (0=Extremely bad, 10=Extremely good)
STFLIFE	How satisfied with life as a whole (0=Extremely dissatisfied, 10=Extremely satisfied)
TRSTEP	Trust in the European Parliament (0=No trust at all, 10=Complete trust)
TRSTLGL	Trust in the legal system (0=No trust at all, 10=Complete trust)
TRSTPLC	Trust in the police (0=No trust at all, 10=Complete trust)
TRSTPLT	Trust in politicians (0=No trust at all, 10=Complete trust)
TRSTPRL	Trust in country's parliament (0=No trust at all, 10=Complete trust)
TRSTPRT	Trust in political parties (0=No trust at all, 10=Complete trust)
TRSTUN	Trust in the United Nations (0=No trust at all, 10=Complete trust)

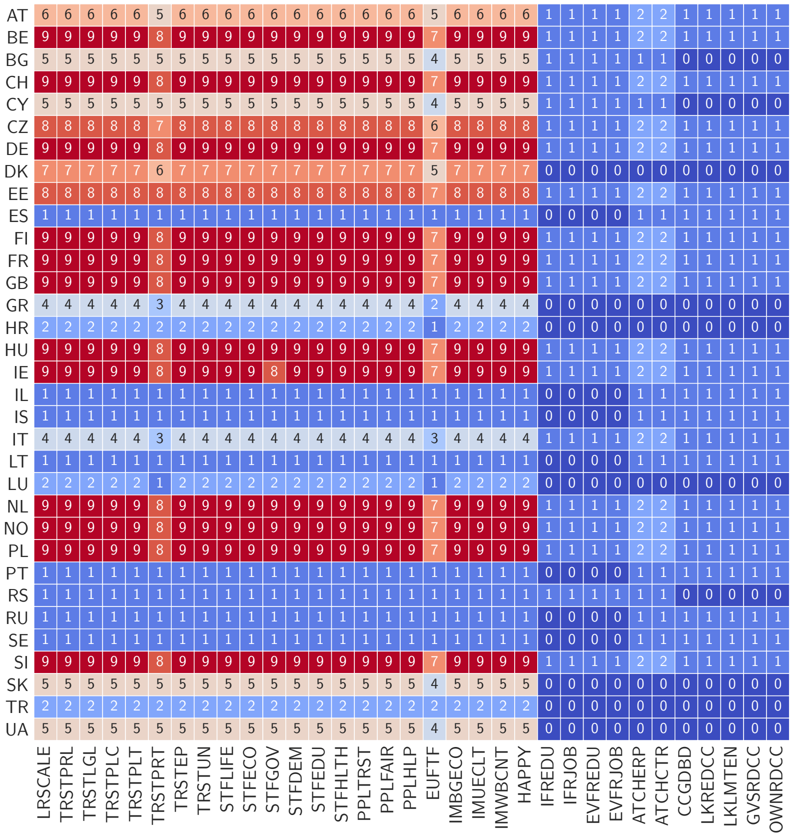

Fig. 1 Amount of rounds a topic is represented in a country.

Appendix 2: Exploration of Peaks on 10- and 11-Point Scales

By exploring peak structure within 10- and 11-point scales, we want to assure that the pentamodal structure is not an artifact mainly driven by the attitude scales. Hypothetically, it could be that the absence of a midpoint in 10-point scales would result in a four mode structure (two off-center peaks and two at the extremes) instead of a pentamodal structure. Therefore, the data set of the Eurobarometer (European Commission And European Parliament, Brussels, 2002 - 2021) which includes the left-right scale on a 10-point scale including a "Don't know" answer is analyzed. The data set includes a total of 3,034 attitude landscapes from 38 different countries in Europe from 2002 to 2020. Additionally, the data set of the European Election Study 2004 (Schmitt et al., 2009) offers 153 attitude landscapes on a 10-point scale which cover various political topics. In Figure 2 we compare the distribution of peaks between all data sets. The left hand side illustrates the fraction of all attitude landscapes where an answer is a peak in the landscape. The right hand side shows the frequencies of the total number of peaks within the attitude landscapes. The first two rows show the data from 10-point answer scales and the bottom two from 11-point scales. We see a very similar structure for both scales including similar frequencies with some differences with respect to the answer 7. Züll and Scholz (2016) already showed that people substitute answer 5 and 6 as "virtual midpoint". We also want to add to the assumption that a fraction of respondents who are considered as centrists are probably not realizing that

Table 2 Response rates in % taken from the documentation report

Country	2002	2004	2006	2008	2010	2012	2014	2016	2018	Mean
Austria		62.41	63.96	62.26	59.60		51.58	52.54	50.87	57.60
Belgium	59.21	61.37	61.01	58.86	53.43	58.74	57.03	56.77	56.18	58.07
Bulgaria			64.75	74.98	81.43	74.74			72.59	73.70
Croatia				45.70	54.49				43.24	47.81
Cyprus			67.32	78.74	69.74	76.75			53.38	69.19
Czech Republic	43.33	55.29		69.49	70.16	68.40	67.93	68.45	67.36	63.80
Denmark	67.56	65.11	50.78	53.88	55.40	49.43	51.85		48.82	55.35
Estonia		79.27	64.97	57.37	56.21	67.83	59.94	68.44	64.06	64.76
Finland	73.21	70.77	64.40	68.44	59.45	67.27	62.67	57.67	52.39	64.03
France	43.09	43.57	45.97	49.38	47.05	52.05	50.94	52.38	48.14	48.06
Germany	55.68	52.60	54.47	47.99	30.52	33.76	31.41	30.61	27.57	40.51
Greece	79.99	78.78		74.27	65.60					74.66
Hungary	69.86	66.52	66.06	61.29	49.15	64.53	52.70	42.71	40.78	57.07
Iceland		51.28				54.65		45.81	40.50	48.06
Ireland	64.46	62.51	56.76	51.55	65.17	67.94	60.74	64.46	62.02	61.73
Israel	70.99			77.69	72.85	78.06	74.35	74.37		74.72
Italy	43.72	60.84				36.04		49.74	53.00	48.67
Latvia			71.20	57.88					38.93	56.00
Lithuania				52.41	39.41	49.61	68.87	64.03	59.21	55.59
Luxembourg	43.90	50.02								46.96
Netherlands	67.85	64.33	59.80	49.83	60.03	55.09	58.61	52.99	51.21	57.75
Norway	65.01	66.24	65.52	60.44	58.04	54.92	53.94	52.82	44.24	57.91
Poland	73.24	74.35	70.19	71.20	70.26	74.87	65.84	69.63	60.80	70.40
Portugal	68.81	70.52	72.76	75.74	67.08	77.12	43.00	45.00	34.92	61.66
Romania			71.80	67.95						69.88
Russia			69.45	67.93	66.64	67.01		63.41		66.89
Slovakia		63.29	73.19	72.55	74.66	74.09			39.55	66.22
Slovenia	70.52	70.24	65.05	59.10	64.39	57.74	52.31	55.93	64.14	62.16
Spain	53.22	54.83	65.94	66.79	68.52	70.28	67.85	67.66	53.81	63.21
Sweden	69.46	65.77	65.88	62.16	50.99	52.44	50.10	43.01	39.00	55.42
Switzerland	33.46	46.85	51.54	49.88	53.31	51.73	52.70	52.21	51.87	49.28
Turkey		50.70		65.24						57.97
Ukraine		66.59	66.42	61.50	64.41	59.10				63.60
United Kingdom	55.52	50.64	54.57	55.77	56.30	53.06	43.56	42.82	40.96	50.36
Mean	60.57	61.72	63.35	62.20	60.15	61.01	56.09	55.37	53.42	60.13

5 is not the midpoint on a 10-point scale. Resulting in a maximum at answer 5 instead of 6, which can be seen in Fig. 2 on the top. Additionally, with the substitution of answer 6 as a midpoint, the probability for answer 7 to become a peak is lower. This is also confirmed with a decrease from 50 to 26% and confirms the assumption of an underlying pentamodal structure.

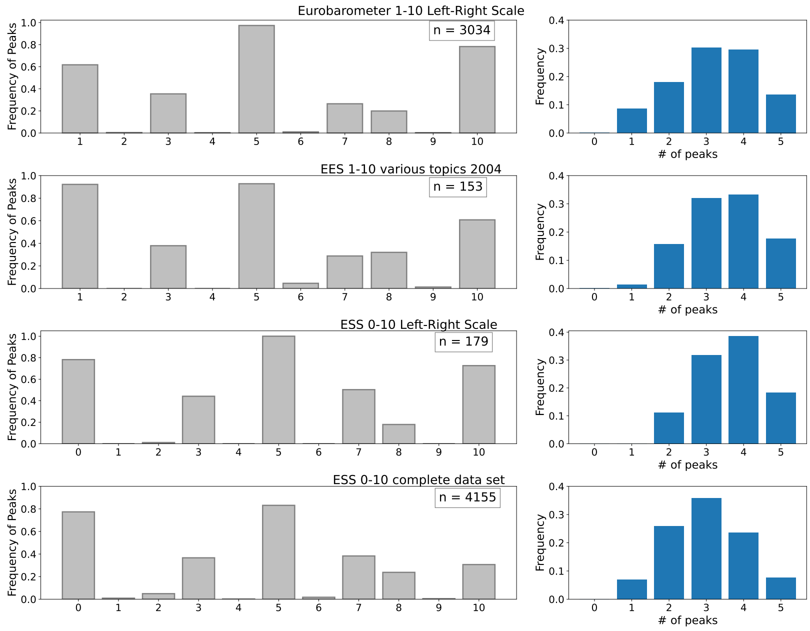

Fig. 2 Comparison of peak distribution between the Eurobarometer from the year 2002 to 2020 (first row), European Election Study from 2004 (second row) and the ESS data set (last two rows). The ESS data set is split into data only from the LRSCALE and the complete data set

Appendix 3: Pentamodal Model Python Code

```
import numpy as np
import scipy.stats as stats
from scipy.optimize import minimize

def Gauss1peak(c , xi):
    Gaussdistr=np.zeros(len(xi))
    for indx,x in enumerate(xi):
        Gaussdistr[indx]= c[0]*(stats.norm.cdf(x+0.5, loc = c[1], scale = c[2])
            - stats.norm.cdf(x-0.5, loc = c[1], scale = c[2]))
    return Gaussdistr

def GaussPenta(c,xi):
    Gaussdistr=np.zeros(len(xi))
    for x in range(11):
        if x==0:
            Gaussdistr[x] = c[0] * stats.norm.cdf(0.5, loc = c[1], scale = c[2])
                 + c[3] * stats.norm.cdf(0.5, loc = c[4], scale = c[5])
        elif x==10:
            Gaussdistr[x] = c[0] + c[3] - c[0] * stats.norm.cdf(9.5, loc = c[1],
                 scale = c[2]) - c[3] * stats.norm.cdf(9.5, loc = c[4], scale =
                c[5])
        else:
```

```
            Gaussdistr[x]=c[0] * (stats.norm.cdf(x+0.5, loc = c[1], scale = c
                [2]) - stats.norm.cdf(x-0.5, loc = c[1], scale = c[2])) + c[3] *
                 (stats.norm.cdf(x+0.5, loc = c[4], scale = c[5]) - stats.norm.
                cdf(x-0.5, loc = c[4], scale = c[5]))
    return Gaussdistr
def penalty(beta, x):
    if x < 0:
        return beta * x**2
    else:
        return 0

def PentamodalModel(Surveydata, DWeights):
                #### Calculate Distribution ####
    Distr , _ = np.histogram(Surveydata,bins=np.arange(-0.5,11),density=True,
         weights=DWeights)
                #### Calculate mean of each side of moderates ####
    Lmean=sum([i*Distr[i] for i in range(0,5)])/sum(Distr[:5])
    Rmean=sum([i*Distr[i] for i in range(6,11)])/sum(Distr[5:])

                #### Left peak fitting from bin 1 to 4 ####
    Leftbounds = np.array([[0. , 2. ],[0. , 5.],[0. , 1.]])
    Leftdata = Distr[1:5]
    Firstfitfunc = lambda p, x, data: (((Gauss1peak(p,x)-data))**2).sum()
    p0Left= [max(Leftdata) , Lmean, 1] ## First estimates
    xLeft = np.arange(1,5)
    pLeft = minimize(Firstfitfunc, p0Left, args = (xLeft,Leftdata), bounds=
         Leftbounds)

                #### Right peak fitting from bin 6 to 9 ####
    Rightbounds= np.array([[0. , 2. ],[5. , 10.],[0. , 1.]])
    Rightdata = Distr[6:10]
    p0Right= [max(Rightdata) , Rmean, 1] ## First estimates
    xRight = np.arange(6,10)
    pRight = minimize(Firstfitfunc, p0Right, args = (xRight,Rightdata), bounds
         = Rightbounds)

                #### Fitting all bins to Pentamodal Model ####
    d0 = np.asarray([1,0,0,0,0,0,0,0,0,0,0])
    d10 = np.asarray([0,0,0,0,0,0,0,0,0,0,1])
    d5 = np.asarray([0,0,0,0,0,1,0,0,0,0,0])
    PentamodalFitfunc = lambda p, x, data: ((p[6]*d0 + p[7]*d10 + p[8]*d5 +
         GaussPenta(p[:6],x)-data)**2).sum() + penalty(20,p[6])+ penalty(20,p
         [7])+ penalty(20,p[8])

    plowerb = np.array([0. , 0. , 0.,0. , 0. , 0., -0.05,-0.05,-0.05])
    pupperb = np.array([1. , 10., 5.,1. , 10., 5., 1, 1, 1])
    bounds = np.c_[plowerb,pupperb]

    p0LR = np.array([pLeft.x, pRight.x,[Distr[0]/3, Distr[10]/3, Distr[5]/3]]).
         flatten()

    xLR=np.arange(0,11)
    constraint=({'type': 'eq','fun': lambda c: 1-c[0]-c[3]-c[6]-c[7]-c[8]})

    pPentamodal = minimize(PentamodalFitfunc , p0LR, args=(xLR, Distr), method=
         'SLSQP', bounds=bounds, options={'maxiter':700},constraints=constraint)
    return pPentamodal.x
```

Appendix 4: Further Evidence for the Pentamodal Structure within Attitude Landscapes

By analyzing an endogenous group – voters of a specific party – this part approaches the theory of normal distributed moderates within our model from a different angle.

First, political parties can also be assigned positions on the left-right scale, like done in the manifesto project (Merz et al., 2016) or other measurement projects as collected by the PARLGOV project (Döring and Manow, 2012). Assuming that voters do not share the position of the party exactly, voters will distribute symmetrically around their party's position. Therefore, the normal distribution is chosen with the same additional conditions as in the Pentamodal Model.

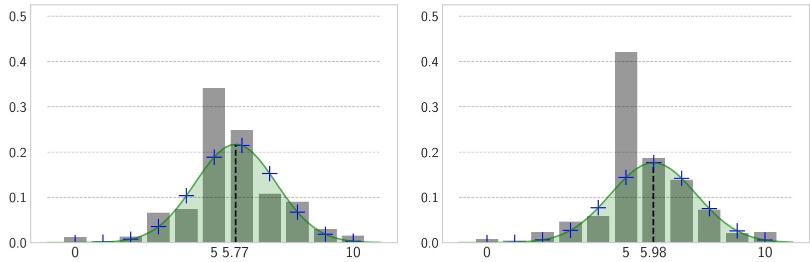

Fig. 3 Distribution of CDU-Voters (2nd Vote) on the Left-Right Scale in 2004 (left) and 2014 (right)

As an example, Figure 3 displays CDU (German conservative party, left-right scale of 6.25 according to PARLGOV) voters in the year 2004 and 2014 on the left-right scale including a fit. As expected, both distributions show irregularities at answer 5 which are already explained in the Pentamodal Modal section and, thus, excluded during the fit. For the year 2014 the fit works well with bigger discrepancies on the left hand side of the distribution. In 2004 the overall fit is worse due to an exceptionally large fraction of answer 6. Furthermore, the mean of both fits are 5.77 (2004) and 5.98 (2014) and is deviating only a small amount to the left of the expected value of 6.25. Looking at the results from various years this theory is far from perfect but the theoretically possible variations of endogenous groups are nearly endless. Nevertheless, from this exemplary data analysis we can conclude two major results: The investigation of moderates and their reasons for their (normal) distribution is more complex than "just" analyzing voters of a specific party and further research to validate that theory is desirable. However, the analysis confirms the assumption of the Pentamodal Model that respondents who are considered moderate right can produce answers on the whole attitude landscapes including 0. Vice versa for the moderate left.

Appendix 5: Details about the Parameter Estimation and the Goodness-of-Fit

Figure 4 shows the distributions of all 9 parameters. Some similarities and differences can be observed. While the weights for the moderates w_{ModR} and w_{ModL} share a similar shape, the standard deviation σ_{R} and σ_{L} differ with σ_{L} being mostly above one and σ_{R} rarely exceeding two. Left moderates tend to have higher and more diverse standard deviations. Due to the lower number of peaks on the left hand side of the scale (see Fig. 2), the moderate left often show a less pronounced peak.

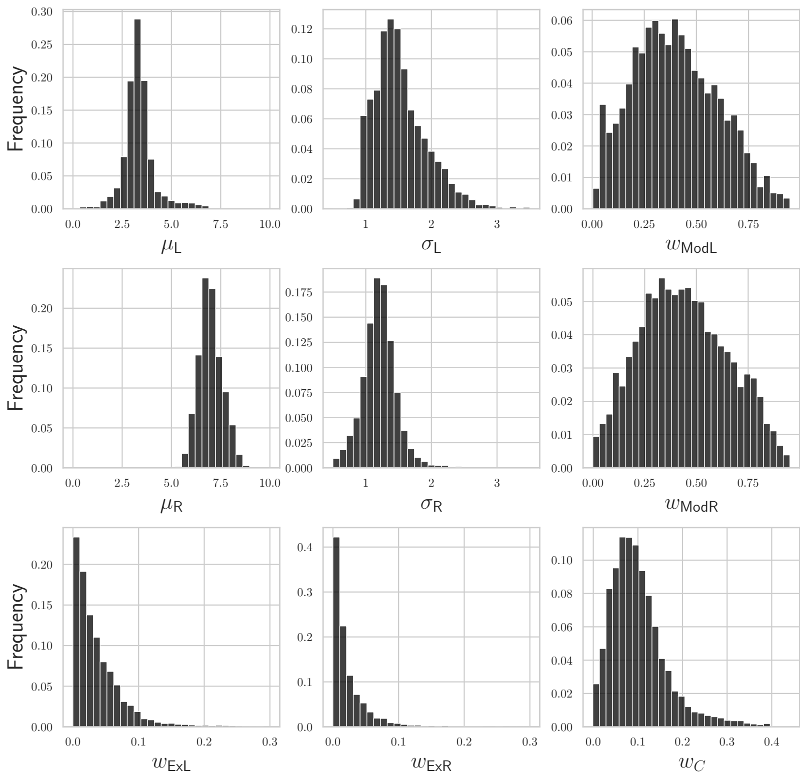

Fig. 4 Distribution of the parameters using the Pentamodal Model on the ESS data set.

The goodness-of-fit can be further investigated by looking at the residual of fit and real data. Figure 5 shows the residuals values for the complete data set as boxplots. Naturally, the residuals for left extremists, right extremists, and centrists are the lowest due to the explicit weights in the model. For the answers that are only influenced by the moderates (1 to 4 and 6 to 9) differences are larger. Nevertheless, the box plots show overall small variation from the zero-line. For answer 7 and 9 the model is mostly producing too small results whereas for answer 1 and 8 results are slightly too large.

Figure 6 shows how the fitting parameter for assessing the three penalty terms influences the median R^2 value. Furthermore, the distribution of the three weights w_{ExL}, w_{ExR}, and w_{C} only for values below zero is shown on the right hand side. All three weights are close to zero and rarely exceed values below -0.0005. These results motivate our choice of the penalty weight $\beta = 20$.

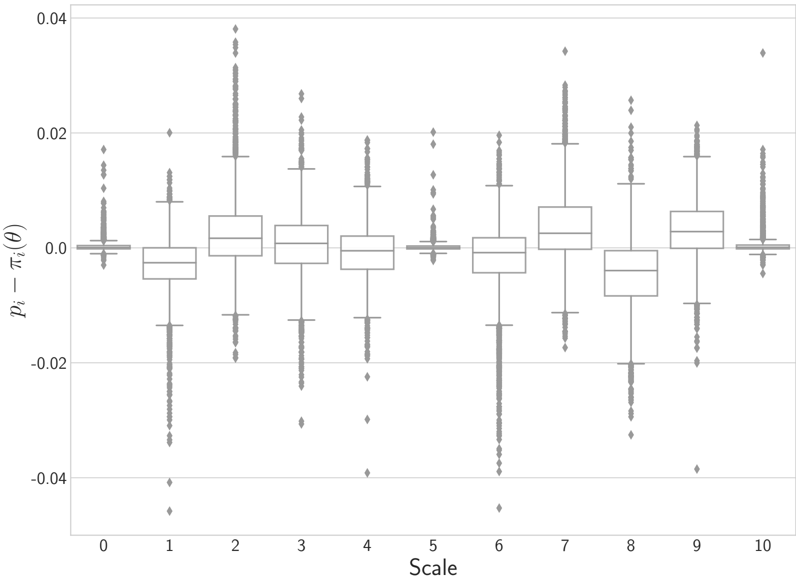

Fig. 5 Distribution of residuals between the empirical data and best-fitted model estimates.

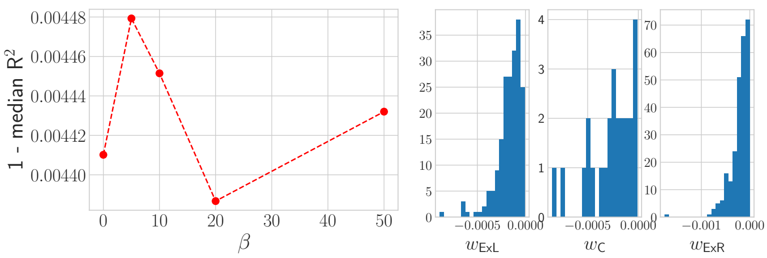

Fig. 6 Left: 1 - Median R^2 for different penalty parameter β shows best result for $\beta = 20$ Right: Absolute distributions of negative residues for the weights w_{ExL}, w_C, and w_{ExR} with $\beta = 20$.

Figure 7 shows the four attitude landscapes and Pentamodal Models with the worst coefficients of determination ($R^2 < 0.9$) in our data set.

These examples have shapes that were not considered when creating the model. Most importantly, all four landscapes show an unusually high p_1, which even appears as a peak in three of them. Also the case of EUFTF in Austria 2018 which is the second most polarized EUFTF in Figure 8 has a peak at answer 1. Overall, this is extremely rare (see also Figure 2 in Appendix Appendix 2:). Such landscapes prevent a good fit of confined normal distributions within the definition of the Pentamodal Model. If the p_1 becomes particularly large, either the corresponding μ must shift close to extreme resulting in way too high extreme bins in the model due to overlapping tails, or, if μ remains moderate between extreme and neutral, p_1 is estimated way too low.

We speculate that some unusually large p_1 values result from errors in the survey interview on the phone. A possible explanation is that some interviewers asked people for values between 1 and 10 instead of 0 and 10. This would need further investigation which we omitted because it is out of the scope of this study and the number of cases is low.

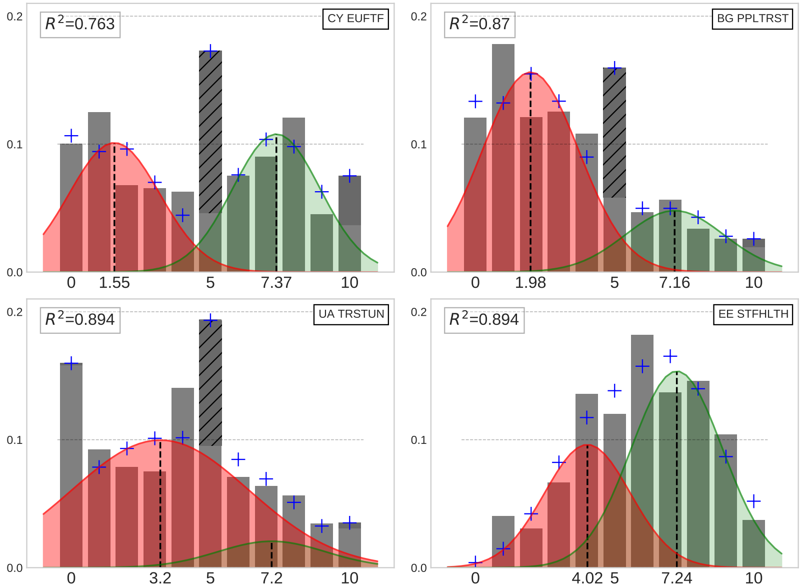

Fig. 7 The four attitude landscapes where the Pentamodal Model achieves the worst goodness-of-fit ($R^2 < 0.9$).

In satisfaction with health, Estonia has $p_0 = 0$ and peaks at p_1, p_4, p_6, and p_8. With two peaks at each side of the centrists, it is impossible to fit two normal distributions properly to it. This also looks like an erroneous shift of answer categories. This is again speculation.

Finally, Ukraine's distribution is shaped like a sloped uniform distribution with a distinct greater amount of answers for bins p_0, p_4, and p_5. Distinguishing five groups within this distribution within the Pentamodal Model is impossible.

The development of the model was focused on core political topics where a group of moderate left and right is a natural assumption. On a trust or a satisfaction scale this is not so much the case. Empirically, satisfaction and trust scales and are responsible for 22 (65 %) of the cases with $R^2 < 0.95$.

Appendix 6: Further Results for Cross-Country and Time Trend Analyses

In this section, further results from ranking polarization cross-country in our core political topics will be presented. Additionally, an overview of time trends for these three topics is included. First, the ranking on left-right polarization in Figure 8 shows less deviation between the most and least polarized country. Comparing highly polarized countries like Hungary or Cyprus with less polarized ones like the Netherlands or Estonia, the histograms share an analogous structure. Furthermore, all measurements of the decomposition do not correlate with the overall ranking.

The topic of immigration in Figure 9 ranking in the upper ranks is similar as for the topic of European unification (compare Figure 8). For the lower ranks of Pol_0, moderate individual-weighted polarization ($\mathrm{Pol}_1^{\mathrm{Mod}}$) becomes larger instead of smaller. This phenomenon originates from higher agreement for immigration in these countries. Therefore, more people answer this question around the mean (μ_R). This is one of the reasons why $\mathrm{Pol}_1^{\mathrm{Mod}}$ correlates negatively with Pol_0.

Figure 10 represent the overall polarization increase and decrease in Europe within the three core political topics. We do not see a general trend.

Country	Pol_0	$\mathrm{Pol}_0^{\mathrm{Ex}}$	$\mathrm{Pol}_0^{\mathrm{resC}}$	$\mathrm{Pol}_1^{\mathrm{Mod}}$	$\mathrm{resPol}_0^{\mathrm{Mod}}$
HU	0.584	0.082	0.084	0.059	0.36
CY	0.569	0.132	0.124	0.035	0.278
RS	0.566	0.164	0.141	0.029	0.233
BG	0.559	0.086	0.102	0.053	0.318
PL	0.553	0.099	0.101	0.051	0.302
NO	0.545	0.059	0.055	0.086	0.344
SI	0.524	0.118	0.122	0.034	0.249
IT	0.524	0.051	0.048	0.08	0.345
FR	0.482	0.062	0.083	0.054	0.284
FI	0.471	0.036	0.073	0.072	0.29
CZ	0.454	0.033	0.065	0.067	0.288
CH	0.442	0.018	0.08	0.061	0.283
NL	0.437	0.026	0.062	0.072	0.277
BE	0.432	0.044	0.079	0.055	0.254
GB	0.416	0.05	0.088	0.046	0.233
DE	0.412	0.044	0.085	0.051	0.231
AT	0.41	0.036	0.089	0.044	0.24
IE	0.385	0.029	0.075	0.049	0.231
EE	0.384	0.042	0.099	0.034	0.209

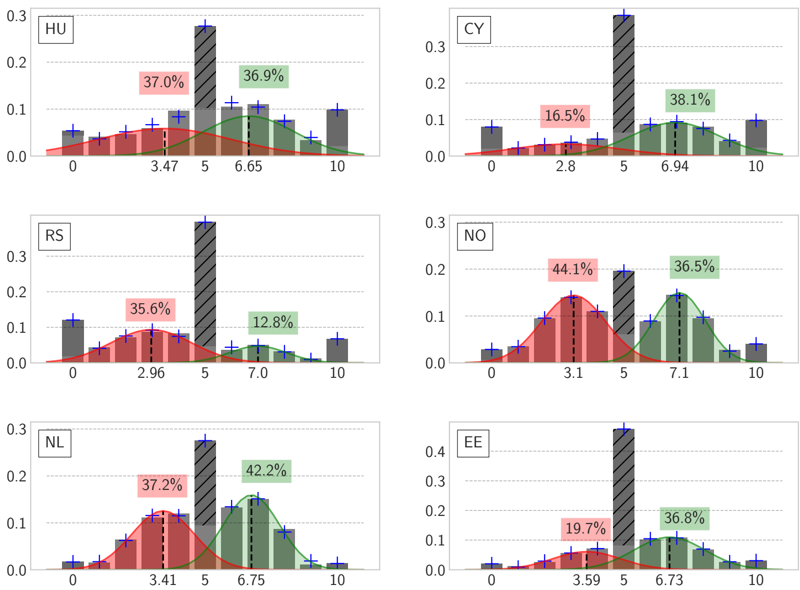

Fig. 8 Left-right scale (LRSCALE) round 9 ranking. Table and histograms are sorted by Pol_0. Histograms from top left to bottom right

Country	Pol_0	$\mathrm{Pol}_0^{\mathrm{Ex}}$	$\mathrm{Pol}_0^{\mathrm{resC}}$	$\mathrm{Pol}_1^{\mathrm{Mod}}$	$\mathrm{resPol}_0^{\mathrm{Mod}}$
RS	0.708	0.252	0.111	0.036	0.309
IT	0.629	0.127	0.04	0.081	0.38
FR	0.6	0.088	0.062	0.078	0.373
AT	0.597	0.095	0.053	0.077	0.371
GB	0.596	0.103	0.053	0.081	0.359
BG	0.585	0.02	0.072	0.084	0.41
SI	0.579	0.082	0.085	0.063	0.35
DE	0.568	0.068	0.052	0.085	0.363
EE	0.545	0.071	0.072	0.068	0.334
PL	0.542	0.089	0.077	0.064	0.312
HU	0.537	0.094	0.05	0.072	0.32
CY	0.535	0.076	0.052	0.079	0.328
IE	0.529	0.055	0.049	0.092	0.334
NO	0.508	0.054	0.074	0.077	0.303
CZ	0.504	0.052	0.041	0.084	0.327
CH	0.492	0.041	0.039	0.094	0.318
BE	0.489	0.044	0.055	0.09	0.3
FI	0.442	0.032	0.048	0.1	0.261
NL	0.435	0.025	0.046	0.097	0.266

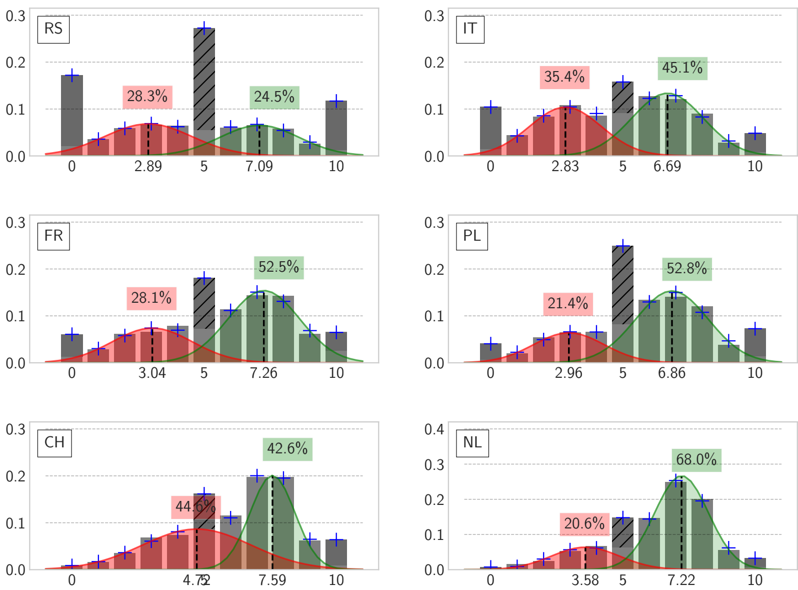

Fig. 9 Immigration undermining or enriching culture (IMUECLT) 2018 ranking. Table and histograms are sorted by Pol_0. Histograms from top left to bottom right

Country	Pol_0	$\mathrm{Pol}_0^{\mathrm{Ex}}$	$\mathrm{Pol}_0^{\mathrm{resC}}$	$\mathrm{Pol}_1^{\mathrm{Mod}}$	$\mathrm{resPol}_0^{\mathrm{Mod}}$
SI	0.0054	0.0032	-0.0006	0.0005	0.0022
FI	0.0034	-0.0005	-0.0007	0.0003	0.0042
PL	0.003	0.0004	-0.0005	0.0002	0.003
GB	0.0023	0.0034	0.0011	-0.0005	-0.0017
DE	0.0017	-0.0014	-0.0023	0.0013	0.0041
NO	0.0012	0.0001	-0.0002	0.0	0.0012
DK	0.001	0.001	-0.0012	0.0008	0.0004
FR	0.0005	-0.001	-0.0013	0.0009	0.0019
CH	-0.0005	0.0001	-0.0011	0.0001	0.0004
IE	-0.0006	0.0026	-0.0008	0.0003	-0.0027
NL	-0.0006	-0.0005	-0.0003	0.0002	-0.0001
BE	-0.0008	-0.0001	-0.0008	0.0006	-0.0005
EE	-0.0008	0.0007	0.0006	-0.0007	-0.0014
CZ	-0.0012	0.0018	-0.002	0.0009	-0.0019
HU	-0.0013	0.0021	-0.0021	0.0007	-0.0019

Country	Pol_0	$\mathrm{Pol}_0^{\mathrm{Ex}}$	$\mathrm{Pol}_0^{\mathrm{resC}}$	$\mathrm{Pol}_1^{\mathrm{Mod}}$	$\mathrm{resPol}_0^{\mathrm{Mod}}$
SI	0.0039	0.002	-0.0013	0.0007	0.0024
PL	0.0037	-0.0004	0.0	-0.0001	0.0042
GB	0.0031	0.0023	0.0013	-0.0006	0.0001
IE	0.0018	0.0029	0.0003	-0.0002	-0.0011
EE	0.0001	0.0022	0.0014	-0.001	-0.0024
NL	-0.0005	0.0016	0.0007	-0.0006	-0.0024
FR	-0.0006	-0.0006	0.0002	0.0001	-0.0002
DE	-0.0012	-0.0016	-0.001	0.0007	0.0007
FI	-0.0016	-0.0009	-0.0001	0.0	-0.0007
HU	-0.0016	-0.0026	-0.0011	0.001	0.001
CH	-0.0017	0.0001	0.001	-0.0011	-0.0016
NO	-0.0023	-0.001	0.0009	-0.0009	-0.0014
BE	-0.0042	-0.0022	0.0003	-0.0001	-0.0022

Country	Pol_0	$\mathrm{Pol}_0^{\mathrm{Ex}}$	$\mathrm{Pol}_0^{\mathrm{resC}}$	$\mathrm{Pol}_1^{\mathrm{Mod}}$	$\mathrm{resPol}_0^{\mathrm{Mod}}$
DK	0.0086	0.0006	-0.0015	0.0016	0.0079
NO	0.0044	0.0013	-0.0005	0.0004	0.0032
GB	0.0037	0.0007	0.0001	0.0005	0.0024
PL	0.003	0.0011	0.0001	0.0004	0.0015
CH	0.0025	0.0003	-0.0002	0.0003	0.0021
HU	0.0023	0.001	-0.0015	0.0006	0.0022
IE	0.0015	0.0012	-0.0005	0.0005	0.0003
SI	0.0015	0.0014	0.0003	0.0	-0.0002
DE	0.0012	0.0007	0.0001	-0.0001	0.0005
FI	0.0012	-0.0	-0.0008	0.0005	0.0015
BE	0.0002	-0.0003	-0.0005	0.0005	0.0006
FR	-0.001	-0.0005	0.0004	-0.0003	-0.0006
NL	-0.0014	-0.0003	0.0004	-0.0003	-0.0013
EE	-0.0015	0.0008	0.0006	-0.0009	-0.002
CZ	-0.0055	-0.0007	-0.001	0.0001	-0.0039

Fig. 10 Slopes of a linear fit applied to polarization measurements for three topics from top to bottom (IMUECLT, EUFTF, LRSCALE). Slopes represent the increase or decrease per year. Tables are sorted by slope of Pol_0.

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