Are attitudes towards immigration changing in Europe? An analysis based on bidimensional latent class IRT models

Genge, Ewa and Bartolucci, Francesco

University of Economics, Katowice, Poland, University of Perugia, Italy

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Ewa Genge

Department of Economic and Financial Analysis, University of Economics, Bogucicka 3a Street, 40-228 Katowice, Poland.

E-mail: ewa.genge@ue.katowice.pl

Francesco Bartolucci

Department of Economics, University of Perugia, Via A. Pascoli, 20, 06123 Perugia, Italy.

E-mail: francesco.bartolucci@unipg.it

Summary. We analyse the changing attitudes towards immigration in EU host countries in the last few years (2010-2016) on the basis of the European Social Survey data. These data are collected by the administration of a questionnaire made of items concerning different aspects related to the immigration phenomenon. For this analysis we rely on a class of item response theory models that allow for: *(i)* multidimensionality; *(ii)* discreteness of the latent trait distribution; *(iii)* time-constant and time-varying covariates; and *(iv)* sample weights. Through these models we find latent classes of Europeans with similar levels of immigration acceptance, we study the effect of different socio-economic covariates on the probability of belonging to these classes, and we assess the item characteristics. In this way we show which countries tend to be more or less positive towards immigration and the temporal dynamics of the phenomenon under study.

Keywords: European Social Survey; Expectation-Maximisation algorithm; Item response theory; Discrete latent variables.

Introduction

Immigration is one of the most pressing challenges the EU countries are facing. According to the UN Refugee Agency, 362,000 refugees and migrants risked their lives crossing the Mediterranean Sea in 2016, with 181,400 people arriving in Italy and 173,450 in Greece. In the first half of 2017, over 105,000 refugees and migrants entered Europe. According to data from the Organisation for Economic Cooperation and Development, the number of new asylum-seekers reached a record of about 1.6 million in 2015 with approximately 22% of refugees coming from Syria, by far the leading country of origin.

To study attitudes towards the immigration phenomenon, we analyse the cross-national ESS (European Social Survey) data that measure changes in social structure, conditions, and opinions in Europe. In particular, we focus on the last four rounds of the survey (i.e., ESS 5, 2010; ESS 6, 2012; ESS 7, 2014; ESS 8, 2016), period in which the problem of immigration has become particularly acute in Europe. Our aim is to characterise homogeneous groups of Europeans presenting similar levels of attitude towards immigration, conceived as a latent trait, and analyse the effect of different socio-economic covariates on the probability of belonging to the different groups. In this way we can show which countries tend to be more positive towards migrants and those whose publics tend to be least welcoming for them. We can also describe the evolution of the tendency towards immigration across time in a dynamic fashion.

The data collected by the ESS highlights both differences and similarities across European countries, providing a context for single country findings as well. The ESS is the most highly regarded cross-national survey program (see `http://www.europeansocialsurvey.org/about/index.html` for more details) in the world, conducting rigorous representative surveys to the highest professional and methodological standards across Europe. Many of the questions fielded in the most recent rounds are repetitions of questions administered over one decade ago (in the first round of the ESS, i.e., ESS 1, 2002). This enables to chart trends over time in attitudes, and compare developments in different European countries. Therefore, the survey provides one of the most authoritative databases to study attitudes towards immigration across countries and time.

Among the items of the questionnaire adopted within ESS, we explore six polythomous items with ordered responses concerning attitudes towards migrants (of the same race, of a different race, and from poorer countries outside Europe) and the perceived costs and benefits of migration (for country's economy, country's cultural life, and country's place to live). Therefore, we propose to equally divide the items into two latent dimensions: *general acceptance of immigration* and *impact of immigration on the host country*.

For the analysis of the responses to the six items at issue, we adopt a class of Item Response Theory (IRT) models (Hambleton and Swaminathan, 1985; Bartolucci et al., 2015). In particular, we rely on the models developed by Bacci et al. (2014) for polythomous ordinal items (see also Bartolucci, 2007) allowing for: *(i)* multidimensionality, so as to consider that distinct latent traits are jointly measured; *(ii)* discreteness of the latent trait distribution, so to give rise to groups of individuals corresponding to latent classes; *(iii)* time constant and time-varying covariates affecting the distribution of the latent classes; and *(iv)* weights to account for the sample design. Among the covariates we include different socio-economic characteristics, time dummies, and dummies for the country of residence. These covariates affect the probability of belonging to the different latent classes. Due to inclusion of dummy explanatory variables for the country, we account for the multilevel structure of the data, though this is based on fixed rather than random effects. The use of fixed effects is justified by the limited number of countries considered and allows us to avoid the specification of parametric distributions that would be necessary with random effects.

The adopted IRT models are estimated by the maximum likelihood method, which is applied by an Expectation-Maximisation (EM) algorithm (Dempster et al., 1977) implemented in `R` package `MultiLCIRT` (see Bartolucci et al., 2016a). It is worth noting that, in addition to the study of the distribution of the latent traits of interest related to the attitude towards immigration, and its dependence on the covariates, the adopted class of models also allows us to test unidimensionality versus bidimensionality, where unidimensionality corresponds to the hypothesis that the two latent traits coincide. Moreover, these models may be used for the analysis of the item characteristics in order to perform a sort of diagnostics of the questionnaire in terms of capability to effectively measure the latent traits of interest.

The remainder of this paper is organised as follows. In the next section we review the relevant literature describing the most important studies concerning immigration and based on the ESS data. Then, we describe the data and outline the adopted class of multidimensional IRT models in Sections 2 and 3. The empirical analysis is presented in Section 4. Final remarks are given in the Section 5.

1. Literature review

Schlueter and Wagner (2008) examined the role that the size of the immigrant population plays in explaining anti-immigrant attitudes within and between European regions. The results prove that a larger size of the regional immigrant population leads to a greater perceived group threat and thereby increases immigrant derogation (social distance). At the same time, the findings also prove that a larger size of the immigrant population increases intergroup contacts and, in turn, reduces perceived group threats and thereby amends anti-immigrant social distance. Their results are based on the first wave (ESS 1, 2002) of data concerning single European regions, which are analysed by means of multilevel structural equation models.

Applying the Scrugg's decommodification index with 14 countries for cross-national Eurobarometer data combined with the ESS 1 data, Crepaz and Damron (2009) claimed that people in generous welfare states are less inclined to agree on that salaries and wages are brought down by immigrants.

Rustenbach (2010) for the first two waves of the ESS, in conjunction with data from Eurostat, tested eight different explanations for anti-immigrant attitudes. Using a hierarchical linear model technique, she found that the size of the immigrant population and the regional GDP have no impact on attitudes, whereas national foreign direct investments and unemployment are shown as negatively associated with anti-immigrant attitudes. The main results of this work indicate that sentiments of uncertainty (e.g., threat of emerging infections, lack of feeling safe in the neighbourhood) may be one of the main reasons why anti-immigrant attitudes arise. Fear is related to anti-immigrant attitudes because they cause uncertainty concerning how immigrants may affect the society from the cultural and economic points of view.

Davidov and Meuleman (2012) tried to investigate the effect of human values (Schwarz, 1992) on attitudes towards immigration using data from the first three rounds of the ESS (ESS 1, 2002; ESS 2, 2004; ESS 3, 2006). Using fixed- and random-effects models, they found that cross-country and longitudinal differences in the rejection of immigration cannot be explained by economic conditions and relative size of immigrant population (see also Scheepers et al., 2002). Improved economy and lower levels of immigration cannot necessarily guarantee more public support for immigration. This findings are opposed to those presented by Schlueter and Wagner (2008) as well as Semyonov et al. (2006). However, the relations between economic conditions, size of immigrant population, and anti-immigrant attitudes are not confirmed in other studies (Sides and Citring, 2007; Strabac and Listhaug, 2008).

Markaki and Longhi (2012) considered four rounds of the ESS data (ESS 1, 2002; ESS 2, 2004; ESS 3, 2006; ESS 4, 2008) using a two-stage OLS estimation approach to explain the regional heterogeneity in immigration attitudes. Their findings suggest that differences in anti-immigration attitudes across regions in Europe may not be so closely related to the current economic conditions of the region but might be driven by concerns over the conditions of the immigrant population in that region, in addition to an overall inflated estimation of the extent of immigration.

More recently, Nagayoshi and Hjerm (2015) analysed data from six ESS rounds (ESS 1, 2002; ESS 2, 2004; ESS 3, 2006; ESS 4, 2008; ESS 5, 2010; ESS 6, 2012) and OECD data using a c-means fuzzy classification, to cluster states according to levels and types of activation, and hierarchical linear models, to examine the effects of the labour market policies on anti-immigration attitudes. They noticed that levels of anti-immigration attitudes rise when a state uses more social expenditures than the average.

Heath and Richards (2016) charted trends over time and showed developments in different European countries based on the 2014 round of the ESS with the questions asked over one decade ago. They mainly presented the changes in the proportion of answers to questions (in 2014 vs 2002) concerning attitudes towards different sorts of migrant or perceptions of the effect of migration for all participating countries together. They explained that the influx of migrants may have caused an increasing competition for job and housing, leading to more negative attitudes. On the other hand, the increasing size of the migrant population means that people are likely to have had increasing contacts with migrants and their children, which can tend to promote slightly positive attitudes.

Two important trends in the overall structure of the public opinion about immigration was found in Britain (see Ford et al., 2012; Ford and Heath, 2014) and across Europe (see Ford and Lymperopoulou, 2017). Public opinion is not, in general, becoming more negative about immigration, even in countries with high rates of migration inflow. However, Europeans are becoming more divided ("polarised") about migration, particularly in the case of attitudes towards migrants from poorer countries outside Europe (see also Ford, 2017). Note that the results presented in Ford and Heath (2014) and Ford (2017) are based on an analysis of only the questionnaire items of ESS 7 (2014) compared to the first round of the survey.

One of our main contributions to the existing empirical literature is that we conceive the attitude towards immigration as a latent (non-observable) construct that we analyse by proper latent trait models, such as the IRT models. In fact, this attitude is not directly measurable and depends on individual characteristics that are not directly observable, such as cultural background, economic status, and political views. People might be more likely to have anti-immigrant attitudes when they cannot relate to the culture of the immigrants (e.g., ethnic background). Economic competition and anti-immigrant attitudes may occur because immigrants are taking native jobs especially at the bottom of the labour hierarchy. Also, right or left political orientations may clarify why differences in anti-immigrant sentiments occur. In fact, according to Dennison (2017): "Attitudes to immigration at the individual level can be powerfully predicted by fundamental psychological traits, with individuals displaying openness and excitability more drawn towards pro-immigration positions and those displaying conscientiousness and concern over safety more drawn towards anti-immigration positions".

Previous studies based on the ESS data are mainly concentrated on different relationships between country policies (i.e., welfare policy or other characteristics such as the size of the immigrant population, economic conditions, and foreign investments) and anti-immigrants attitudes for the previous rounds. In contrast, the present work focuses on the evolution of the individual attitudes towards immigration in the different EU host countries in the last few years (2010-2016), in which the problem of immigration has become particularly acute. With respect to previous works, we study the level of support for immigration in a more sophisticated way, and not only on the basis of the simple balance of opinions or mean score comparisons for separate items in the first and last rounds of the survey. We account, in particular, for two latent traits (general acceptance of immigration and impact of immigration on the host country) that are simultaneously considered and each of the six items (measured in 2010-2016) is associated with one of them. Furthermore, we consider both baseline and time-varying socio-demographic characteristics that are assumed to impact on the immigration attitudes evolving over time.

2. Data Presentation

The ESS is an academically driven cross-national survey that has been conducted across Europe since its establishment in 2001. Every two years, face-to-face interviews are conducted with newly selected cross-sectional samples. The survey measures the attitudes, beliefs, and behaviour patterns of diverse populations in different nations. The public dataset and more information can be found at `http://www.europeansocialsurvey.org/about/index.html`.

Here we focus, in particular, on the changing attitudes in the EU countries in the last years (2010-2016), that is, the last four rounds of the survey (ESS 5, 2010; ESS 6, 2012; ESS 7, 2014; ESS 8, 2016). Therefore, we consider six items concerning the different aspects of immigration acceptance with ordinal responses that measure two dimensions: *general acceptance of immigration* and *impact of immigration on the host country*. The analysed dataset is referred to a sample of 81,789 respondents living in 12 European countries who take a part in all of the ESS rounds of interest.

The first three items given below measure the first dimension (referring to the extent the [country] should accept different groups of immigrants) and the others three (concerning different effects of immigration for a [country]) define the second one:

- Y_1 – *allow many/few immigrants of the same race/ethnic group as majority population* (1–allow none, 2–allow few, 3–allow some, 4–allow many to come and live here);
- Y_2 – *allow many/few immigrants of different race/ethnic group from majority population* (1–allow none, 2–allow few, 3–allow some, 4–allow many to come and live here);
- Y_3 – *allow many/few immigrants from poorer countries outside Europe* (1–allow none, 2–allow few, 3–allow some, 4–allow many to come and live here);
- Y_4 – *immigration bad or good for country's economy* (1–very bad, 2–rather bad, 3–rather good, 4–very good for the economy);
- Y_5 – *country's cultural life undermined or enriched by immigrants* (1–undermined, 2–partly undermined, 3–partly enriched, 4–enriched cultural life);
- Y_6 – *immigrants make country a worse or better place to live* (1–worse, 2–rather worse, 3–rather better, 4–better place to live).

Originally, the first three items (Y_1–Y_3) had the reverse order of the (four) response categories. In turn, the last three items (Y_4–Y_6) originally had a 11-point Likert type scale, from 0 for "bad for the economy" to 10 for "good for the economy". In fact, we know from previous studies that the immigration attitudes in the last years are becoming rather slightly positive; therefore, we prefer to analyse the immigration attitudes, as opposed to more popular anti-immigration analyses. Moreover, in order to have a clearer interpretation of the results, the response categories of the items corresponding to the second dimension are also arranged in four categories increasingly ordered.

Regarding the literature, Davidov and Meuleman (2012) analysed the scaled variable *reject* of immigrants as the average of the first three items (Y_1–Y_3) for the first three rounds of the ESS survey. Markaki and Longhi (2012), in their analyses, converted the 11-point scales of items Y_4–Y_6 (corresponding to our second latent dimension) into binary variables for certain rounds (ESS 1, 2002; ESS 2, 2004; ESS 3, 2006; and ESS 4, 2008). Moreover, most of these works (see also Ervasti et al., 2008; Schlueter and Wagner, 2008; Gorodzeisky and Semyonov, 2009; Meuleman et al., 2009; Gorodzeisky, 2011) are focused on the negative perception, that is, the anti-immigrant attitude, perceived threat of immigration, or immigrant derogation.

Table 1 reports the distribution of the item responses of the ESS rounds of interest, covering the period 2010-2016, whereas Table 2 shows the distribution of each response variable for every country. The mean $\bar{Y}_j$ is computed for each item after assigning score 1 to 4 to the four increasing categories, respectively. We emphasise that since our study is based on combining data from different countries and rounds, the design weights in combination with population size weights (European Social Survey, 2014, Sec. 2 and 3) are applied in the frequency tables as well as in the estimation part of our analysis.

Overall, responses are mainly concentrated on the third category for both dimensions, whereas category 1, corresponding to the lowest level of immigration

Table 1. Weighted frequency distribution for each response variable (%), in years 2010-2016, and weighted average scores ($\bar{Y}_j$)

2010	1	2	3	4	$\bar{Y}_j$
Y_1	6.55	23.69	50.13	19.63	2.83
Y_2	10.37	32.30	44.25	13.09	2.60
Y_3	13.39	33.97	40.90	11.74	2.51
Y_4	16.75	19.57	49.96	13.71	2.61
Y_5	13.53	16.06	46.92	23.49	2.80
Y_6	15.04	19.77	51.98	13.21	2.63
2012	1	2	3	4	$\bar{Y}_j$
Y_1	5.19	19.71	51.72	23.39	2.93
Y_2	9.39	28.65	47.21	14.75	2.67
Y_3	12.64	29.60	43.94	13.81	2.59
Y_4	15.22	18.86	48.86	17.05	2.68
Y_5	12.21	14.74	45.12	27.93	2.89
Y_6	13.71	18.15	52.95	15.19	2.70
2014	1	2	3	4	$\bar{Y}_j$
Y_1	5.35	18.95	50.38	25.33	2.96
Y_2	8.96	26.59	47.90	16.56	2.72
Y_3	14.66	30.90	40.51	13.93	2.54
Y_4	16.24	17.87	48.48	17.41	2.67
Y_5	12.33	15.49	44.68	27.51	2.87
Y_6	13.15	18.23	52.86	15.76	2.71
2016	1	2	3	4	$\bar{Y}_j$
Y_1	4.61	16.70	52.37	26.31	3.00
Y_2	8.58	26.70	48.07	16.64	2.73
Y_3	9.79	28.39	45.95	15.87	2.68
Y_4	12.93	16.09	50.48	20.51	2.79
Y_5	12.57	14.79	44.67	27.96	2.88
Y_6	11.72	17.40	54.52	16.36	2.76

Table 2. Weighted frequency distributions for each response variable (%), separated by country, and weighted average scores ($\bar{Y}_j$)

Germany	1	2	3	4	$\bar{Y}_j$
Y_1	1.76	10.33	47.51	40.41	3.27
Y_2	4.77	24.33	49.27	21.63	2.88
Y_3	6.66	27.62	46.42	19.29	2.78
Y_4	9.51	14.98	51.07	24.44	2.90
Y_5	8.54	13.16	46.75	31.54	3.01
Y_6	10.45	17.97	54.46	17.11	2.78
Czech Republic	1	2	3	4	$\bar{Y}_j$
Y_1	16.93	39.35	36.41	7.31	2.34
Y_2	28.34	42.57	26.35	2.73	2.03
Y_3	27.38	44.05	25.26	3.31	2.05
Y_4	28.23	28.14	38.26	5.37	2.21
Y_5	26.92	29.75	37.98	5.34	2.22
Y_6	25.50	31.27	37.78	5.45	2.23
Belgium	1	2	3	4	$\bar{Y}_j$
Y_1	6.45	19.51	55.04	19.00	2.87
Y_2	12.19	29.40	47.57	10.84	2.57
Y_3	13.98	29.35	45.53	11.14	2.54
Y_4	18.39	22.29	50.51	8.81	2.50
Y_5	9.81	14.91	52.69	22.59	2.88
Y_6	13.96	22.43	53.58	10.03	2.60
Estonia	1	2	3	4	$\bar{Y}_j$
Y_1	5.05	23.66	45.73	25.55	2.92
Y_2	16.01	38.62	36.50	8.87	2.38
Y_3	29.22	38.41	27.02	5.35	2.09
Y_4	17.33	21.94	49.95	10.78	2.54
Y_5	14.00	17.00	50.16	18.84	2.74
Y_6	16.72	24.16	50.75	8.37	2.51
Finland	1	2	3	4	$\bar{Y}_j$
Y_1	2.04	33.09	49.24	15.63	2.78
Y_2	7.59	46.46	35.68	10.28	2.49
Y_3	11.74	51.71	28.53	8.02	2.33
Y_4	10.46	19.54	52.90	17.10	2.77
Y_5	3.25	6.34	44.69	45.73	3.33
Y_6	7.13	16.53	59.03	17.30	2.87
France	1	2	3	4	$\bar{Y}_j$
Y_1	6.01	21.34	56.46	16.18	2.83
Y_2	10.40	30.21	48.22	11.18	2.60
Y_3	15.38	30.90	43.39	10.32	2.49
Y_4	20.04	19.57	47.83	12.56	2.53
Y_5	18.22	17.20	42.36	22.22	2.69
Y_6	17.40	19.23	53.64	9.74	2.56
United Kingdom	1	2	3	4	$\bar{Y}_j$
Y_1	8.82	26.61	51.61	12.96	2.69
Y_2	12.88	31.10	45.67	10.36	2.54
Y_3	18.95	33.43	38.38	9.24	2.38
Y_4	18.75	18.38	47.63	15.24	2.59
Y_5	17.72	19.00	42.01	21.27	2.67
Y_6	18.51	20.02	46.02	15.45	2.58
Ireland	1	2	3	4	$\bar{Y}_j$
Y_1	9.45	24.70	47.10	18.75	2.75
Y_2	12.93	30.34	42.71	14.02	2.58
Y_3	16.32	31.37	40.28	12.03	2.48
Y_4	17.59	18.27	45.59	18.54	2.65
Y_5	12.69	15.84	47.03	24.44	2.83
Y_6	12.76	15.08	48.65	23.51	2.83
Netherland	1	2	3	4	$\bar{Y}_j$
Y_1	4.95	23.24	56.26	15.55	2.82
Y_2	6.26	27.19	52.61	13.95	2.74
Y_3	11.29	32.23	45.22	11.26	2.56
Y_4	10.07	20.44	59.73	9.76	2.69
Y_5	5.22	13.50	56.29	24.99	3.01
Y_6	6.59	19.85	62.68	10.88	2.78
Poland	1	2	3	4	$\bar{Y}_j$
Y_1	5.65	21.59	50.06	22.70	2.90
Y_2	9.84	29.61	44.07	16.47	2.67
Y_3	9.18	30.53	44.34	15.96	2.67
Y_4	14.37	17.22	48.55	19.85	2.74
Y_5	7.95	10.61	49.07	32.37	3.06
Y_6	6.97	11.91	61.20	19.92	2.94
Sweden	1	2	3	4	$\bar{Y}_j$
Y_1	0.63	6.62	52.22	40.53	3.33
Y_2	1.01	9.10	51.93	37.95	3.27
Y_3	1.76	11.47	51.62	35.15	3.20
Y_4	8.18	15.90	52.45	23.47	2.91
Y_5	3.80	7.81	38.53	49.85	3.34
Y_6	4.36	10.21	50.33	35.10	3.16
Slovenia	1	2	3	4	$\bar{Y}_j$
Y_1	6.28	20.76	54.16	18.80	2.85
Y_2	9.92	30.26	48.29	11.53	2.61
Y_3	14.67	32.80	42.64	9.89	2.48
Y_4	27.62	22.04	40.61	9.74	2.32
Y_5	16.83	17.32	46.63	19.22	2.68
Y_6	18.65	20.15	52.00	9.20	2.52

acceptance, is selected less than 20% of the times for each item. We also observe a higher percentage of acceptance for immigrants of the same race/ethnic group than for immigrants from poorer countries outside Europe. However, in the last round we observe the clear decrease of those who allow no immigrants from poorer countries outside Europe and the public opinion is not so "polarised" as in the previous rounds. In this regard, Ford (2017) comparing just two rounds of the survey concluded that attitudes have became somewhat more "polarised" between 2002 and 2014, particularly in the case of attitudes towards migrants from poorer countries outside Europe. He showed an increase from 11% (in 2012) to 20% (in 2014) of those who felt that none of these migrants should be allowed to come. At the same time, it was observed an increase in the percentage of people who felt that many such migrants should be allowed to enter, from 11% to 12%.

In terms of preferred immigrants, some differences are also observed among countries. In most of the countries there is a higher percentage of those who believe that cultural life is enriched by immigrants or immigration makes the country a better place to live than those who believe that immigration is good for economy. Sweden, Germany, and Finland are the most positive toward immigrants, especially as far as the items corresponding to the second dimension are concerned. On the contrary, the Czech Republic is the most negative, characterised by the lowest average scores for all the six items.

We also consider important socio-economic background characteristics of the respondents introduced by a suitable structure of covariates (with possible categories indicated in brackets for categorical variables):

- *round* – included by dummy variables ("Round 5, 2010" as reference category, "Round 6, 2012", "Round 7, 2014", "Round 8, 2016");
- *country* – included by dummy variables ("DE–Germany" as reference country, "CZ–Czech Republic", "BE–Belgium", "EE–Estonia", "FI–Finland", "FR–France", "GB–United Kingdom", "IE–Ireland", "NL–Netherland", "PL–Poland", "SE–Sweden", "SI–Slovenia");
- *gndr* – gender (0–"female" (F) as reference category, 1–"male" (M));
- *agea* – age of respondent;
- *domcil* – place of living, included by dummy variables (1–"big city" (BC), 2–"suburbs or outskirts of big city" (SBC), 3–"town or small city" (T) as reference category, 4–"country village" (V), 5–"farm or home in countryside" (C));
- *ctzcntr* – citizen of the country (0–"no", 1–"yes" as reference category);
- *eisced* – highest level of education (0–"not possible to harmonise", 1–"less than lower secondary", 2–"lower secondary", 3–"upper secondary", 4–"advanced vocational, sub-degree", 5–"lower tertiary education, BA level", 6–"higher tertiary education, MA level", 7–"other"). This original covariate was included in the model as a dummy covariate "NH", for those with non-harmonised and

Table 3. Weighted frequency distribution for each covariate (%) in years 2010-2016

Covariate	mean	0	1	2	3	4	5	6	7
round5		76.10	23.90						
round6		75.14	24.86						
round7		74.51	25.49						
round8		74.25	25.75						
DE		71.84	28.16						
CZ		97.13	2.87						
BE		96.36	3.64						
EE		99.56	0.44						
FI		98.10	1.90						
FR		78.85	21.15						
GB		79.69	20.31						
IE		98.71	1.29						
NL		94.44	5.56						
PL		89.14	10.86						
SE		96.78	3.22						
SI		99.39	0.61						
gndr		50.77	49.23						
age	49.12								
domcil			15.59	12.81	35.37	31.46	4.77		
ctzcntr		4.03	95.97						
eisced		8.85	14.31	24.13	14.11	15.56	8.94	13.50	0.60
eduyrs	13.45								
wrkac6m		94.59	5.41						
uemp3m		69.39	30.61						
pdwrk		41.11	58.89						
hincfel			2.90	13.03	48.73	35.34			

"other" educational level and as an ordinal covariate "D" for those achieving any educational degree (1–"less than lower secondary", 2–"lower secondary", 3–"upper secondary", 4–"advanced vocational, sub-degree", 5–"lower tertiary education, BA level", 6–"higher tertiary education, MA level" and 0–"NH" for for those with non-harmonised and "other" educational level);

- *eduyrs* – number of years of full-time education completed;
- *wrkac6m* – paid work in another country, period more than 6 months in the last 10 years (0–"no" as reference category, 1–"yes");
- *uemp3m* – ever unemployed and seeking work for a period more than three months (0–"no" as reference category, 1–"yes");
- *pdwrk* – paid work during the last 7 years (0–"no", 1–"yes" as reference category);
- *hincfel* – feeling about household's income nowadays (1–"very difficult on present income", 2–"difficult on present income", 3–"coping on present income", 4–"living comfortably on present income").

Summary statistics for the distribution of the covariates are reported in Table 3. We notice that the majority of respondents are citizen of the country, females, with upper secondary education (with an average years of education equal to 13.4), living in towns or small cities. The respondents are mainly adults with an average age of over 49. Most of them report to cope on the present income and to have a paid work (58.89% of the respondents) during the last seven years. Over 5% of the respondents had a paid work in another country during a period longer than 6 months and over 30% of the respondents had experience of being unemployed and seeking work for a period more than three months.

3. Multidimensional latent class IRT models with covariates

For the analysis of the data described in the previous section and to address our research questions about the evolution of attitudes towards immigration, we adopt the latent class IRT approach for polythomous ordinal items proposed in Bacci et al. (2014) that extends the approach introduced by Bartolucci (2007) for dichotomous items. We suppose that the items measure a certain number of latent traits (general acceptance of immigration and impact of immigration on the host country in the context of our study). A crucial assumption characterising the models at issue is the discreteness of the distribution of the latent traits, giving rise to a finite number of latent classes, each one characterised by the same latent trait levels (support points). Moreover, we include individual covariates affecting the probability of belonging to the different classes. Among these covariates we consider the country of the respondent, so that the adopted models account for the multilevel data structure by fixed effects.

Let Y_{ij} denote the response variable for individual i and item j, where $i = 1, \dots, n$ and $j = 1, \dots, r$, with n denoting the overall number of individuals in the survey (81,789 in our application) and r denoting the number of items (6 in our application). Each variable Y_{ij} has l_j categories indexed from 0 to $l_j - 1$; in our application $l_j = 4$ for all j. The observed responses y_{ij} are collected in the vectors $\boldsymbol{y}_i = (y_{i1}, \dots, y_{ir})'$ and we also observe a column vector of fixed covariates $\boldsymbol{x}_i$ for every i.

Let q be the number of different latent traits measured by the items, also called dimensions (2 in our case), let $\boldsymbol{\Theta}_i = (\Theta_{i1}, \dots, \Theta_{iq})'$ be the vector of corresponding latent variables, and let $\boldsymbol{\theta}_i = (\theta_{i1}, \dots, \theta_{iq})'$ denote a possible realisation of the latter. Every random vector $\boldsymbol{\Theta}_i$ is assumed to have a discrete distribution with k support points denoted by $\boldsymbol{\xi}_u$, $u = 1, \dots, k$, and probabilities $\pi_u(\boldsymbol{x}_i) = p(\boldsymbol{\Theta}_i = \boldsymbol{\xi}_u | \boldsymbol{x}_i)$ depending on the individual covariates in a way that is specified below. We also denote the conditional response probability that subject i responds with category y to item j as $\phi_{jy}(\boldsymbol{\theta}_i) = p(Y_{ij} = y | \boldsymbol{\theta}_i)$. These probabilities are collected in the vectors $\boldsymbol{\phi}_j(\boldsymbol{\theta}_i) = (\phi_{j0}(\boldsymbol{\theta}_i), \cdots, \phi_{j,l_j-1}(\boldsymbol{\theta}_i))'$, the elements of which sum up to 1.

In general, the adopted IRT models assume that

$$g_y(\boldsymbol{\phi}_j(\boldsymbol{\theta}_i)) = \alpha_j(\sum_{d=1}^{q} \delta_{jd}\theta_{id} - \tau_{jy}), \quad i = 1, \dots, n,\ j = 1, \dots, r,\ y = 1, \dots, l_j - 1,$$

where δ_{jd} is a dummy variable equal to 1 if item j measures latent trait of type d and to 0 otherwise, with $d = 1, \dots, q$ and $j = 1, \dots, r$. Moreover, $g_y(\cdot)$ is a link function specific of category y and α_j and τ_{jy} are item parameters, usually identified as discriminating and difficulty indices and on which suitable constraints need to be assumed. Among the possible parametrisations, for the full list see Bacci et al. (2014), we adopt that based on so-called global logits that are strongly related to the cumulative logits for ordinal variables (Agresti, 2012, Ch. 8). This leads to a latent class (and also multidimensional) version of the popular Graded Response Model of Samejima (1969), here denoted by LC-GRM. This model is based on the assumption that

$$\frac{p(Y_{ij} \geq y|\boldsymbol{\theta}_i)}{p(Y_{ij} < y|\boldsymbol{\theta}_i)} = \alpha_j(\sum_{d=1}^{q} \delta_{jd}\theta_{id} - \tau_{jy}), \quad i = 1, \ldots, n,\ j = 1, \ldots, r,\ y = 1, \ldots, l_j - 1. \tag{1}$$

We also consider two simplified versions of the model based on the previous assumption. The first makes use of equally spaced difficulty parameters τ_{jy} and is related to the rating scale version of the GRM introduced by Muraki (1990). The resulting model, which will be denoted by LC-RS-GRM, makes sense when all items have the same number of response categories and is based on the constraint

$$\tau_{jy} = \tau_j + \nu_y, \quad j = 1, \ldots, r,\ y = 1, \ldots, l_j - 1, \tag{2}$$

where τ_j is a unique difficulty measure for item j and ν_y are common cutpoints. Another constraint of interest is that all discrimination parameters α_j are equal to 1 (or to an arbitrary positive value), that is,

$$\alpha_j = 1, \quad j = 1, \ldots, r, \tag{3}$$

leading to the LC-1PL-GRM, where 1PL stands for one-parameter logistic parametrisation using the IRT terminology, or to LC-1PL-RS-GRM when also constraint (2) is adopted; see also Van der Ark (2001).

The effect of the covariates on the probabilities $\pi_u(\boldsymbol{x}_i)$ is modelled through a global logit parametrisation that is of easier interpretation with respect to the classical multinomial logit parametrisation when the latent classes can be ordered according to the latent traits they represent. In particular, we assume that

$$\log \frac{\pi_u(\boldsymbol{x}_i) + \ldots + \pi_k(\boldsymbol{x}_i)}{\pi_1(\boldsymbol{x}_i) + \ldots + \pi_{u-1}(\boldsymbol{x}_i)} = \beta_{0u} + \boldsymbol{x}_i'\boldsymbol{\beta}, \quad u = 2, \ldots, k, \tag{4}$$

where the intercepts β_{0u} depend on u, whereas the regression parameters $\boldsymbol{\beta}$ are common to all classes and are of simple interpretation. In fact, if one coefficient in $\boldsymbol{\beta}$ is positive then the corresponding covariate in $\boldsymbol{x}_i$ has an increasing effect on the ability level (the probability of belonging to the latent classes with greater index u increases).

To estimate the models illustrated above accounting for the sample design, we maximise a likelihood function involving the sampling weights, indicated by w_i for individual i, which are normalised so that $\sum_{i=1}^{n} w_i = n$. This has implication on the model selection criteria, as will be explained in the following. The weighted likelihood function has logarithm

$$\ell(\boldsymbol{\theta}) = \sum_{i=1}^{n} w_i \log p(\boldsymbol{y}_i|\boldsymbol{x}_i), \tag{5}$$

where $p(\boldsymbol{y}_i|\boldsymbol{x}_i)$ is the manifest probability of the observed sequence of responses for this individual, given the covariates. This probability may be computed as

$$p(\boldsymbol{y}_i|\boldsymbol{x}_i) = \sum_{u=1}^{k} p(\boldsymbol{y}_i|\boldsymbol{\xi}_u)\pi_u(\boldsymbol{x}_i),$$

with $p(\boldsymbol{y}_i|\boldsymbol{\theta}_i) = \prod_{j=1}^{J} p(y_{ij}|\boldsymbol{\theta}_i)$ and where the conditional probabilities $p(y_{ij}|\boldsymbol{\theta}_i)$ are computed according to (1). Maximum likelihood estimation is performed by the EM algorithm (Dempster et al., 1977), and in particular we use the implementation available in the `R` package `MultiLCIRT` (Bartolucci et al., 2016a) described in Bartolucci et al. (2014). For a deep description of this algorithm in the content of latent class IRT models see Bartolucci (2007).

In applications, a crucial point is the selection of the most suitable model for the data at hand in terms of number of latent classes (k), number of dimensions (q), and the possible constraints on the item parameters expressed in (2) and (3). In particular, we rely on information criteria such as the Akaike Information Criterion (AIC Akaike, 1973), the Bayesian Information Criterion (Schwarz, 1978, BIC), and the Integrated Completed Likelihood (Biernacki et al., 2000, ICL) criterion. We recall that these criteria are based on the following indices that must be minimised:

$$\begin{aligned} AIC &= -2\hat{\ell} + 2\#\text{par}, && (6)\\ BIC &= -2\hat{\ell} + \log(n)\#\text{par}, && (7)\\ ICL &= BIC + 2EN, && (8)\\ EN &= -\sum_{u=1}^{k}\sum_{i=1}^{n} w_i \hat{p}(u|\boldsymbol{y}_i)\log \hat{p}(u|\boldsymbol{y}_i). \end{aligned}$$

In the previous formula, $\hat{\ell}$ denotes the maximum log-likelihood of the model at issue, $\hat{p}(u|\boldsymbol{y}_i)$ denotes the estimate of the posterior probability that individual i belongs to latent class u, that is, the estimate of

$$p(u|\boldsymbol{y}_i) = \frac{p(\boldsymbol{y}_i|\boldsymbol{\xi}_u)\pi_u(\boldsymbol{x}_i)}{p(\boldsymbol{y}_i|\boldsymbol{x}_i)},$$

and #par denotes the number of free parameters of the model. In applying these criteria we look for the most parsimonious model specification when they lead to different choices.

In certain cases, we can also rely on the Likelihood Ratio (LR) statistic when the focus is on testing a certain hypothesis by comparing two nested models. As is well known, this statistic is equal to

$$LR = -2(\hat{\ell}_0 - \hat{\ell}_1),$$

where $\hat{\ell}_0$ is the maximum log-likelihood of the smaller model (holding under the hypothesis to be tested) and $\hat{\ell}_1$ is that of the larger model. If the usual regularity conditions are satisfied, the observed value of LR is compared with a χ^2 distribution with a number of degrees of freedom equal to the number of constrains used to formulate the smaller model as a particular case of the larger model.

Table 4. Information criteria, log-likelihood values ($\hat{\ell}$), number of parameters (#par) for the bidimensional LC-GRM with covariates and global logit link function (in bold the lowest values of ICL)

k	$\hat{\ell}$	#par	AIC	BIC	EN	ICL
1	-601413.1	18	1202862.2	1203029.8	0	1203029.8
2	-516335.6	55	1032781.2	1033293.4	8023.5	1049340.4
3	-481474.4	58	963064.8	963604.8	9766.4	983137.6
4	-467119.7	61	934361.5	934929.5	15173.5	965276.5
5	-461270.0	64	922667.9	923263.9	20505.9	964275.7
6	-455269.4	67	910672.7	911296.6	24853.9	**961004.4**
7	-452542.8	70	905225.5	905877.4	27896.5	961670.4

4. Empirical Analysis

In applying the approach described in the previous section to the data illustrated in Section 2, we first deal with model selection, regarding in particular the optimal number of latent classes and the item parameterisation. We carry on with testing unidimensionality, corresponding to the hypothesis that the two latent traits may be reduced to only one, and other hypotheses of interest. Then we deal with the analysis of the ability distribution and identification of the significant covariates.

4.1. Model selection and testing

We apply the LC-GRMs for polythomous ordinal items based on parametrisation (1), allowing for: *(i)* bidimensionality (the items are allocated into two dimensions which measure two distinct latent traits); *(ii)* discreteness of the latent trait distribution; *(iii)* time constant and time-varying covariates under the global logit parameterisation formulated in (4); and *(iv)* sample weights, to account for the sample design, introduced in the log-likelihood function in (5).

A crucial point is the choice of the number of latent classes (k) to be adopted. We base our choice on the selection criteria listed at the end of the previous section; the results are reported in Table 4 for k from 1 to 7. We note that the lowest value of ICL (see definition (8)) is reached for $k = 6$ although the same is not found for the other two criteria, AIC and BIC, defined in (6) and (7), respectively. We rely mainly on the ICL because it leads to the most parsimonious choice. In conclusion, we choose six as the most suitable number of latent classes for the data at hand, leading to a model with 67 free parameters.

The next stage of our analysis is focused on the test of unidimensionality. As suggested by the structure of the questionnaire, we group items into two dimensions corresponding to “general acceptance of immigrants” (Y_1-Y_3) and “impact of immigration on host countries” (Y_4-Y_6), respectively. We then test, by the LR statistic, if these two dimensions may be reduced to only one by comparing the bidimensional model with six classes with its unidimensional counterpart (see Bartolucci, 2007, for details). On the basis of these results, which are reported in Table 5, we reject the hypothesis of unidimensionality.

We also test for other hypotheses expressed, in particular, by constraints (2) and

Table 5. Information criteria, log-likelihood values ($\hat{\ell}$), number of parameters (#par), and LR statistics and corresponding p-values for different versions of the bidimensional LC-GRM with 6 classes, covariates, and global logit link function

Model	$\hat{\ell}$	#par	LR	p-value	Compared models
1dim LC-GRM	-467103.3	63			
2dim LC-GRM	-455268.9	67	23667.8	0.000	(LC-GRM 1dim vs LC-GRM 2dim)
2dim LC-RS-GRM	-459490.5	57	8443.2	0.000	(LC-RS-GRM vs LC-GRM)
2dim LC-1P-GRM	-459935.9	63	9333.0	0.000	(LC-1P-GRM vs LC-GRM)
2dim LC-1P-RS-GRM	-461094.5	53	11651.2	0.000	(LC-1P-RS-GRM vs LC-GRM)

Table 6. Estimated standardised support points and average prior probabilities under the bidimensional LC-GRM with 6 classes, covariates, and global logit link function

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6
$\hat{\xi}_{u1}$	-2.073	-0.797	-0.797	0.242	0.310	1.849
$\hat{\xi}_{u2}$	-1.821	-1.452	-0.012	-0.002	1.417	1.248
$\hat{\pi}_u(\mathbf{x})$	0.063	0.158	0.166	0.352	0.117	0.144

(3). This amounts to compare different types of the bidimensional LC-GRM with free and constrained discriminating indices as well as free and constrained threshold difficulty parameters, for each item, leading to LC-RS-GRM, LC-1PL-GRM, and LC-1PL-RS-GRM. The results, presented again in the Table 5, show that both hypotheses must be rejected. Then, we retain the bidimensional LC-GRM with six classes for the analysis of the data at hand.

4.2. Results

In Table 6 we report the support points for the two dimensions ($\hat{\xi}_{u1}, \hat{\xi}_{u2}$, $u = 1, \dots, k$), estimated under the selected model, and the corresponding prior probabilities ($\hat{\pi}_u(\mathbf{x})$, $u = 1, \dots, k$) averaged over all the observed covariate configurations. These estimates are also represented in Figure 1. The support points are standardised so as to have null mean and unitary variance. The item parameters are transformed accordingly; see Bartolucci et al. (2015, Sec. 4.6) for details.

We observe that most subjects (35.2%) belong to class 4 (shown with the biggest circle in the Fig. 1), which is characterised by an upper intermediate level of general immigration acceptance and opinion about impact of immigration on the host country ($\hat{\xi}_{41} = 0.242$, $\hat{\xi}_{42} = -0.002$). This class is also characterised by the highest conditional probabilities for the third category ($y = 3$) among all classes (especially for Y_1, Y_4, Y_5, Y_6). Over 6% of subjects are in class 1 (represented by the smallest circle in Fig. 1) and over 14% of subjects are in class 6, corresponding to the lowest and highest levels of immigration attitudes, respectively.

The estimates of the standardised item parameters (discriminant and difficulty parameters) for the selected model are given in Table 7. The most difficult item (see the highest threshold parameters) is the third, concerning acceptance of immigrants from poorer countries outside Europe, as confirmed by the frequency distribution (previously reported in Tab. 1), followed by the second item (acceptance of immigrants of different race, ethnic group) considered to have the highest discriminating

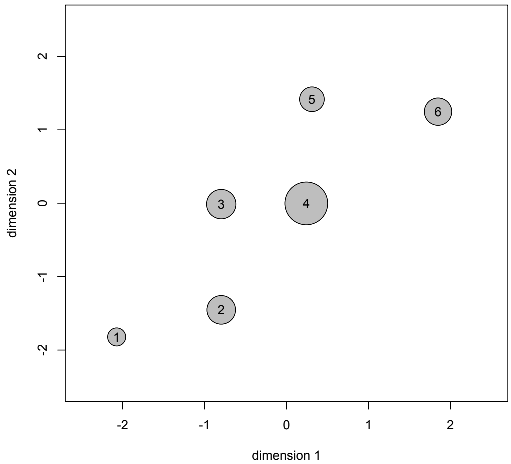

Fig. 1. Estimated standardised support points and prior probabilities under the bidimensional LC-GRM with 6 classes, covariates, and global logit link function (the number in each circle indicates the latent class and its surface is proportional to its average prior probability)

Table 7. Estimated standardised item parameters under the bidimensional LC-GRM with 6 classes, covariates, and global logit link function (in bold the largest value in each column)

Item	τ_1	τ_2	τ_3	α_j
Y_1	-1.802	-0.733	0.686	3.336
Y_2	-1.292	-0.339	1.075	**4.446**
Y_3	**-1.251**	**-0.199**	1.319	3.093
Y_4	-1.428	-0.534	1.294	1.971
Y_5	-1.554	-0.723	0.842	2.130
Y_6	-1.486	-0.540	**1.345**	2.285

power as well. The fourth item is the least discriminant (with the lowest α_j); it concerns the immigration impact on the country's economy.

Using the results in Tables 6 and 7, we obtain the conditional probabilities presented in Table 8. These probabilities confirm that the chance of answering with a high response category (corresponding to a high level of immigration support) increases from class 1 to 6, whereas the probabilities of answering with a low response category (corresponding to a low level of acceptance) decrease under the same condition.

We now consider the estimates of the covariate regression coefficients entering the global logit parametrisation, see assumption (4). These estimates are displayed in Table 9, together with the corresponding standard errors, and t-statistics and p-values for the hypothesis that each coefficient is equal to 0. Moreover, the effect of certain covariates of interest is illustrated in Figures 2-6, which show the evolution

Table 8. Estimates of the conditional response probabilities $\phi_{jy}(\boldsymbol{\xi}_u)$ under the bidimensional LC-GRM with 6 classes, covariates, and global logit link function

		$\phi_{jy}(\boldsymbol{\xi}_u)$			
j	u	$y=0$	$y=1$	$y=2$	$y=3$
1	1	0.712	0.277	0.011	0.000
	2	0.034	0.519	0.440	0.007
	3	0.034	0.519	0.440	0.007
	4	0.001	0.036	0.777	0.185
	5	0.001	0.029	0.748	0.222
	6	0.000	0.000	0.020	0.980
2	1	0.970	0.030	0.000	0.000
	2	0.100	0.785	0.115	0.000
	3	0.100	0.785	0.115	0.000
	4	0.001	0.069	0.906	0.024
	5	0.001	0.052	0.915	0.032
	6	0.000	0.000	0.031	0.969
3	1	0.927	0.070	0.003	0.000
	2	0.197	0.667	0.135	0.001
	3	0.197	0.667	0.135	0.001
	4	0.010	0.194	0.762	0.035
	5	0.008	0.163	0.786	0.042
	6	0.000	0.002	0.161	0.838
4	1	0.638	0.242	0.071	0.002
	2	0.512	0.348	0.136	0.004
	3	0.058	0.206	0.666	0.071
	4	0.057	0.203	0.668	0.072
	5	0.004	0.017	0.419	0.560
	6	0.005	0.024	0.494	0.477
5	1	0.683	0.274	0.085	0.003
	2	0.446	0.379	0.167	0.007
	3	0.036	0.144	0.680	0.139
	4	0.035	0.142	0.681	0.142
	5	0.002	0.009	0.217	0.773
	6	0.003	0.012	0.282	0.703
6	1	0.683	0.266	0.050	0.001
	2	0.481	0.408	0.109	0.002
	3	0.033	0.197	0.727	0.043
	4	0.033	0.194	0.730	0.044
	5	0.001	0.010	0.448	0.541
	6	0.002	0.015	0.539	0.445

of the prior probabilities of the six classes according to the category of the each of these covariates and the evolution of the weighted average standardised support points for both dimensions.

We observe that most of the considered covariates are significant at the 5% level. The most interesting estimates concern the effect of time (included by time dummies *round*) and *country*, which may be interpreted considering that the six latent classes of individuals are ordered from that with the lowest to that with the highest level of immigration acceptance. Regarding the first aspect, we conclude that European publics are becoming slightly more tolerant, with a significant difference between round 5 and the other rounds. Moreover, as the regression parameters for most of the country covariates are negative in comparison to Germany, Europeans in all the other countries (with exception of Sweden) tend to be more negative toward immigrants, especially in Czech Republic, Estonia, and United Kingdom. These results are in agreement with the conclusions of Heath and Richards (2016), who compared the frequencies for the selected questions asked in 2002 and 2014.

In Figure 2 (left panel) we can observe the decreasing probability to belong to the first three classes (characterised by low and intermediate immigration acceptance) with respect to the round and the increasing probability to belong to the other classes, especially to the sixth class. At the same time we observe (right panel of Fig. 2) the increasing tendency (with a small exception for ESS 7) of immigration acceptance expressed by the weighted levels of the bidimensional latent trait. A slightly higher support for *impact of immigration on the host country* dimension (compared to *general acceptance of immigration*) can be observed, especially with rounds ESS 5, ESS 6, and ESS 7.

Figure 3 confirms that the highest probability of belonging to the first and second class is for Czech. Regarding the third class, the highest probability is observed for Estonia, followed by Czech. As far as the classes with upper-intermediate and high immigration acceptance are concerned (i.e., latent classes 4 to 6), Czech is the country with the lowest chance to belong to those groups (followed by Estonia).

As opposed to Czech and Estonia, the lowest probability to belong to the first three classes and the highest probability to belong to the last two classes is observed for Sweden and Germany. We observe that most countries are prone to belong to class 4 characterised by the upper intermediate level of immigration acceptance (for both dimensions) with the prior probability over than 0.35, especially for Germany, Poland, Netherland, Finland, France, and Ireland. The results represented in the right panel of Figure 3 also show that Sweden and Germany are the countries with the highest levels of immigration acceptance (support points equal to 0.627 and 0.577 for the first and the second dimensions for Sweden and 0.199 and 0.202 for Germany) as opposed to Czech with the lowest, negative levels of support points equal to -0.671 and -0.698 for general acceptance and impact of immigration on the host country, respectively. We also observe that Europeans in most of the countries (with exception of Czech, Estonia, Netherland and Sweden) tend be more supportive for the second dimension of the latent trait and thus it is more difficult to accept immigrants in general than to express positive opinions concerning impact of immigration on a country.

Table 9. Estimates of the covariates coefficients and related statistics under the bidimensional LC-GRM with 6 classes, covariates, and global logit link function

Covariate	Category	est.	s.e.	t-test	p-value
cutoff	1	1.639	0.011	151.683	0.000
	2	0.061	0.006	9.430	0.000
	3	-0.869	0.007	-125.482	0.000
	4	-2.635	0.006	-405.820	0.000
	5	-3.476	0.008	-422.371	0.000
round	6	0.177	0.011	16.307	0.000
	7	0.161	0.011	15.023	0.000
	8	0.268	0.011	24.979	0.000
country	CZ	-1.913	0.001	-2192.487	0.000
	BE	-0.735	0.001	-1250.786	0.000
	EE	-1.171	0.000	-17145.950	0.000
	FI	-0.617	0.000	-2494.713	0.000
	FR	-0.657	0.011	-61.259	0.000
	GB	-0.881	0.010	-84.914	0.000
	IE	-0.667	0.000	-4094.377	0.000
	NL	-0.430	0.001	-363.873	0.000
	PL	–0.075	0.004	-20.292	0.000
	SE	0.904	0.001	1324.729	0.000
	SI	-0.732	0.000	-7694.357	0.000
gender	M	0.034	0.013	2.547	0.008
age		-0.013	0.002	-6.942	0.000
age2		0.000	0.000	1.740	0.082
domcil	BC	0.278	0.008	36.579	0.000
	SBC	0.133	0.005	29.226	0.000
	V	-0.074	0.012	-6.148	0.000
	C	-0.098	0.001	-97.478	0.000
ctzcntr	No	0.564	0.001	677.941	0.000
eisced	NH	-0.003	0.002	-1.622	0.105
eisced (D)		0.182	0.005	33.489	0.000
eduyears		0.067	0.006	11.015	0.000
eduyears^2		0.000	0.000	0.489	0.625
wrkac6m	Yes	0.148	0.001	182.162	0.000
uemp3m	Yes	0.041	0.014	2.882	0.004
pdwrk	Yes	0.033	0.016	2.091	0.036
hincfel		0.307	0.009	33.935	0.000

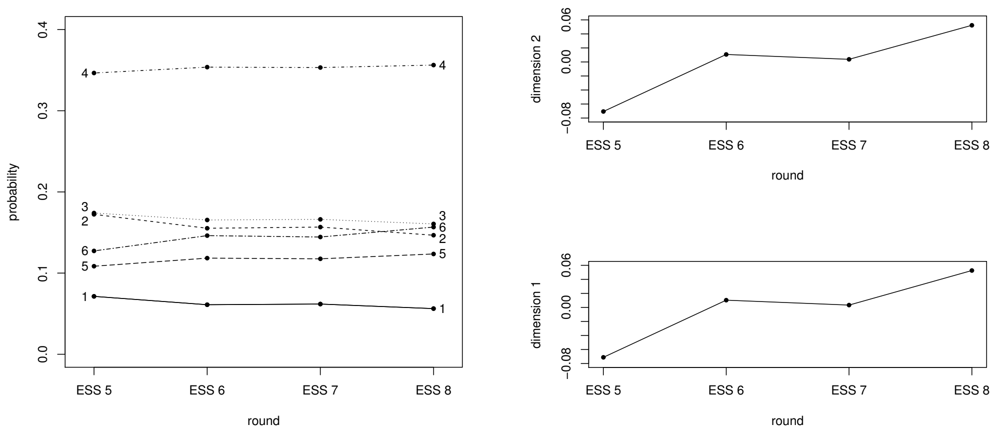

Fig. 2. Estimated prior probabilities (left) and weighted standardised support points (right) according to the round under the bidimensional LC-GRM with 6 classes, covariates, and global logit link function

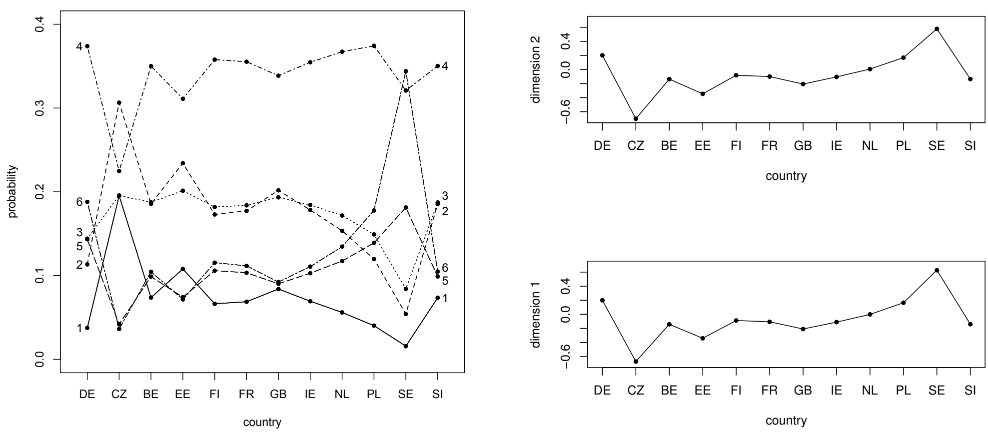

Fig. 3. Estimated prior probabilities (left) and weighted standardised support points (right) according to the country under the bidimensional LC-GRM with 6 classes, covariates, and global logit link function

Concerning the other socio-economic features considered in our analysis, squared values of age, years of education completed as well as the non-harmonised educational level (NH) and paid work during the last seven years ($pdwrk$), these are not significant (see Tab. 9). We observe the positive regression parameters for educational level degree (D), income level perception ($hincfel$), and place of living (BC, SBC). As the educational level increases, the level of immigration acceptance also increases. These results are reasonable and in agreement with previous researches (Coenders and Scheepers, 2003; Kunovich, 2004; Nagayoshi and Hjerm, 2015; Rustenbach, 2010).

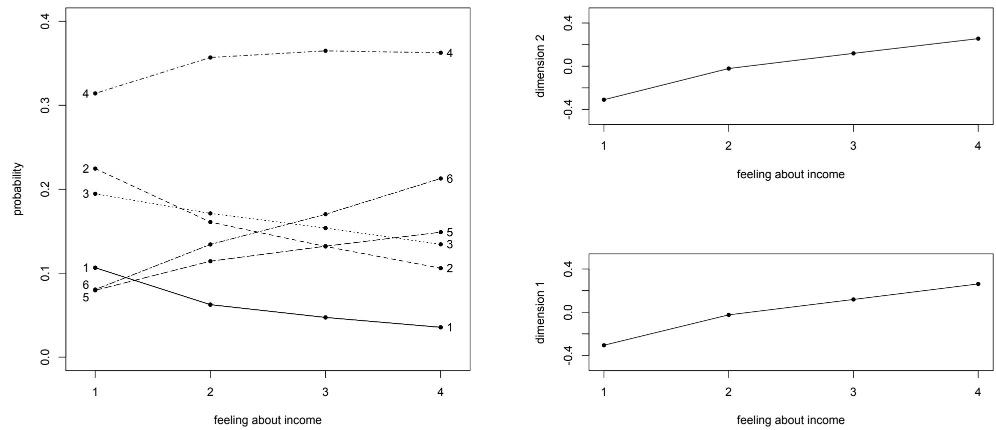

Fig. 4. Estimated prior probabilities (left) and weighted standardised support points (right) according to the income perception under the bidimensional LC-GRM with 6 classes, covariates, and global logit link function

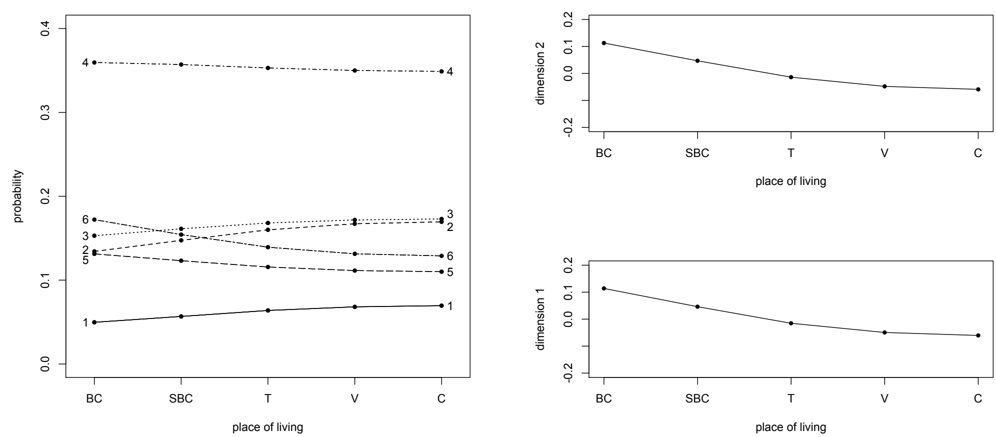

Fig. 5. Estimated prior probabilities (left) and weighted standardised support points (right) according to the place of living under the bidimensional LC-GRM with 6 classes, covariates, and global logit link function

The attitude towards immigration increases with the feeling about household's income and the size of place of living (Tab. 9). The increasing values for support points and the increasing probabilities to belong to the classes with upper-intermediate and high immigration acceptance with higher levels of income perceptions are also observed in Figure 4. Europeans living comfortably on present income are considerably more prone to belong to classes 5 and 6 and they tend to be the most supportive for both dimensions of the latent trait, compared to those living very difficult or difficult on present income.

Those living in villages (V) or having homes in countryside (C) tend to be

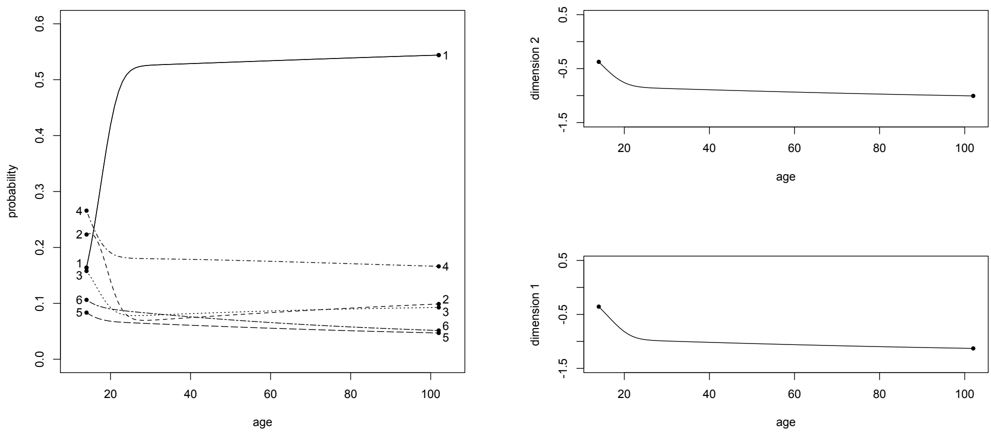

Fig. 6. Estimated prior probabilities (left) and weighted standardised support points (right) according to age under the bidimensional LC-GRM with 6 classes, covariates, and global logit link function

more negative about immigration compared to those living in towns or small cities (see also Davidov and Meuleman, 2012; Markaki and Longhi, 2012). The results given in Figure 5 present negative values of latent trait levels for respondents living in those three areas of European countries, with the lowest points for residents of countrysides opposed to the respondents living in the big cities (BC) or in the suburbs (SBC) of Europe.

Based on the results presented in Table 9 we also conclude that men (compared to women) and those ever unemployed and seeking work for a period of more than three months are slightly more positive about immigration. Moreover, respondents who had a paid work in another country for a period longer than 6 months in the last 10 years and people not having citizenship of the country tend to be more supportive of immigration phenomena. However, older people seem to be less prone to accept immigrants in their countries of origin. Figure 6 presents a noticeably decreasing trend for supportive immigration attitudes (for both dimensions) especially for people at least 24 years old. These results are in line with depicted prior probabilities showing increasing tendency to belong to the first class (with the lowest acceptance levels) for people younger than 24. The increasing tendency for the second class is observed only for the youngest respondents with age 14 and 15. The propensity to belong to the third and fourth classes is considerably higher for people younger than 24. As far as the classes with the highest immigration attitudes are concerned rather stable, a tendency decreasing with age is observed.

5. Discussion

Providing information concerning immigrant attitudes in different countries across time might be a powerful means for policies designed to decrease the distances between members of the host society and to promote intergroup contacts. To evaluate the changing attitudes to immigrants in EU countries we apply an extended class of Item Response Theory (IRT) models for ordinal polythomously-scored items with discrete latent variables and allowing for covariates that influence the weights of the latent structures. The approach is applied to the analysis of cross-national ESS (European Social Survey) data for the period 2010-2016.

This research makes two clear contributions to our understanding in explaining attitudes towards immigration of European public opinion in the years with the highest immigration dynamics in Europe. First, differently from previous researches, we show that the analysed (heterogenous) survey data can be explained by six latent class corresponding to homogeneous groups of Europeans with the similar levels of immigration acceptance, which is represented by two latent traits (bidimensional structure). Based on the questionnaire structure we allocate the questionnaire items between two dimensions and present the tendency of general immigration acceptance and the impact of immigrants on host countries in the recent years. This extension of the traditional IRT models, based on the assumptions of discreteness and also multidimensionality of the latent trait, may be especially useful in socio-economic data analyses where the normality and unidimensional assumptions of the latent trait (explicitly introduced) are very often too restrictive (Bartolucci et al., 2014; Genge, 2017). Second, we characterise the item parameters for six response variables as well. Moreover, we present the effect of different socio-economic covariates and show that in the period considered Europeans are becoming slightly more positive in their attitudes towards migrants, but this tendency can be especially observed in countries such as Germany or Sweden.

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