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Executive Summary

This report , the third deliverable of the project ENCLOSE, presents a comprehensive investigation into attitudes toward immigration across Europe by integrating data from two major cross-national surveys: the **European Social Survey (ESS)** and the **Eurobarometer**. The primary goal is to construct a harmonized, multilevel dataset that combines the strengths of both sources to support robust comparative analysis of public opinion on immigration.

Section 1: Exploring Attitudes Toward Immigration The report begins with an empirical overview of immigration attitudes across European countries, using ESS data to examine cross-national patterns and underlying socio-political dynamics.

Section 2: Estimating Latent Traits through Multilevel IRT Models To measure complex constructs such as trust in institutions, immigration rejection, and perceived benefits of immigration, multilevel Item Response Theory (IRT) models are employed. These models allow for the estimation of individual-level latent traits while accounting for clustering at the country level.

Section 3: Data Harmonization A key component of the integration effort involves harmonizing observed and latent variables across the ESS and Eurobarometer datasets. This includes:

- Assessing agreement on **common socio-demographic variables** (e.g., gender, occupation, domicile, political orientation, age).
- Aligning **latent constructs** such as trust in institutions and attitudes toward immigration.
- Identifying and modeling **target latent variables** (e.g., immigration rejection, perceived benefits of immigration) and **control variables** (e.g., aversion to immigrants).

The harmonization process ensures comparability and compatibility across sources, which is a prerequisite for successful data integration.

Section 4: Statistical Matching for Data Integration This section presents a suite of **statistical matching (SM)** methods used to impute unobserved latent traits in the Eurobarometer using information from the ESS:

- **Nonparametric approaches**, including nearest-neighbor matching implemented via the `StatMatch` package.
- **Parametric multilevel imputation approaches**, focusing on **Fully Conditional Specification (FCS)** and **Joint Modelling (JM)** using the `mice` and `mitml` packages, respectively.
- A novel **Bayesian hierarchical framework** for matching latent variables in multilevel data, enabling integrated inference and improved consistency across imputations.
- **Deep learning techniques**, including applications of the `rMIDAS` package, which leverage neural network architectures for flexible and scalable statistical matching.

The performance of each approach is evaluated by comparing the distribution of imputed variables in the Eurobarometer to the reference distributions from the ESS. Results highlight the importance of accounting for multilevel structure and latent variable dependencies in order to produce reliable imputations.

Section 5: Conclusion The report concludes by emphasizing the feasibility and advantages of **statistical matching for survey integration** in a multilevel, latent variable framework. The findings demonstrate that, with careful harmonization and model specification, it is possible to recover nuanced attitudinal patterns across different survey sources. This integration enhances the analytical potential of public opinion research in Europe, enabling deeper insights into how immigration attitudes are shaped across countries and populations.

Contents

1 Investigating attitudes towards immigration across Europe

In our first case study, we will focus on exploring attitudes toward immigration across Europe. Both the ESS Round 10 (hereafter ESS10) and Eurobarometer 93.1 offer resources for understanding the complexities of public opinion on immigration within the broader context of European challenges.

- **ESS10**
  The study of attitudes toward migration is conducted using a specific set of questions that have been included since the first edition of the ESS. This core module explores individuals' opinions and behaviors toward immigrants, evaluates perceived effects of immigration, examines feelings of belonging to a discriminated group, and investigates the factors that shape attitudes toward immigrants. Data collection was conducted on a sample of individuals aged 15 and over residing in one of the 31 countries that participated in the survey (see Deliverable 1 for more details).
- **Eurobarometer93.1**:
  The standard modules examine attitudes toward European unification, institutions, and policies. As part of this framework, they also address public opinion on a common European migration policy, exploring citizens' views on its desirability. This module offers important insights into how Europeans perceive coordinated migration strategies at the EU level and their potential impact on member states. Data collection was conducted on a sample of individuals aged 15 and over residing in one of the 34 countries that participated in the survey (see Deliverable 1 for more details).

This study investigates how attitudes toward immigration shape European citizens' support for a common EU immigration agenda. We primarily use data from the Eurobarometer Standard Survey, which captures general public opinion on a unified EU migration policy, asylum system, and border controls. To deepen our analysis, we supplement this with data from the European Social Survey (ESS), which provides more detailed questions on attitudes towards immigration. By integrating both sources, we aim to achieve a more comprehensive understanding of public opinion on EU-level migration governance.

The opinions on a unified European migration agenda are captured through the following Eurobarometer questions:

- "What is your opinion on each of the following statements? Please tell me for each statement, whether you are for it or against it."
  - A common European policy on migration (`qb5_4`).
  - A common European Asylum system (`qb6_1`).
  - A reinforcement of EU external borders with more European border guards and coast guards (`qb6_2`).

We treat these items as observed indicators of a shared latent dimension (η). Given that responses are coded as 1: "For" and 2: "Against", we interpret this latent trait as opposition to a unified European migration agenda and it will be referred to as "*Euroskepticism on Migration Governance*".

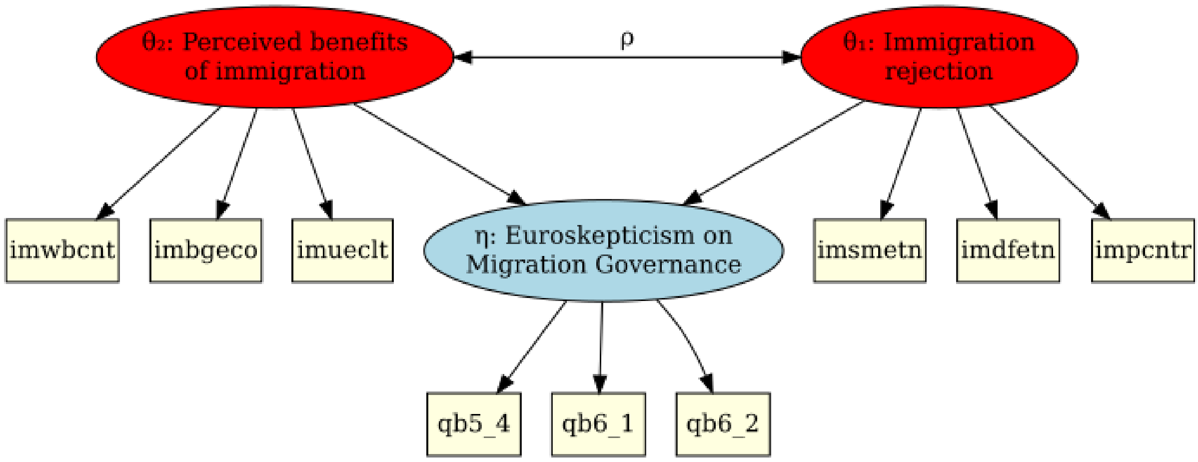

Figure 1: Path diagram of the hypothesized relationships between the latent variables and their corresponding observed indicators.

Attitudes toward immigration are captured in the ESS using the following questions:

1. "To what extent do you think [our country] should allow people of the same race or ethnic group as most [country] people to come and live here?" (`imsmetn`).
2. "To what extent should [our country] allow people of a different race or ethnic group from most [country] people to come and live here?" (`imdfetn`).
3. "To what extent should [our country] allow people from poorer countries outside Europe to come and live here?" (`impcntr`).
4. "Would you say that people who come to live here generally make the country's economy better or worse?" (`imbgeco`).
5. "Would you say that people who come to live here make the country's cultural life richer or poorer?" (`imueclt`).
6. "Would you say that people who come to live here make [our country] a better or worse place to live?" (`imwbcnt`).

We conceptualize these items as measuring two distinct latent constructs (θ_1 and θ_2). The first three questions reflect the degree of openness toward different types of immigrants and are therefore interpreted as indicators of a latent trait we label "*Immigration rejection*". Responses to these items are coded as follows: 1 – "Allow many," 2 – "Allow some," 3 – "Allow a few," and 4 – "Allow none," with higher values indicating stronger rejection. The last three items assess perceived effects of immigration on economic conditions, cultural life, and overall quality of life in the country. These items are measured on an 11-point scale ranging from 0 ("Extremely negative") to 10 ("Extremely positive"), and collectively represent a latent trait we refer to as " *Perceived benefits of immigration*".
Figure 1 offers a graphical representation of the hypothesized relationships between the latent variables and their corresponding observed indicators.

To estimate the effects of attitudes toward immigration expressed in terms of "Immigration rejection" and "Perceived benefits of immigration", on "Euroskepticism toward a unified migration governance", we consider the Eurobarometer dataset as the recipient dataset, due to its smaller sample size, and the ESS dataset as the donor dataset in the data integration procedure. The countries considered and the common variables used for integration are summarized in the following sections. It is worth noting that the common variables encompass both observed covariates and a latent traits, namely " Trust in Institutions", jointly estimated from the two surveys after harmonization of the correspondign items categories.

To assess the quality of the matching procedures, considering the Eurobarometer dataset as the recipient, we will evaluate the correlation of the imputed latent traits $\tilde{\theta}_1$ and $\tilde{\theta}_2$ with a latent variable (ψ) measuring the aversion to immigrants and derived from the Eurobarometer survey, considering the following questions:

- Please tell me whether each of the following statements evokes a positive or negative feeling for you?
    1. Immigration of people from other EU Member States (qb7_1)
    2. Immigration of people from outside the EU (qb7_2)
- For each of the following statements, please tell me whether you totally agree, tend to agree, tend to disagree or totally disagree.
    3. Immigrants contribute a lot to (OUR COUNTRY) (qb8_1)
    4. (OUR COUNTRY) should help refugees (qb8_2)

Responses to the items are on a 4-point Likert scale (Items 1 and 2: 1="Very positive", 4="Very negative"; Items 3 and 4: 1="Totally agree", 4="Totally disagree") .

2 Multilevel IRT models for latent traits estimation

Item response theory (IRT) constitutes a prominent approach for addressing the measurement of unobservable traits through estimation and analysis of latent variables. The IRT models are especially suited for dealing with categorical indicators, such as dichotomous and ordinal observed variables (de Ayala, 2009). In the IRT literature, several item factor analytic models have been proposed for ordered polytomous data (Ostini & Nering, 2005), differing in the item response function and the number of parameters included in the formulation. In our study, we focus on the two parameter formulation, which is more appropriate for the type of data most often encountered in psychological and sociological research. In fact, for rating data it has been argued that there is no guessing or any similar phenomenon that requires lower or upper asymptote parameters (see Maydeu-Olivares et al., 2011, and references therein). As for the specification of the response function, we consider the multidimensional generalisation of the Samejima's graded model (Samejima, 1969).

Given a test consisting of K ordered categorical variables and assuming M latent traits, the two-parameter normal ogive (2PNO) formulation of the multidimensional graded response model is given by (Béguin & Glas, 2001):

$$P(Y_{i,k} = c|\boldsymbol{\theta}_i, \boldsymbol{\alpha}_k, \boldsymbol{\gamma}_k) = \Phi\left(\boldsymbol{\alpha}_k'\boldsymbol{\theta}_i - \gamma_{k,c-1}\right) - \Phi\left(\boldsymbol{\alpha}_k'\boldsymbol{\theta}_i - \gamma_{k,c}\right). \tag{1}$$

In this equation, $Y_{i,k}$ is the observed response of person i (i=1,...,N) to item k; c denotes the category of the ordered response scale ($c = 1, ..., C$), and Φ is the standard normal cumulative distribution function. The probability of responding a certain category c depends on the M-dimensional vector $\boldsymbol{\theta}_i = (\theta_{i,1}, \ldots, \theta_{i,M})' \sim \mathcal{N}(\boldsymbol{\mu}_\theta, \boldsymbol{\Sigma}_\theta)$ of the unobserved latent trait scores for subject i, on the M-dimensional vector $\boldsymbol{\alpha}_k = (\alpha_{k,1} \ldots, \alpha_{k,M})'$ of item discrimination parameters (also defined as factor loadings) and on the $(C-1)$-dimensional vector $\boldsymbol{\gamma}_k = (\gamma_{k,1} \ldots \gamma_{k,C-1})'$ of ordered category thresholds for item k. In the IRT literature, the latent traits are known as person parameters, while the discriminations and thresholds are referred to as item parameters. The factorial structure of the model is represented by the $(K \times M)$ matrix $\boldsymbol{A}$ containing the discrimination parameters.

Using data augmentation technique (Tanner & Wong, 1987) and considering that a continuous variable Z_k underlies the observed ordinal measure Y_k, and that there is a linear relationship between item and person parameters and the underlying variable, the model can be equivalent expressed as

$$Z_{i,k} = \boldsymbol{\alpha}_k' \boldsymbol{\theta}_i + \epsilon_{i,k}, \text{ with } \epsilon_{i,k} \sim \mathcal{N}(0,1), \ \forall i, k. \tag{2}$$

The relation between the observed items and the underlying variables is given by the threshold model

$$Y_{i,k} = c \quad if \ \gamma_{k,c-1} \leq Z_{i,k} \leq \gamma_{k,c}, \ c = 1, \ldots, C; \ \gamma_{k,0} = -\infty, \gamma_{k,C} = \infty \tag{3}$$

The multilevel and multidimensional formulations of the IRT model in equation 1 is given by

$$P(Y_{ijk} = c | \boldsymbol{\theta}_{ij}, \boldsymbol{\alpha}_{kj}, \boldsymbol{\gamma}_{kj}) = \Phi\left(\boldsymbol{\alpha}_{kj}' \boldsymbol{\theta}_{ij} - \gamma_{kj,c-1}\right) - \Phi\left(\boldsymbol{\alpha}_{kj}' \boldsymbol{\theta}_{ij} - \gamma_{kj,c}\right) \tag{4}$$

where $j = 1, \ldots, J$ denotes the group.

Adopting a confirmative approach, we consider a multi-unidimensional IRT model, where each of the M correlated constructs is being measured by its own set of items, Ω_m, and each item loads only onto a latent trait. Furthermore, we assume configurational invariance, meaning that the models in different countries all share the same measurement formulation.

Given the ESS and the Eurobarometer datasets, harmonized as detailed in Section 3, we fit the following IRT models:

- "Immigration rejection" and "Perceived benefits of immigration" are jointly estimated on the ESS dataset using a bidimensional IRT model;
- "Euroskepticism toward a unified migration governance" and "Aversion to immigrants" are estimated on the Eurobarometer dataset using two separate unidimensional models;
- "Trust in institutions" is estimated through a unidimensional IRT model applied to the combined harmonized datasets.

Model estimation is implemented using the `mirt` package for R (Chalmers, 2012). For each model, we compare:

- a fully constrained unidimensional IRT formulation, in which latent means and variances are fixed, and both the item discrimination and threshold parameters are held constant across groups (strict invariance);

- a formulation where latent means and variances are free to vary across groups, while slopes and intercepts are constrained to be equal (scalar invariance);
- completely separate analyses across countries, where each group has its own item slopes and intercepts (configural invariance).

The results of these analyses are reported and discussed in Sections 3.3, 3.4 and 3.5.

3 Data Harmonization

Several common variables were identified for the integration of data from ESS10 and Eurobarometer93.1. Table 1 shows the common variables. For all these common variables, cases with missing values were removed from the integration.

Table 1: Common variables

Common variables	**Measurement level**	**Type**
Country	nominal	observed
Age	numeric	observed
Gender	nominal	observed
Occupation	nominal	observed
Domicile	nominal	observed
Nationality - Citizenship	nominal	observed
Subjective income	ordinal	observed
Political Orientation	ordinal	observed
Attachment to country	ordinal	observed
Life Satisfaction	ordinal	observed
Satisfaction with national economy	ordinal	observed
Trust in Institutions	numeric	latent

Given the low percentage (around 4% in the ESS and 5% in the Eurobarometer) of respondents holding a nationality different from that of the survey country, the analysis was restricted to citizens. The EU countries common to both surveys are listed in Table 2, along with the number of individuals in each country with complete records for the variables considered.

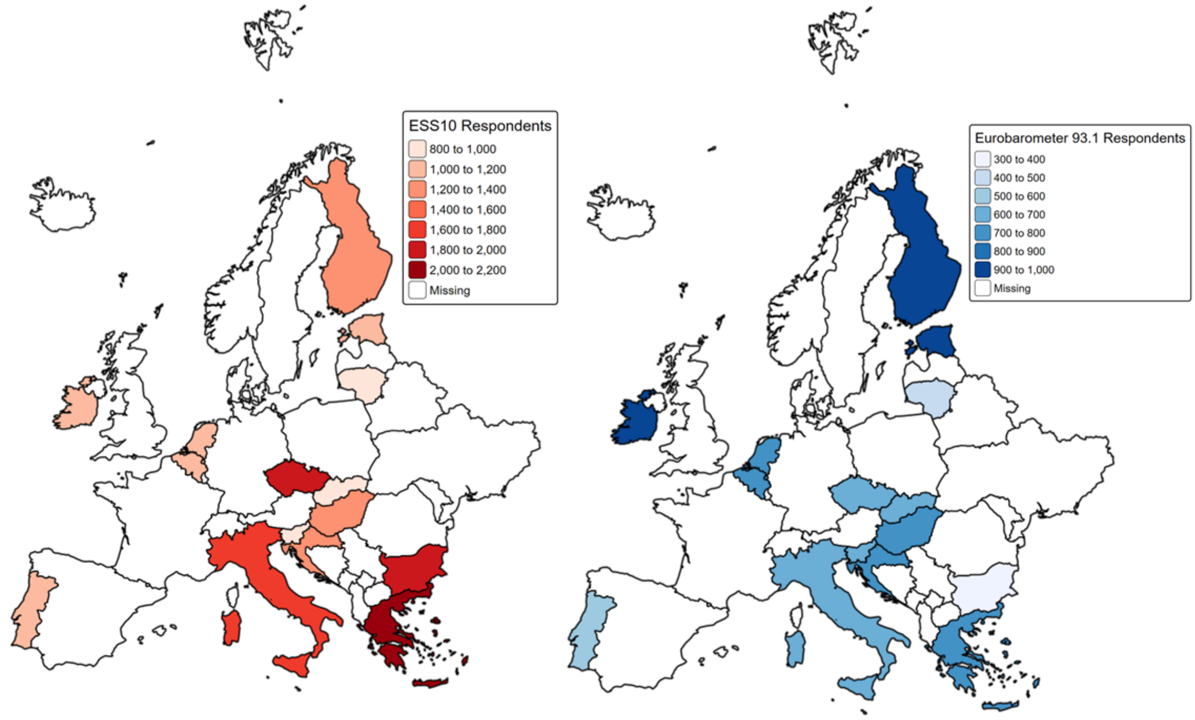

Figure 2: Common countries and number of respondents.

Table 2: Common countries and number of respondents

Country	ESS10	Eurobarometer93.1
BE	1057	766
BG	1958	360
CZ	1816	623
EE	1139	985
FI	1383	997
FR	1424	501
GR	2062	782
HR	1215	757
HU	1241	763
IE	1092	949
IT	1609	633
LT	891	404
NL	1154	747
PT	1094	562
SI	897	615
SK	943	642
Total	**20975**	**11086**

Further details on the data harmonization procedure are provided in Deliverable 1. In Section 3.1, we offer a comprehensive overview of the key characteristics of the observed common variables employed in both surveys, including an examination of their distributions across the EU countries represented in the samples.

3.1 Common observed variables distributions across the ESS and the Eurobarometer

Table 3 presents the marginal distributions of the categorical variables jointly observed in both datasets and used for the statistical matching procedure.

Table 3: Distribution of respondents for the categorical variables

Variable	**Category**	**Code**	**ESS**	**Eurobarometer**
Gender	Man	1	0.478	0.476
	Woman	2	0.522	0.524
Occupation	Employed	1	0.555	0.601
	Unemployed	2	0.102	0.062
	Retired	3	0.284	0.280
	In education	4	0.059	0.057
Domicile	Big city or large town	1	0.345	0.300
	Small or middle town	2	0.291	0.369
	Rural area or village	3	0.365	0.331
Economic difficulties	No	1	0.770	0.634
	Yes	2	0.230	0.366
Political orientation	Left	1	0.196	0.162
	Centre	2	0.625	0.679
	Right	3	0.180	0.159
Attachment to country	Not at all attached	1	0.022	0.011
	Not very attached	2	0.092	0.057
	Fairly attached	3	0.398	0.334
	Very attached	4	0.488	0.597
Life satisfaction	Not at all satisfied	1	0.031	0.032
	Not very satisfied	2	0.174	0.138
	Fairly satisfied	3	0.560	0.604
	Very satisfied	4	0.235	0.226
Economy satisfaction	Very bad	1	0.186	0.158
	Rather bad	2	0.413	0.454
	Rather good	3	0.369	0.357
	Very good	4	0.032	0.031
Sample size			**20,975**	**11,086**

Overall, the distributions across the ESS and Eurobarometer samples are broadly comparable. Some differences, however, are notable—particularly in the distribution of economic difficulties, domicile, and employment status. In particular, the proportion of respondents reporting economic difficulties is higher in the Eurobarometer (36.6%) than in the ESS (23.0%), a 13.6 percentage point difference, suggesting variation in economic profiles that may reflect different sampling frames or question contexts. Similarly, the share of employed respondents is higher in the Eurobarometer (60.1%) compared to the ESS (55.5%), while unemployment is more frequently reported in the ESS (10.2% vs. 6.2%). The Eurobarometer also includes a higher proportion of respondents from small or middle towns (36.9% vs. 29.1%), whereas the ESS sample is slightly more urban (34.5% vs. 30.0% in large cities). Moreover, national attachment is notably stronger in the Eurobarometer, with 59.7% of respondents declaring themselves "very attached" to their country, compared to 48.8% in the ESS. These distributional mismatches may introduce bias if not properly accounted for during imputation and suggest the need for robust matching models that condition on multiple covariates to mitigate inconsistencies between the two sources.

A detailed country-level analysis of the distributions of the observed common variables is provided in in the following sections.

In addition to the graphical comparison, to assess the degree of similarity in the distribution of a categorical variable across the two surveys (ESS and Eurobarometer), we compute several statistical indicators using the `comp.prop` function available in StatMatch,. Let V_{ESS} and V_{ZA} be two random variables representing the same categorical variable from the *European Social Survey* (ESS) and the *Eurobarometer* (ZA), respectively. Suppose V_{ESS} and V_{ZA} take on K discrete categories $v_1, v_2, \ldots, v_K$, and let use the following notation

- $\mathbb{P}(V_{\text{ESS}} = v_k)$ for the probability of observing category v_k in the ESS data,
- $\mathbb{P}(V_{\text{ZA}} = v_k)$ for the probability of observing category v_k in the Eurobarometer data.

To assess the similarity in the distribution of the given variable in the two surveys we compute the following measures, using the StatMatch package in R (D'Orazio, 2014, 2015).

- Overlap:

$$O(V_{\text{ESS}}, V_{\text{ZA}}) = \sum_{k=1}^{K} \text{min}\left(\mathbb{P}(V_{\text{ESS}} = v_k), \mathbb{P}(V_{\text{ZA}} = v_k)\right) \tag{5}$$

It is a measure of similarity which ranges from 0 to 1 (the distributions are equal). It can also be computed as

$$O(V_{\text{ESS}}, V_{\text{ZA}}) = 1 - \frac{1}{2}\sum_{k=1}^{K} |\mathbb{P}(V_{\text{ESS}} = v_k) - \mathbb{P}(V_{\text{ZA}} = v_k)| = 1 - TVD(V_{\text{ESS}}, V_{\text{ZA}})$$

where TVD is the Dissimilarity index or total variation distance. TVD can be interpreted as the smallest fraction of units that need to be reclassified in order to make the distributions equal and values lower than 0.03 denotes proximity.

- Bhattacharyya coefficient

$$B(V_{\text{ESS}}, V_{\text{ZA}}) = \sum_{k=1}^{K} \sqrt{(\mathbb{P}(V_{\text{ESS}} = v_k), \mathbb{P} \times (V_{\text{ZA}} = v_k)} \tag{6}$$

It is a measure of similarity and ranges from 0 to 1 (the distributions are equal).

- Hellinger distance

$$HD(V_{\text{ESS}}, V_{\text{ZA}}) = \frac{1}{\sqrt{2}}\sqrt{\sum_{k=1}^{K}\left(\sqrt{\mathbb{P}(V_{\text{ESS}} = v_k)} - \sqrt{\mathbb{P}(V_{\text{ZA}} = v_k)}\right)^2} \tag{7}$$

HD is a distance measure bounded between 0 and 1, where 0 indicates identical distributions and 1 indicates complete dissimilarity.

For categorical variable we will present also the Chi-Square statistics, although the Chi-Square a test would not be useful when the distribution are estimated from samples selected from a finite population using complex selection schemes (D'Orazio et al., 2006)

For continuous variables, using the `comp.cont` available in StatMatch, we compute average of absolute and squared differences between the quantiles of the variable distribution in the two surveys; the dissimilarity measures between the estimated empirical cumulative distribution functions and the distance between the distributions after discretization of the given variable. We use the Kolmogorov–Smirnov (KS) test. We exploit this non-parametric test to compare the empirical distribution functions of a variable between the harmonized ESS and Eurobarometer datasets. The Kolmogorov–Smirnov statistic quantifies a distance between the empirical cumulative distribution functions of two sample. A small p-value suggests that the two samples are drawn from different distributions.

3.1.1 Gender

Table 4 shows that, overall, the distributions for gender from the two surveys are highly similar across countries, as reflected by low Hellinger values, and high overlap and Bhattacharyya coefficients. Greece (GR) shows perfect alignment between the two distributions, while countries like Portugal (PT) and Slovakia (SK) present the largest divergences. Nevertheless, even in these cases, the differences remain relatively modest.

Table 4: Comparison of distributions by gender between ESS and Eurobarometer.

Country	Overlap	Bhattacharyya Coefficient	Hellinger Distance	Chi-square
Overall	0.998	1.000	0.002	0.150
BE	0.956	0.999	0.031	3.615
BG	0.978	1.000	0.016	0.612
CZ	0.993	1.000	0.005	0.098
EE	0.967	0.999	0.024	2.373
FI	0.981	1.000	0.014	0.877
FR	0.976	1.000	0.017	0.855
GR	1.000	1.000	0.000	0.001
HR	0.969	1.000	0.022	1.830
HU	0.968	0.999	0.023	2.051
IE	0.956	0.999	0.031	3.970
IT	0.987	1.000	0.009	0.301
LT	0.954	0.999	0.033	2.468
NL	0.979	1.000	0.015	0.796
PT	0.944	0.998	0.040	4.805
SI	0.975	1.000	0.018	0.899
SK	0.946	0.999	0.039	4.526

3.1.2 Occupation

For the distribution according to the variable occupation (Table 5), the overall overlap coefficient between the ESS and Eurobarometer distributions is very high (0.953), and the Bhattacharyya coefficient (0.997) similarly indicates a high degree of distributional similarity. The Hellinger distance is low (0.054), confirming minimal divergence, while the chi-square statistic is relatively high (159.246), likely due to the large sample size inflating sensitivity to small differences.

At the country level, most countries show high overlap and Bhattacharyya coefficients (typically greater than 0.95), with low Hellinger distances (below 0.1), suggesting strong distributional alignment. Exceptions include:

- *Netherlands (NL)*: the lowest overlap (0.739) and the highest Hellinger distance

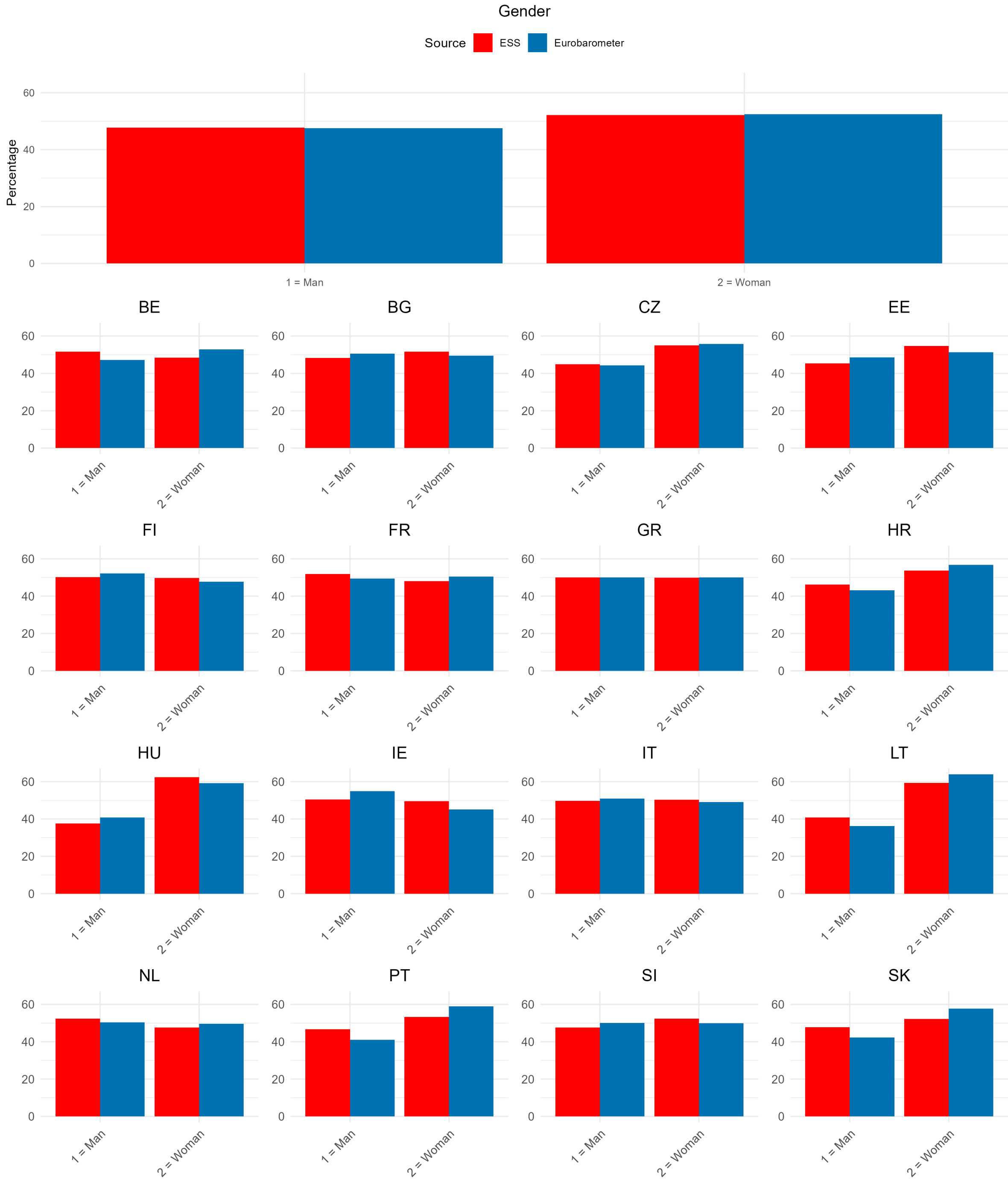

Figure 3: Respondents by gender in the ESS and Eurobarometer datasets and for each country.

(0.202), indicating notable differences between the two distributions, also reflected in a high chi-square value (147.3).

- *Croatia (HR)* and *Czechia (CZ)*: show moderately low overlaps and higher Hellinger distances (above 0.13), also corresponding to substantial chi-square values.

Conversely, *Belgium (BE)*, *France (FR)*, and *Slovenia (SI)* exhibit nearly perfect alignment (overlap greater than 0.96, Bhattacharyya equal to 1.000, Hellinger below 0.02), with minimal chi-square values, indicating excellent concordance between surveys in these countries.

Overall, these results suggest that while the harmonized data in the two surveys generally produce consistent distributions across countries, there are a few countries—most notably the Netherlands—where the differences are more pronounced and warrant further investigation.

Table 5: Comparison of distributions by occupation between ESS and Eurobarometer.

Country	**Overlap**	**Bhattacharyya Coefficient**	**Hellinger Distance**	**Chi-square**
Overall	0.953	0.997	0.054	159.246
BE	0.986	1.000	0.014	0.738
BG	0.870	0.989	0.104	24.374
CZ	0.828	0.982	0.135	62.146
EE	0.950	0.998	0.047	9.189
FI	0.952	0.995	0.070	20.816
FR	0.971	1.000	0.022	1.411
GR	0.925	0.992	0.088	33.385
HR	0.802	0.979	0.145	76.498
HU	0.960	0.997	0.050	8.833
IE	0.903	0.991	0.097	37.044
IT	0.891	0.987	0.114	40.425
LT	0.900	0.994	0.076	13.231
NL	0.739	0.959	0.202	147.308
PT	0.902	0.995	0.073	15.696
SI	0.965	0.998	0.046	6.088
SK	0.867	0.986	0.116	40.588

3.1.3 Domicile

The comparison of the *Domicile* variable across surveys (Table 6) indicates moderate divergence at the overall level, with a total variation distance of 0.08 and a Hellinger distance of 0.06. While the overlap coefficient remains high (0.92), the chi-square test signals a statistically significant difference (215.29), likely influenced by the large sample size.

Looking at the country-level results, *Italy (IT)* shows the most substantial discrepancy, with a total variation distance of 0.388, the lowest overlap (0.612), and the highest Hellinger distance (0.330), all confirmed by a very large chi-square statistic (303.54). *France (FR)* and *Croatia (HR)* also display considerable differences.

In contrast, countries like *Slovenia (SI)*, *Ireland (IE)*, and *Bulgaria (BG)* show high levels of agreement between the two surveys, with low divergence metrics and minimal chi-square statistics.

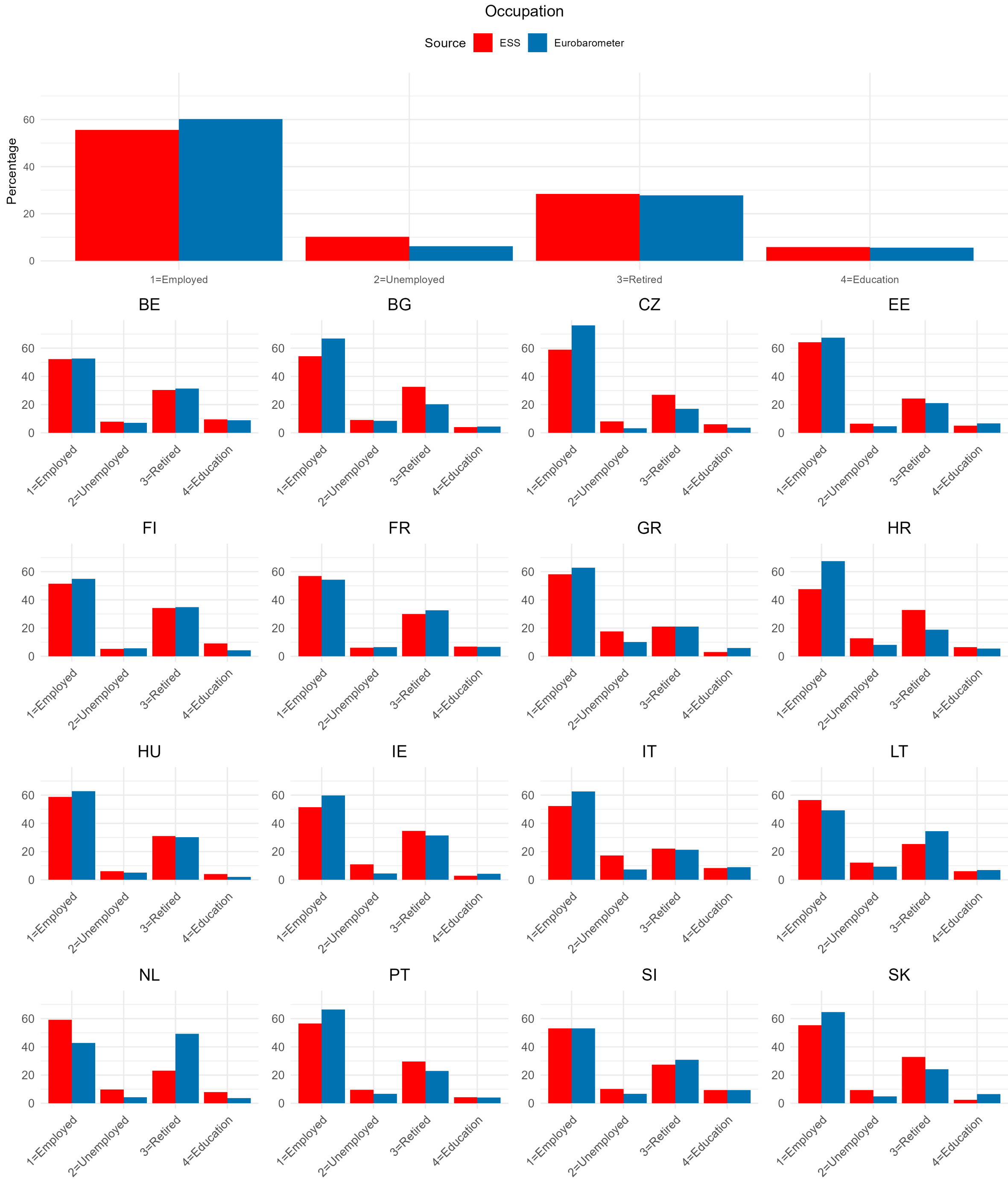

Figure 4: Respondents by occupation in the ESS and Eurobarometer datasets and for each country.

Overall, while most countries show a good level of alignment for this variable, a few countries present important discrepancies that merit closer examination.

Table 6: Comparison of distributions by domicile between ESS and Eurobarometer.

Country	Overlap	Bhattacharyya Coefficient	Hellinger Distance	Chi-square
Overall	0.920	0.996	0.060	215.286
BE	0.827	0.981	0.138	69.81
BG	0.939	0.997	0.059	8.41
CZ	0.934	0.997	0.057	12.07
EE	0.902	0.994	0.079	26.68
FI	0.909	0.995	0.069	22.05
FR	0.760	0.970	0.174	92.09
GR	0.911	0.995	0.070	23.26
HR	0.826	0.983	0.129	63.18
HU	0.887	0.993	0.086	28.03
IE	0.950	0.998	0.042	7.29
IT	0.612	0.891	0.330	303.54
LT	0.816	0.980	0.140	42.24
NL	0.834	0.976	0.156	82.54
PT	0.855	0.984	0.126	46.17
SI	0.977	1.000	0.018	0.94
SK	0.880	0.992	0.091	25.45

3.1.4 Economic difficulties

The comparison of the *Economic Difficulties* variable (Table 7) across countries highlights significant variations in the perception of economic hardship between the ESS and Eurobarometer datasets. The overall metrics show a relatively high degree of distributional similarity, with an overlap score of 0.864 and a low Hellinger distance of 0.106. However, the chi-square statistic (674.69) suggests that, despite the general alignment, some differences are statistically significant due to varying country-specific economic contexts.

Country-specific results reveal notable differences:

- Belgium (BE), Bulgaria (BG), and Finland (FI) show relatively high overlap scores (around 0.86–0.91), indicating that the perception of economic difficulties is quite similar across the two surveys in these countries. However, the moderate chi-square statistics (ranging from 69.81 to 62.61) suggest some variations in the way economic hardships are reported in the different datasets.
- Italy (IT) stands out with the lowest overlap score (0.542), indicating a more significant divergence in the perception of economic difficulties between the two harmonised surveys. The higher Hellinger distance (0.351) and chi-square statistic (488.45) suggest that respondents in Italy reported more pronounced differences in their experiences or perceptions of economic difficulties, possibly reflecting different wording in the questions of the two surveys.
- Netherlands (NL) exhibits the highest overlap (0.984), indicating an almost identical distribution between the two surveys, which may suggest a more uniform perception of economic difficulties in the Netherlands.

These differences may be indicative of differing ways in which economic difficulties are investigated, perceived or reported in the two surveys.

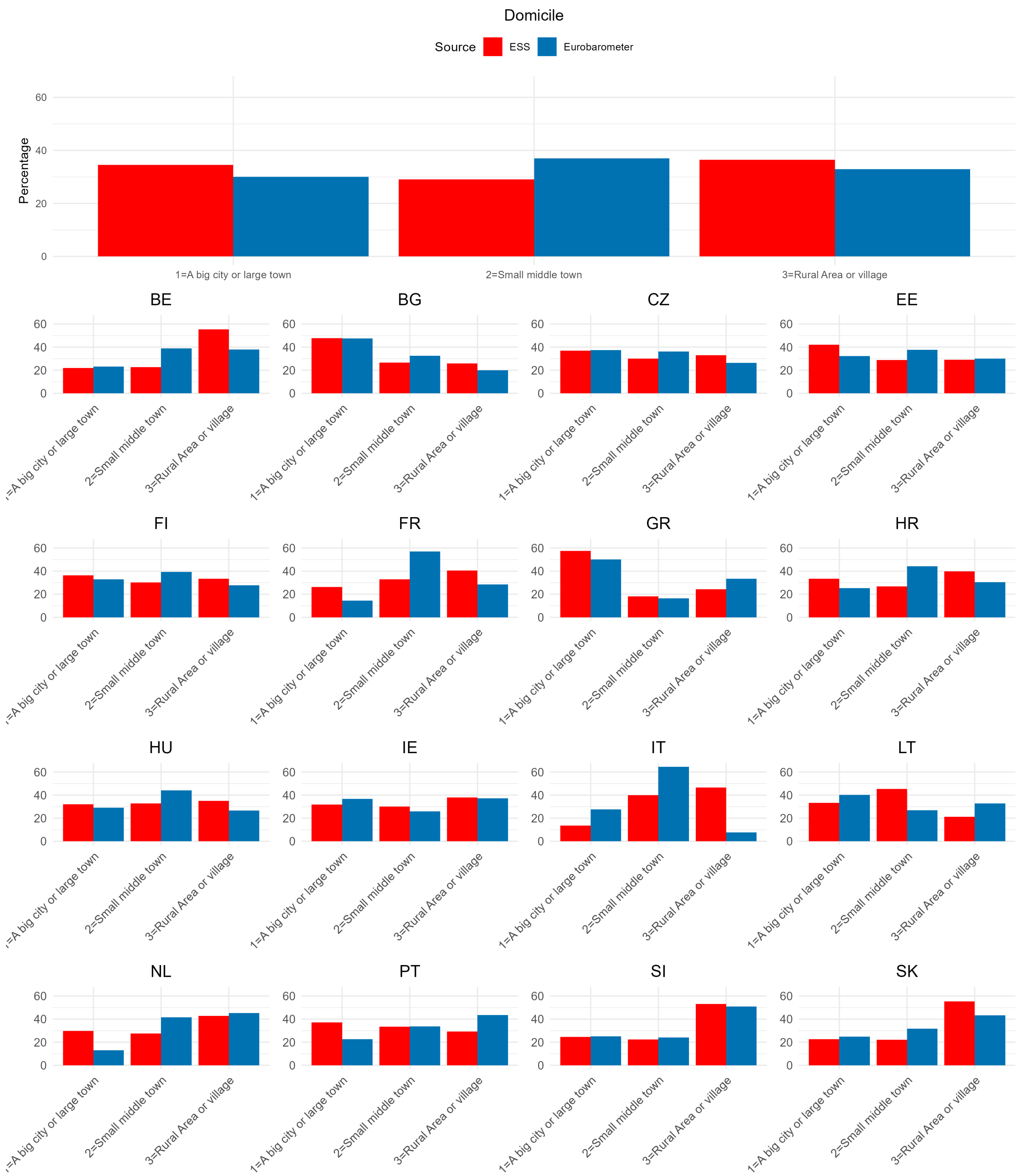

Figure 5: Respondents by domicile in the ESS and Eurobarometer datasets and for each country.

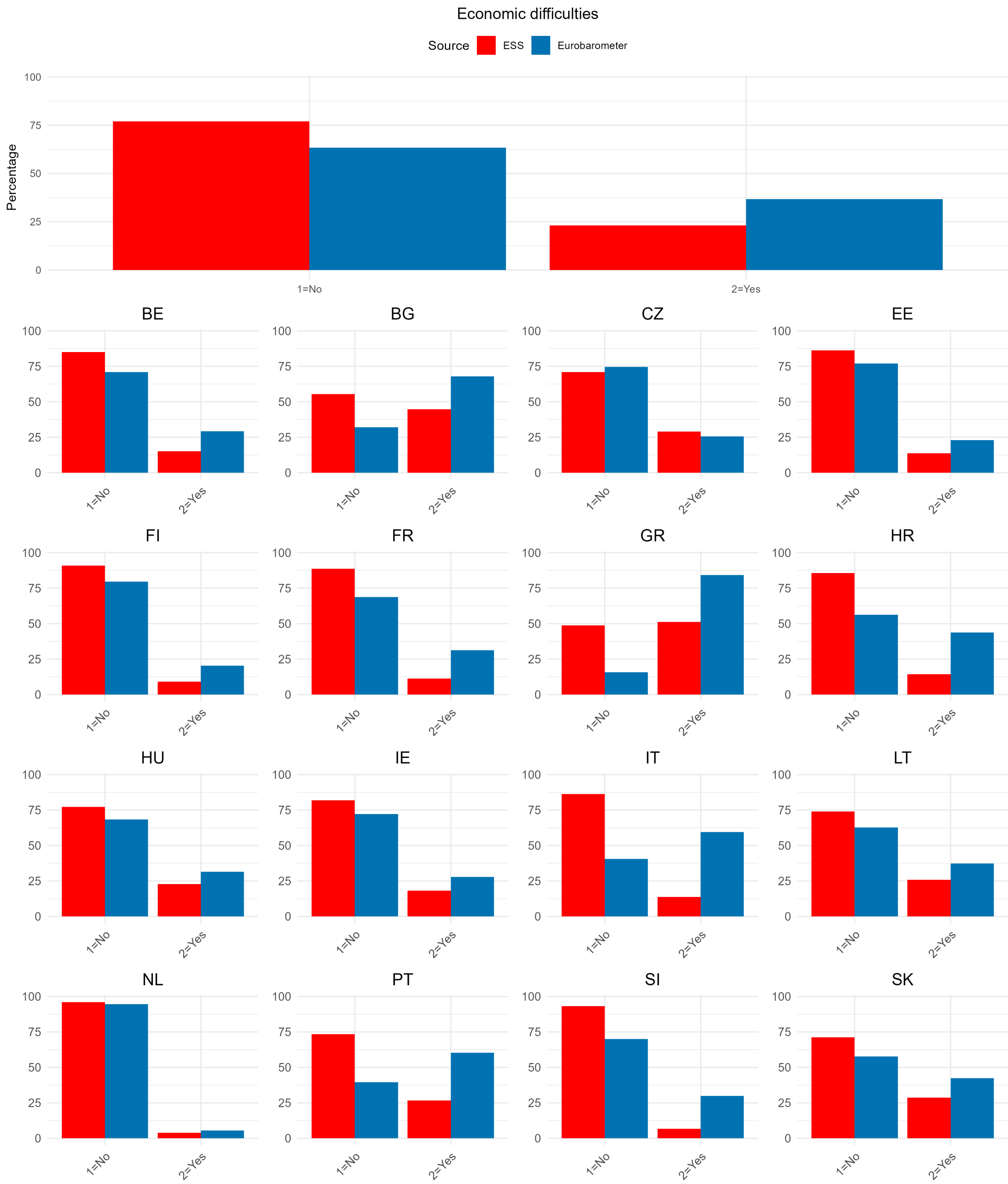

Figure 6: Respondents by economic difficulties in the ESS and Eurobarometer datasets and for each country.

Table 7: Comparison of distributions by economic difficulties between ESS and Eurobarometer.

Country	Overlap	Bhattacharyya Coefficient	Hellinger Distance	Chi-square
Overall	0.864	0.989	0.106	674.685
BE	0.859	0.985	0.121	54.41
BG	0.767	0.972	0.167	66.53
CZ	0.964	0.999	0.028	2.93
EE	0.907	0.993	0.085	30.83
FI	0.887	0.987	0.115	62.61
FR	0.800	0.969	0.177	108.87
GR	0.670	0.934	0.256	257.94
HR	0.707	0.945	0.235	211.09
HU	0.911	0.995	0.071	19.24
IE	0.904	0.993	0.081	27.40
IT	0.542	0.877	0.351	488.45
LT	0.885	0.992	0.087	17.52
NL	0.984	0.999	0.026	2.61
PT	0.662	0.940	0.245	180.00
SI	0.768	0.951	0.222	144.38
SK	0.864	0.990	0.101	31.24

3.1.5 Political orientation

The comparison of *Political Orientation* across countries (Table 8) reveals generally high similarity between the distributions of the two datasets, as indicated by the overall *Overlap* score of 0.945 and a very low *Hellinger Distance* of 0.041. This suggests that the political orientations in the two datasets are closely aligned in most countries, with only subtle variations observed in specific countries.

Table 8: Comparison of Political Orientation distributions between ESS and Eurobarometer.

Country	Overlap	Bhattacharyya Coefficient	Hellinger Distance	Chi-square
Overall	0.945	0.998	0.041	97.879
BE	0.927	0.996	0.062	13.638
BG	0.982	1.000	0.017	0.666
CZ	0.922	0.996	0.061	13.519
EE	0.907	0.993	0.081	27.718
FI	0.960	0.999	0.029	3.919
FR	0.970	0.999	0.023	1.605
GR	0.922	0.996	0.061	16.148
HR	0.951	0.998	0.046	7.617
HU	0.925	0.997	0.056	11.871
IE	0.928	0.993	0.082	26.883
IT	0.846	0.982	0.133	57.330
LT	0.978	1.000	0.020	0.883
NL	0.958	0.998	0.046	7.446
PT	0.867	0.989	0.103	30.301
SI	0.966	0.999	0.029	2.455
SK	0.889	0.993	0.084	21.265

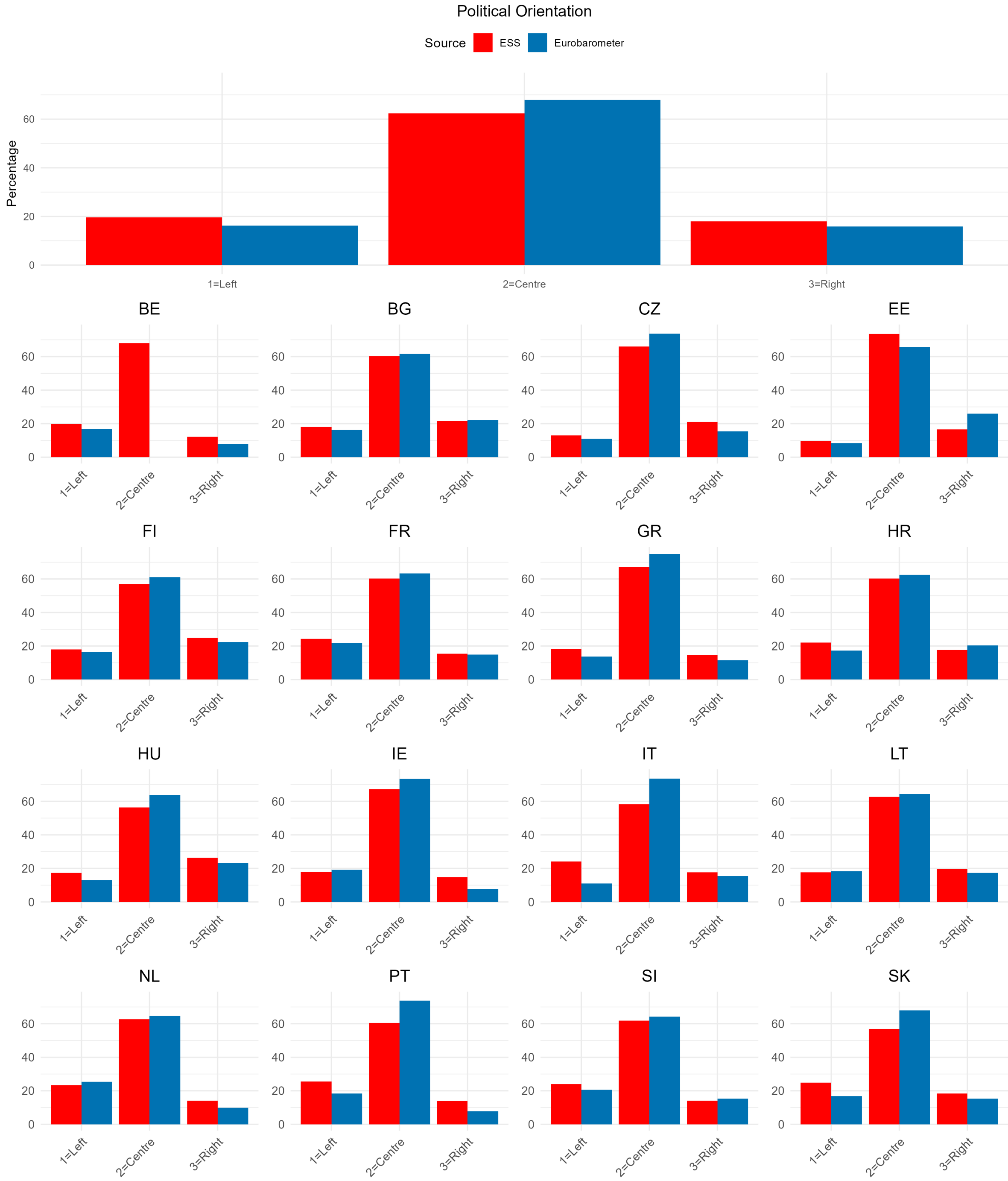

Figure 7: Respondents by political orientation in the ESS and Eurobarometer datasets and for each country.

3.1.6 Attachment to country

The comparison of Attachment to Own Country (Table 9) across countries shows a generally high degree of similarity between the datasets, with an overall Overlap score of 0.895 and a low Hellinger Distance of 0.081. These metrics suggest that respondents in both surveys generally share similar attachment levels to their home countries, although certain countries show more variation, as evidenced by the higher Chi-square values. Czech Republic stands out with a near-perfect match between the two datasets, showing an overlap of 0.968 and a Bhattacharyya index of 0.999. The very low Chi-square statistic (3.83) suggests that the two surveys aligned well in how they measured attachment to the home country, indicating effective harmonization of the questions in this case. Netherlands and Ireland have relatively low overlap scores (0.684 and 0.723), with notably higher Chi-square values (212.05 and 165.49). This indicates substantial differences between the two surveys in these countries, particularly regarding how respondents express attachment to their country.

The overall high level of agreement between the two datasets indicates that attachment to one's country was measured similarly in most cases. However, there are dome exceptions, where the discrepancies may be linked to differences in survey question wording, measurement strategies, or other contextual factors.

Table 9: Comparison of attachment to country distributions between ESS and Eurobarometer.

Country	Overlap	Bhattacharyya Coefficient	Hellinger Distance	Chi-square
Overall	0.895	0.993	0.081	370.822
BE	0.795	0.973	0.165	99.522
BG	0.906	0.987	0.115	22.435
CZ	0.968	0.999	0.034	3.831
EE	0.944	0.996	0.060	14.105
FI	0.965	0.997	0.054	13.127
FR	0.890	0.993	0.082	19.840
GR	0.823	0.975	0.157	97.715
HR	0.934	0.996	0.062	14.010
HU	0.821	0.982	0.136	66.481
IE	0.723	0.959	0.203	165.486
IT	0.939	0.998	0.047	7.888
LT	0.804	0.972	0.167	53.511
NL	0.684	0.942	0.241	212.046
PT	0.918	0.970	0.174	47.428
SI	0.852	0.984	0.126	44.035
SK	0.812	0.947	0.231	117.154

3.1.7 Life satisfaction

For life satisfaction (Table 10), the data shows varying levels of alignment across different countries. The "Overlap" values are generally high, indicating that the survey responses align well across the two datasets, with most countries showing values above 0.8. For example, Belgium (BE) and the Netherlands (NL) show near-perfect overlaps (0.990 and 0.984, respectively), suggesting a strong consistency in life satisfaction responses between the datasets. The Hellinger distance values are mostly low, further confirming that the distributions of responses

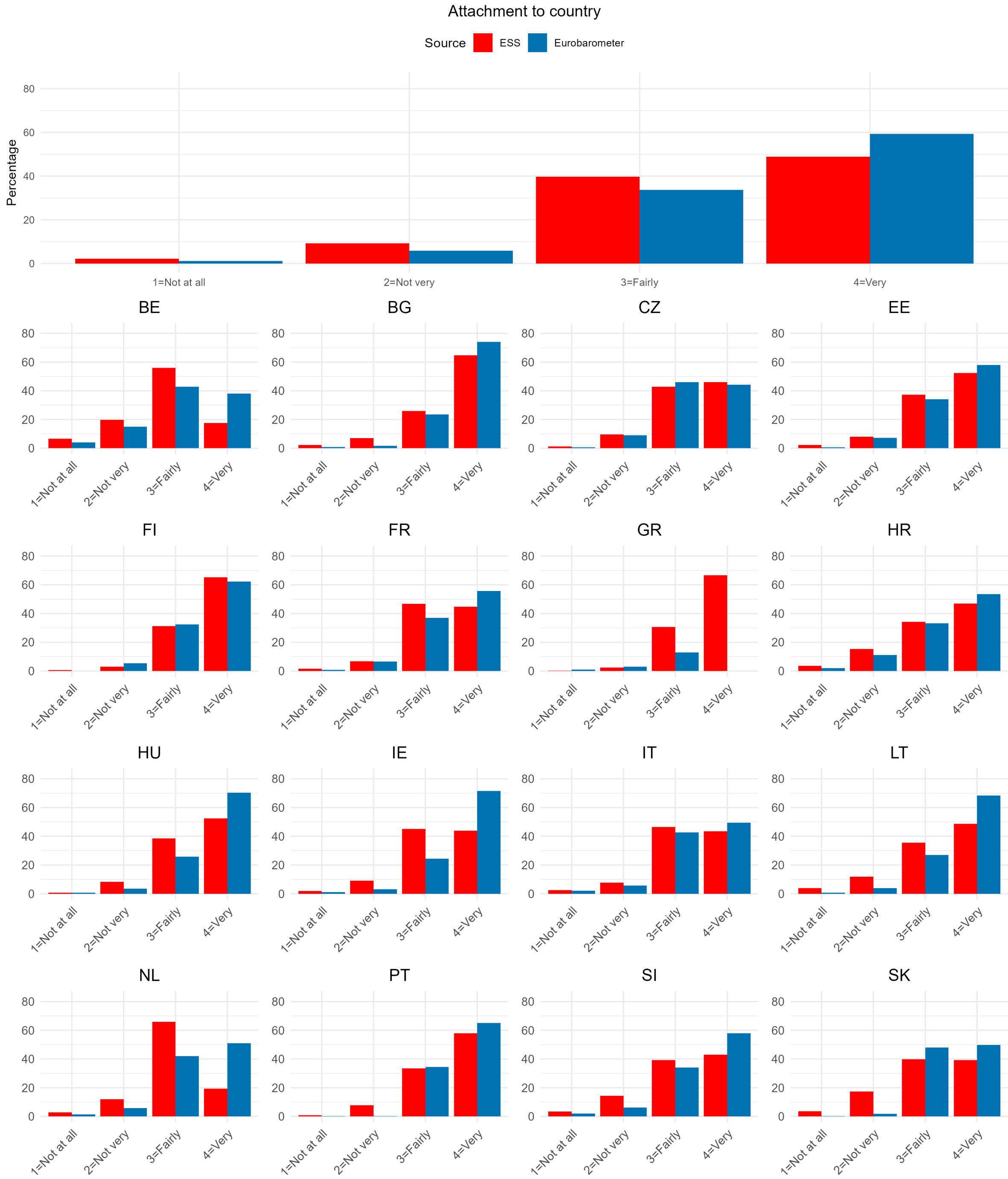

Figure 8: Respondents by attachment to country in the ESS and Eurobarometer datasets and for each country.

in both datasets are similar across countries. The exceptions, such as Greece (GR) and Portugal (PT), have higher Hellinger distances, which might reflect differences in how life satisfaction is conceptualized or measured in these countries.

This pattern of results is consistent with the harmonization phase in data integration, where the alignment of the two surveys can depend on how the questions are framed and whether they are interpreted similarly across countries.

Table 10: Comparison of life satisfaction distributions between ESS and Eurobarometer.

Country	Overlap	Bhattacharyya Coefficient	Hellinger Distance	Chi-square
Overall	0.955	0.998	0.039	86.930
BE	0.990	0.999	0.033	3.589
BG	0.914	0.987	0.113	31.369
CZ	0.900	0.988	0.108	37.919
EE	0.805	0.969	0.175	120.818
FI	0.801	0.979	0.146	96.797
FR	0.958	0.998	0.043	5.258
GR	0.887	0.985	0.124	82.779
HR	0.886	0.992	0.087	28.004
HU	0.925	0.997	0.058	12.584
IE	0.909	0.991	0.097	37.966
IT	0.845	0.977	0.151	88.993
LT	0.888	0.991	0.095	18.464
NL	0.777	0.973	0.163	95.327
PT	0.839	0.967	0.180	73.822
SI	0.865	0.989	0.105	30.564
SK	0.869	0.990	0.100	30.119

3.1.8 Satisfaction with the national economy

The similarity measures for the variable related to satisfaction with the national economy (Table 11)reveal a moderate to high degree of comparability between the two data sources after harmonization. The overall overlap coefficient is 0.960 and the Bhattacharyya coefficient is nearly perfect (0.999), suggesting a strong alignment in the general distribution of responses. The Hellinger distance remains very low (0.034), further indicating closeness in the probability distributions, while the chi-square statistic is moderately elevated (66.114), hinting at some residual differences.

However, when we examine country-specific results, notable discrepancies appear. For example, Italy (IT) shows the lowest overlap (0.787) and the highest Hellinger distance (0.217), along with a high chi-square value (165.781), suggesting substantial divergence in the distribution of responses. Similarly, Greece (GR) and Finland (FI) also display relatively low overlap and high chi-square values, reflecting less successful alignment in those contexts.

Conversely, countries like Croatia (HR) and Slovenia (SI) exhibit very high similarity, with high overlap and Bhattacharyya coefficients and low Hellinger distances and chi-square statistics, indicating excellent harmonization results.

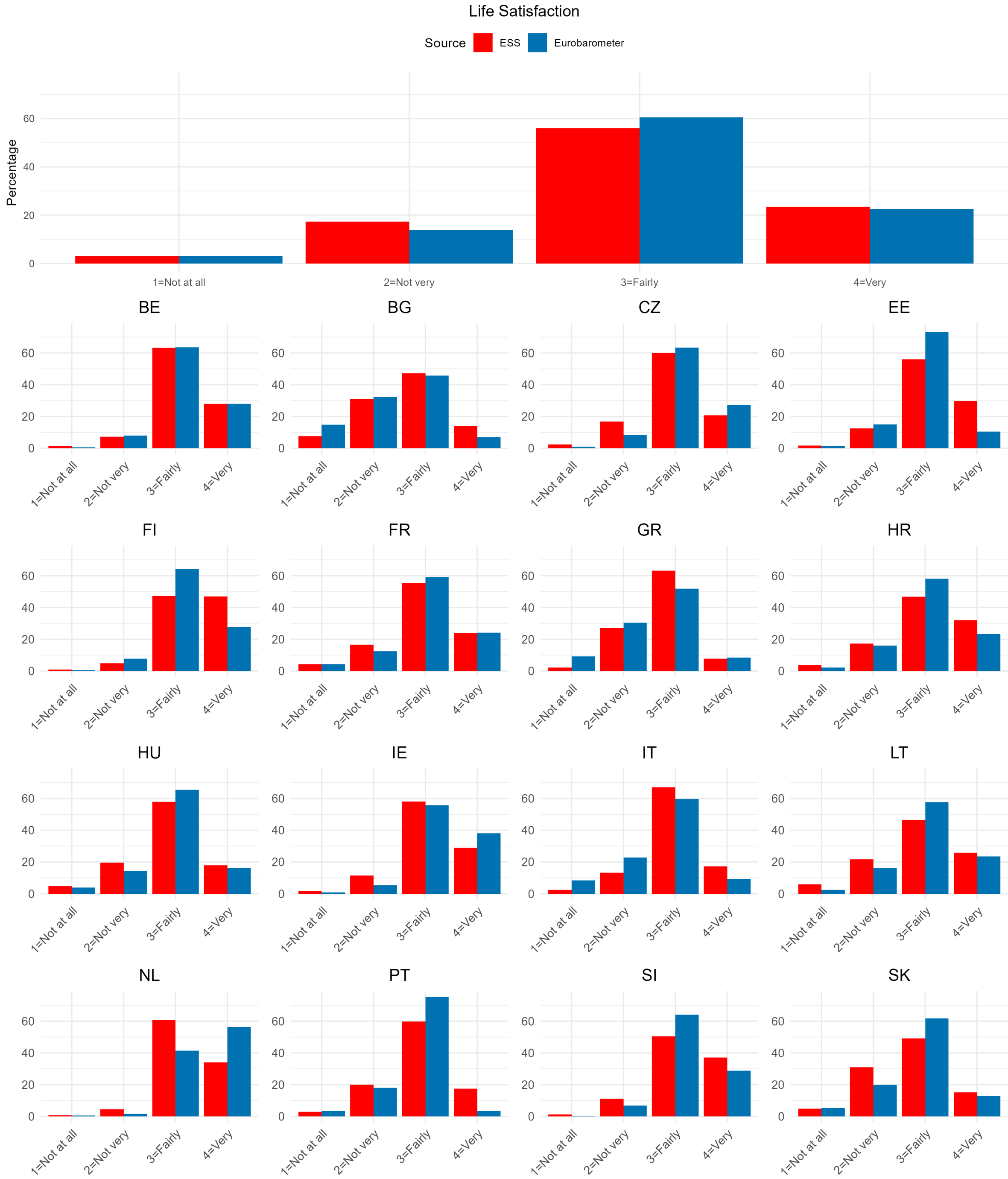

Figure 9: Respondents by life satisfaction in the ESS and Eurobarometer datasets and for each country.

Figure 10: Respondents by satisfaction with the national economy in the ESS and Eurobarometer datasets and for each country.

Table 11: Comparison of Satisfaction with the national economy distributions between ESS and Eurobarometer.

Country	Overlap	Bhattacharyya Coefficient	Hellinger Distance	Chi-square
Overall	0.960	0.999	0.034	66.114
BE	0.847	0.988	0.110	43.557
BG	0.954	0.995	0.072	17.501
CZ	0.870	0.991	0.094	32.623
EE	0.899	0.980	0.143	73.984
FI	0.814	0.977	0.152	104.562
FR	0.837	0.982	0.135	51.027
GR	0.844	0.971	0.171	112.181
HR	0.920	0.997	0.059	12.808
HU	0.909	0.990	0.099	33.515
IE	0.907	0.988	0.107	45.435
IT	0.787	0.953	0.217	165.781
LT	0.828	0.966	0.185	57.826
NL	0.919	0.988	0.110	44.466
PT	0.860	0.988	0.110	33.568
SI	0.939	0.993	0.085	17.629
SK	0.868	0.988	0.107	32.701

3.1.9 Age distribution

The comparison of the variable Age (Table 12) between the two surveys reveals significant discrepancies in several countries, as indicated by relatively high values in the average absolute differences and root squared differences (e.g., NL, HR, CZ, BG). The Kolmogorov–Smirnov (KS) test confirms that for several countries, the age distributions are statistically different (p-value < 0.05), with a particularly strong divergence in the Netherlands, where the KS statistic reaches 0.325 and the overlap is particularly low (0.644), alongside a Hellinger distance of 0.338.

3.1.10 Agreement between Harmonized ESS and Eurobarometer on Common Variables: a summary

The comparison across a wide range of variables between the two harmonized datasets reveals generally strong agreement, though the degree of consistency varies across topics and countries.

The variable with the highest agreement is gender. Across all countries, the distributions are nearly identical, with total variation distances close to zero, overlaps very close to 1, and negligible chi-square values. This outcome is expected, as gender is a simple binary categorical variable that is typically collected in a highly standardized way, and rarely subject to cultural or measurement variation.

Other variables that also show very high levels of agreement are political orientation and life satisfaction. These attitudinal items generally yield high overlap coefficients (above 0.92), low Hellinger distances, and small chi-square statistics. Their consistent performance across countries suggests that the harmonization process for these items was effective, likely aided by relatively comparable question wording and response scales in the original surveys.

Moderate agreement is observed for variables such as attachment to one's own country and satisfaction with the national economy. While the overlap remains generally high (around 0.85–0.95), several countries show notable discrepancies.

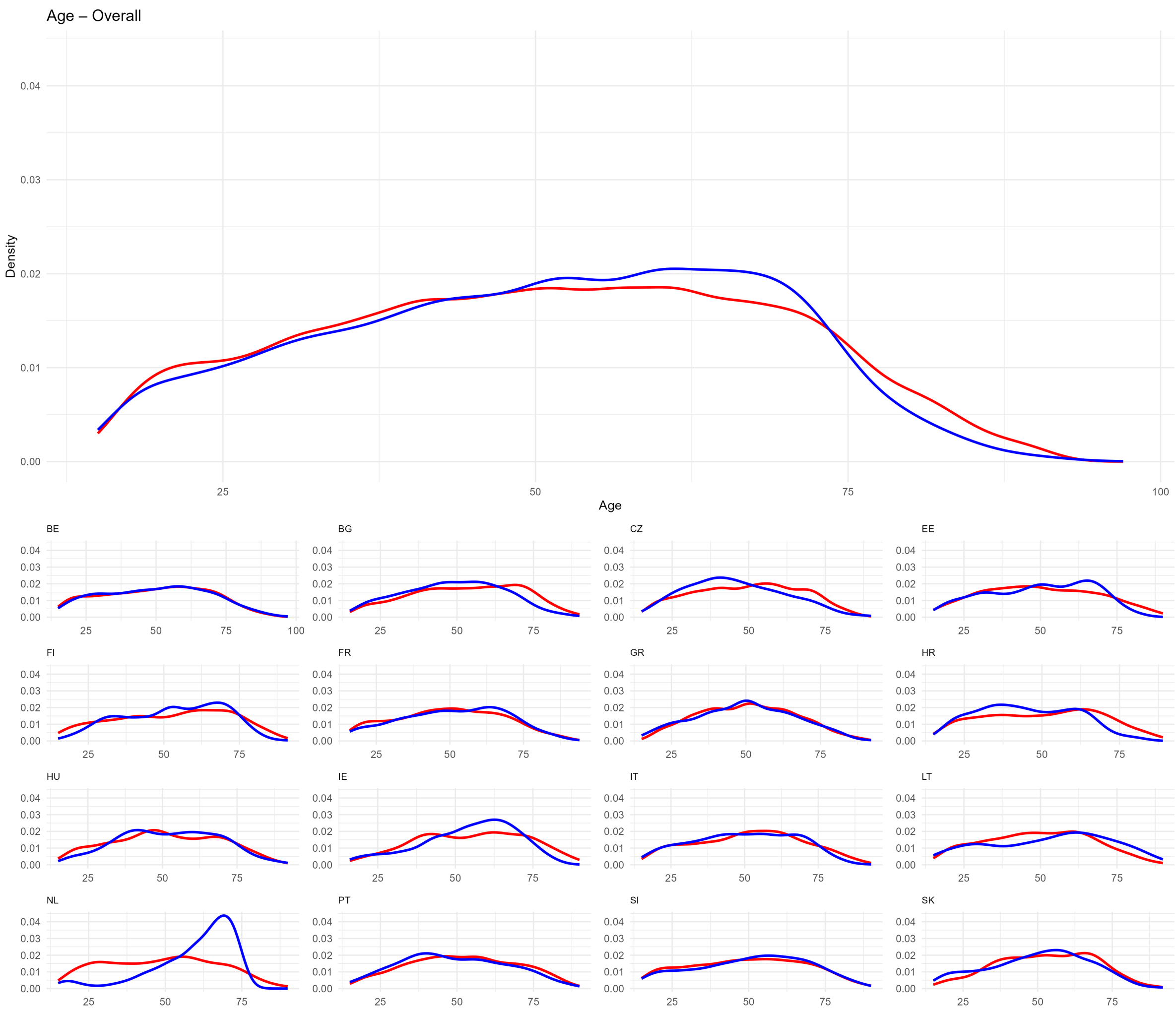

Figure 11: Density plots for the common variable age in the ESS and Eurobarometer datasets and for each country.

Table 12: Similarity measures for the variable *Age* across the ESS and Eurobarometer.

Country	Avg. Absolute Difference	Avg. Root Sq. Difference	Overlap	Hellinger Distance	KS Statistic	KS pvalue
Overall	0.947	1.170	0.944	0.059	0.032	0.000
BE	0.411	0.688	0.964	0.052	0.022	0.977
BG	4.329	4.730	0.861	0.127	0.139	0.000
CZ	4.592	5.033	0.865	0.110	0.138	0.000
EE	1.868	2.525	0.884	0.132	0.070	0.012
FI	2.426	2.964	0.879	0.138	0.066	0.012
FR	1.737	1.972	0.936	0.060	0.059	0.148
GR	0.624	1.045	0.924	0.077	0.040	0.326
HR	5.450	6.291	0.852	0.171	0.149	0.000
HU	2.042	2.456	0.894	0.095	0.066	0.031
IE	2.555	3.120	0.844	0.166	0.094	0.000
IT	1.937	2.360	0.896	0.104	0.057	0.098
LT	4.005	4.377	0.871	0.123	0.121	0.001
NL	12.018	13.624	0.644	0.338	0.325	0.000
PT	2.950	3.112	0.919	0.070	0.081	0.016
SI	1.589	1.893	0.935	0.054	0.051	0.291
SK	2.442	2.814	0.890	0.097	0.082	0.012

These variations may be attributed to differences in national sentiment, translation effects, or slight inconsistencies in the response format and question framing.

By contrast, variables like economic difficulties and domicile (urban/rural) exhibit lower levels of agreement, with marked divergence in some countries (e.g., Italy, Greece, and Croatia). This suggests difficulties in harmonizing questions related to perceived material conditions or residential classification, potentially due to culturally specific interpretations, timing of data collection, or differing operational definitions.

Finally, the Age variable—although conceptually straightforward—presents substantial discrepancies in several countries (e.g., Netherlands, Croatia, Bulgaria), with large average differences, high Hellinger distances, and statistically significant Kolmogorov–Smirnov tests. This points to challenges not just in harmonization but also in sample structure, or selection biases across the surveys.

In conclusion, the harmonized datasets demonstrate excellent agreement on basic demographic variables like gender, strong agreement on subjective attitudes, moderate agreement on identity and evaluative measures, and lower agreement on socio-economic or context-dependent variables, emphasizing the importance of harmonization protocols and careful attention to measurement equivalence in comparative research.

3.2 Common Latent trait: Trust in Institutions

The latent trait "Trust in Institutions" is measured using indicators that are common to both surveys. To harmonize the response formats between the ESS and the Eurobarometer, we recode the ESS items into binary indicators aligned with the Eurobarometer structure. Specifically, the latent trait scores are derived from binary variables indicating trust in the national parliament, the legal system, the police, political parties, the European Parliament, and the United Nations.

Table 13 presents the results of model comparisons for a unidimensional IRT model measuring "Trust in Institutions" under varying assumptions of measurement invariance across groups. The strict invariance model, which constrains item slopes, intercepts, and fixes latent means and variances across groups, shows the poorest fit, with the highest AIC and BIC values. Relaxing constraints on latent means and variances, the scalar invariance model significantly improves model fit, as shown by a large drop in AIC and BIC, and a statistically significant chi-square test, indicating that allowing group-specific means and variances captures substantial between-group differences.

Further relaxing the constraints on item parameters, the configural invariance model, which estimates item slopes and intercepts separately by group, results in the best overall fit (lowest AIC and BIC).

Table 13: IRT model for Trust: model comparison

Model	AIC	BIC	logLik	χ^2	df	p
Strict invariance	201132.4	201232.9	-100554.2			
Scalar Invariance	195662.1	196014.0	-97789.1	5530.2	30	0
Configural invariance	188386.4	189995.2	-94001.2	7575.7	150	0

The results from the configural invariance model (see Table 14) show substantial cross-country variability in both discrimination coefficients and thresholds for the six items measuring "Trust in Institutions". Discrimination parameters vary widely, suggesting that the strength of the relationship between each item and the latent trait differs across contexts. For instance, "Trust in the EU" consistently shows high discrimination in most countries (e.g., 6.45 in Lithuania, 4.72 in Croatia), while in Hungary, it drops markedly (1.18), indicating a weaker link to overall trust in institutions. Conversely, institutions like the police or political parties tend to have lower and more stable discrimination across countries. Threshold parameters also reflect notable variation, pointing to differences in baseline levels of endorsement or trust. For example, Finland and the Netherlands show generally negative thresholds, indicating higher overall trust levels, while Bulgaria and Croatia exhibit positive thresholds, suggesting lower trust.

Table 14: IRT model for Trust: estimates of discrimination parameters and thresholds.

		Parliament	Legal system	Police	Political parties	EU	UN
Discrimination coefficients	BE	2.91	1.93	1.31	2.55	4.25	2.50
	BG	2.19	1.84	1.73	1.98	4.17	2.98
	CZ	2.76	2.03	1.78	3.02	4.16	3.78
	EE	1.68	2.12	2.05	1.55	3.43	2.48
	FI	2.96	2.19	1.66	2.73	3.60	2.22
	FR	2.30	1.99	1.19	1.78	4.26	1.94
	GR	2.66	2.08	1.71	2.25	3.25	2.10
	HR	2.21	2.34	1.83	2.26	4.72	3.84
	HU	3.29	3.55	2.99	2.64	1.18	1.29
	IE	2.58	2.27	1.82	2.69	3.04	2.07
	IT	3.23	2.40	1.52	2.52	4.39	2.41
	LT	1.72	1.41	1.42	1.89	6.45	4.02
	NL	2.92	2.07	1.55	2.52	2.51	1.82
	PT	2.58	1.92	1.41	2.73	3.69	2.83
	SI	1.79	1.52	1.45	2.14	3.23	2.82
	SK	3.13	2.17	2.02	2.95	4.42	3.47
Trehsholds	BE	0.34	-0.08	-1.11	0.93	0.17	0.02
	BG	1.62	1.31	0.49	1.91	0.39	0.45
	CZ	0.33	-0.15	-0.75	0.67	0.14	0.00
	EE	0.18	-0.64	-1.34	1.29	0.04	-0.08
	FI	-0.61	-1.27	-2.27	0.08	-0.12	-0.63
	FR	0.50	0.05	-0.96	1.61	0.43	0.11
	GR	0.57	-0.62	-0.87	1.20	0.45	0.48
	HR	1.19	1.17	0.08	1.68	0.35	0.35
	HU	0.21	-0.09	-0.44	0.57	-0.08	-0.17
	IE	-0.01	-0.57	-1.08	0.60	-0.40	-0.58
	IT	0.52	0.12	-0.85	1.19	0.21	0.17
	LT	0.89	0.07	-0.99	1.24	-0.14	-0.18
	NL	-0.57	-1.16	-1.83	-0.21	-0.16	-0.53
	PT	0.21	0.44	-0.98	1.13	-0.09	-0.34
	SI	0.93	0.58	-0.67	1.59	0.28	0.24
	SK	0.81	0.82	0.17	1.19	0.40	0.32

Table 15 compare the distribution of the latent traits associated with the ESS and the Eurobarometer surveys. The results indicate a moderate overall agreement, with an overlap coefficient of 0.866 and a Hellinger distance of 0.112. However, cross-country differences are notable. Countries like France, the Netherlands, Slovenia, and Hungary show relatively high agreement (overlap > 0.87, Hellinger < 0.11), while Lithuania, Portugal, Czechia, and Finland display lower agreement (overlap ≤ 0.77, Hellinger ≥ 0.18). These discrepancies likely reflect differences in question wording and response scales. The density plots are depicted in Figure 12.

Table 15: Similarity measures for the variable *Trust in Istitutions* across the ESS and Eurobarometer.

Country	Avg. Absolute Difference	Avg. Root Sq. Difference	Overlap	Hellinger Distance	KS Statistic	KS pvalue
Overall	0.076	0.087	0.866	0.112	0.052	0.000
BE	0.155	0.231	0.882	0.102	0.089	0.001
BG	0.378	0.489	0.805	0.147	0.225	0.000
CZ	0.292	0.392	0.765	0.204	0.167	0.000
EE	0.281	0.338	0.774	0.190	0.185	0.000
FI	0.368	0.486	0.762	0.186	0.240	0.000
FR	0.093	0.173	0.907	0.073	0.056	0.184
GR	0.170	0.249	0.865	0.109	0.108	0.000
HR	0.286	0.362	0.847	0.113	0.150	0.000
HU	0.076	0.132	0.878	0.105	0.069	0.021
IE	0.362	0.453	0.817	0.183	0.206	0.000
IT	0.303	0.370	0.843	0.130	0.172	0.000
LT	0.418	0.494	0.691	0.256	0.265	0.000
NL	0.094	0.186	0.898	0.102	0.063	0.056
PT	0.500	0.565	0.763	0.204	0.282	0.000
SI	0.112	0.187	0.892	0.100	0.086	0.009
SK	0.130	0.204	0.880	0.127	0.088	0.005

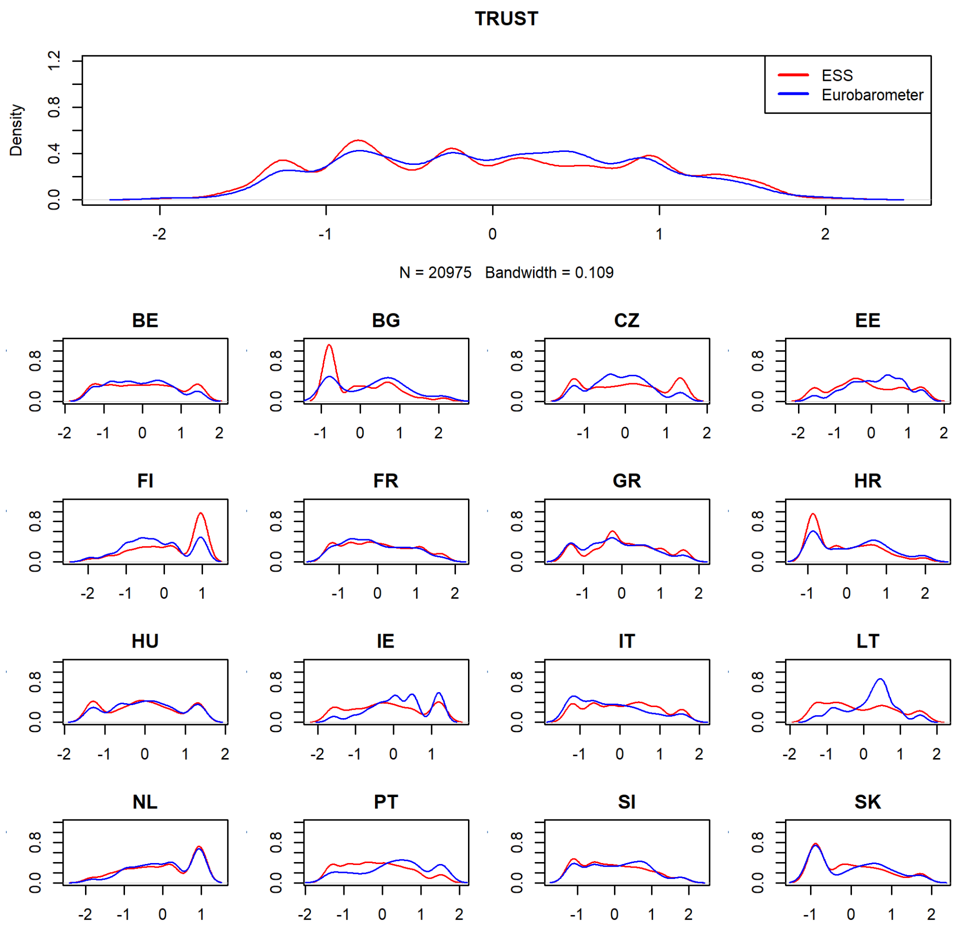

Figure 12: Density plots for the common latent variable Trust in the ESS and Eurobarometer datasets and for each country.

3.3 Target latent variables: "Immigration rejection" and "Perceived benefits of immigration"

As described in Sections 1 and 2, the target variables estimated from the harmonized ESS dataset, namely 'Immigration rejection" and "Perceived benefits of immigration", are obtained using a bi-dimensional IRT model that assumes an independent cluster structure and allows for correlation between the two latent traits.

Model comparisons (see Table 16) favors a configural invariance formulation.

Table 16: Bidimensional IRT model for "Immigration rejection" and "Perceived benefits of immigration": model comparison

Model	AIC	BIC	logLik	χ^2	df	p
Strict invariance	240471.9	240790.0	-120196.0			
Scalar Invariance	234402.6	235197.7	-117101.3	6189.3	60	0
Configural invariance	227125.6	230306.1	-113162.8	7877.0	300	0

The results from the configural invariance model (see Table 17) reveal substantial cross-country variation in both discrimination coefficients and location parameters.

For "Immigration rejection", the item "Allow different race" shows particularly high discrimination in countries such as Ireland, the Netherlands , and Croatia, indicating that this item is especially effective at distinguishing between respondents with varying levels of rejection in these contexts. In contrast, lower discrimination values are observed in countries like Greece and Slovenia. Regarding "Perceived benefits of immigration", the discrimination coefficients tend to be more moderate and consistent across countries, although some variability remains. The location parameters highlight different national tendencies in baseline attitudes. For "Immigration rejection", countries like Finland, Portugal, and the Netherlands show more favorable (lower) location parameters, suggesting lower baseline levels of rejection. In terms of "Perceived benefits of immigration", more negative location parameters in Finland, Ireland, and Portugal suggest these countries are more likely to perceive immigration as beneficial, while countries such as Hungary, Czech Republic, and Greece exhibit more neutral or even slightly negative perceptions. Overall, the results support the presence of considerable heterogeneity in how different European populations respond to immigration-related items, justifying the use of a configural invariance model.

Table 17: Bidimensional IRT model for "Immigration rejection" and "Perceived benefits of immigration": estimates of discrimination parameters and thresholds.

		Immigration rejection			Perceived benefits of immigration		
		Allow same race	Allow different race	Allow poor countries	Impact on economy	Impact on cultural life	Impact on the country
Discrimination coefficients	BE	3.48	8.24	3.44	2.17	2.17	2.35
	BG	2.15	5.66	3.27	3.49	3.52	3.65
	CZ	2.53	5.43	4.08	2.23	3.65	3.00
	EE	1.68	8.09	3.16	2.53	3.18	3.57
	FI	2.03	11.26	3.62	2.42	2.50	4.11
	FR	3.73	9.42	4.04	2.56	3.18	4.17
	GR	0.92	4.32	3.78	2.97	4.34	2.51
	HR	3.19	12.77	3.79	2.42	3.02	4.04
	HU	1.72	7.76	3.10	4.04	3.50	3.13
	IE	4.41	18.89	5.18	2.75	3.29	3.94
	IT	3.76	10.40	4.09	3.70	3.81	3.24
	LT	1.97	7.67	2.63	2.22	2.86	2.96
	NL	5.67	23.20	3.52	1.84	2.16	2.30
	PT	5.76	13.92	5.08	2.47	2.88	2.54
	SI	2.16	4.26	3.18	2.18	2.51	3.02
	SK	3.35	5.19	4.21	2.96	2.63	3.31
Location parameter	BE	0.94	0.54	0.55	-0.72	-1.06	-0.76
	BG	0.73	-0.06	-0.28	-0.21	-0.23	-0.17
	CZ	-0.29	-0.78	-0.77	-0.06	0.21	0.21
	EE	0.99	0.09	-0.20	-0.53	-0.50	-0.28
	FI	1.30	0.17	0.09	-1.00	-1.60	-0.78
	FR	0.73	0.39	0.38	-0.53	-0.60	-0.39
	GR	0.81	-0.79	-0.91	0.17	0.08	0.01
	HR	0.64	0.30	0.28	-0.25	-0.46	-0.36
	HU	-0.39	-0.96	-1.17	0.28	0.08	0.16
	IE	0.59	0.39	0.33	-1.00	-0.99	-1.05
	IT	0.54	0.22	0.28	-0.24	-0.27	-0.05
	LT	0.95	0.21	0.02	-0.41	-0.29	-0.43
	NL	0.61	0.53	0.37	-0.94	-1.29	-0.85
	PT	0.58	0.39	0.46	-1.12	-1.03	-0.77
	SI	0.94	0.12	0.11	-0.27	-0.39	-0.25
	SK	-0.13	-0.52	-0.56	0.29	0.22	0.27

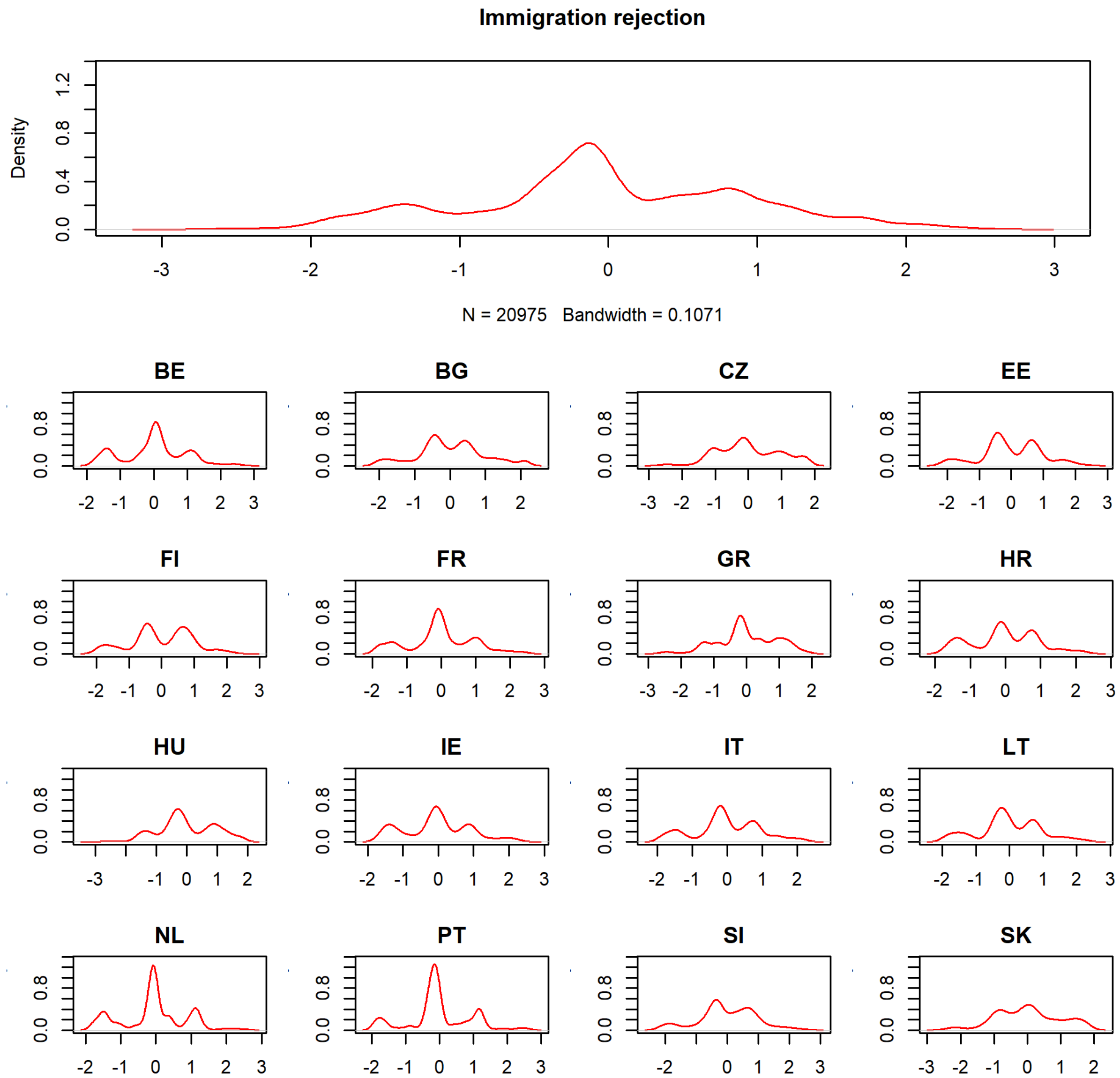

Figure 13: Density plots for the TARGET latent variable “Immigration rejection” in the ESS dataset and for each country.

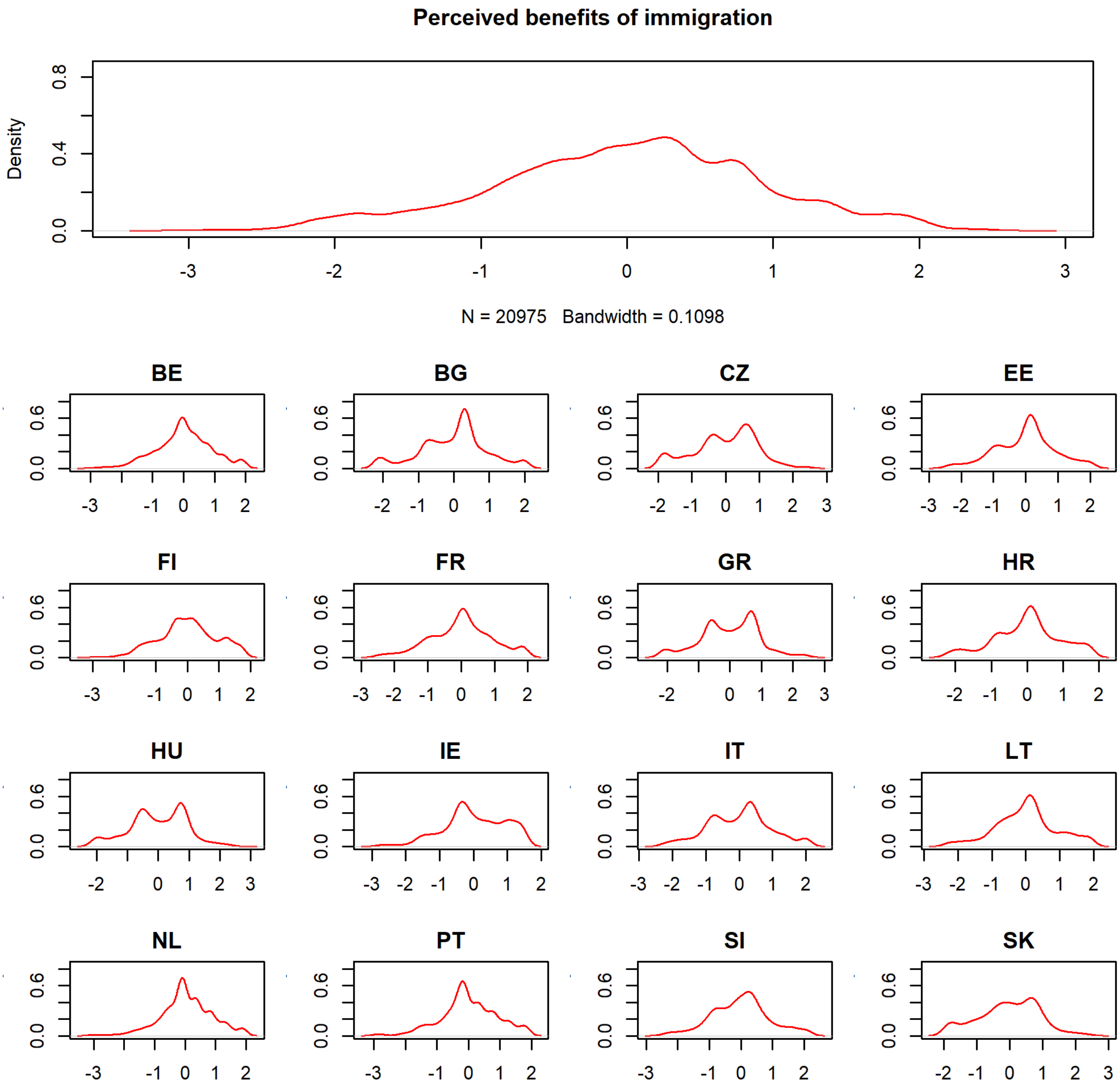

Figure 14: Density plots for the TARGET latent variable "Perceived benefits of immigration" in the ESS dataset and for each country.

The correlation between the two latent traits (see Table 18) is relatively high and stable across the analyzed countries.

Table 18: Correlation between "Immigration rejection" and "Perceived benefits of immigration"

Country	Correlation coefficient
BE	-0.68
BG	-0.71
CZ	-0.77
EE	-0.66
FI	-0.67
FR	-0.78
GR	-0.56
HR	-0.60
HU	-0.66
IE	-0.62
IT	-0.78
LT	-0.69
NL	-0.66
PT	-0.67
SI	-0.70
SK	-0.71

3.4 Variable of interest in the Eurobarometer survey: "Euroskepticism on Migration Governance"

The model comparison (Table 19 for estimating the latent trait "Euroskepticism on Migration Governance" from items extracted from the harmonized Eurobarometer dataset confirms once again the choice of the less restrictive model.

Table 19: IRT model for "Euroskepticism on Migration Governance": model comparison

Model	AIC	BIC	logLik	χ^2	df	p
Strict invariance	35707.9	35751.9	-17848.0			
Scalar Invariance	34310.7	34574.4	-17119.4	1457.2	30	0
Configural invariance	33383.1	34086.2	-16595.5	1047.7	60	0

The results for the configural invariance model (Table 20) reveal notable cross-country differences in both discrimination and threshold parameters. Most countries exhibit high discrimination for the Common policy item, suggesting that agreement or disagreement with this item is a strong indicator of the latent trait. In contrast, the External border item shows very low or even negative discrimination in many countries, indicating it contributes weakly, or inconsistently, to the measurement of the latent trait. Threshold parameters for the External border item vary, with high positive values in Belgium and Portugal, and large negative values in countries like Ireland and France, reflecting stark differences in item endorsement levels. Overall, the Common policy and Asylum system items appear to function more consistently and informatively across countries, while External border may require closer scrutiny or reconsideration for comparative analysis.

Table 20: IRT model for "Euroskepticism on Migration Governance": estimates of discrimination parameters and thresholds.

		Common policy	Asylum system	External border
Discrimination coefficients	BE	5.53	2.70	0.22
	BG	2.08	3.01	1.49
	CZ	1.98	9.30	0.44
	EE	6.48	1.63	-0.23
	FI	5.29	1.90	-0.36
	FR	3.35	1.79	-0.11
	GR	2.61	4.92	2.50
	HR	3.16	3.12	1.97
	HU	2.47	11.95	0.68
	IE	2.45	2.52	-0.06
	IT	3.55	2.78	1.50
	LT	1.75	7.58	0.92
	NL	3.98	3.42	-0.11
	PT	2.22	15.33	0.47
	SI	2.03	3.89	0.43
	SK	2.40	5.96	3.14
Trehsholds	BE	1.04	0.99	5.39
	BG	0.57	0.52	1.82
	CZ	-0.48	-0.43	3.13
	EE	0.24	-0.01	-7.92
	FI	0.32	0.54	-4.18
	FR	0.75	0.74	-10.07
	GR	1.17	1.10	1.86
	HR	0.54	0.60	1.02
	HU	0.14	0.19	3.22
	IE	1.17	1.02	-11.35
	IT	0.70	0.63	1.07
	LT	1.18	0.49	2.22
	NL	1.39	1.29	-8.45
	PT	1.11	0.59	3.99
	SI	0.87	0.66	2.82
	SK	-0.31	-0.03	0.97

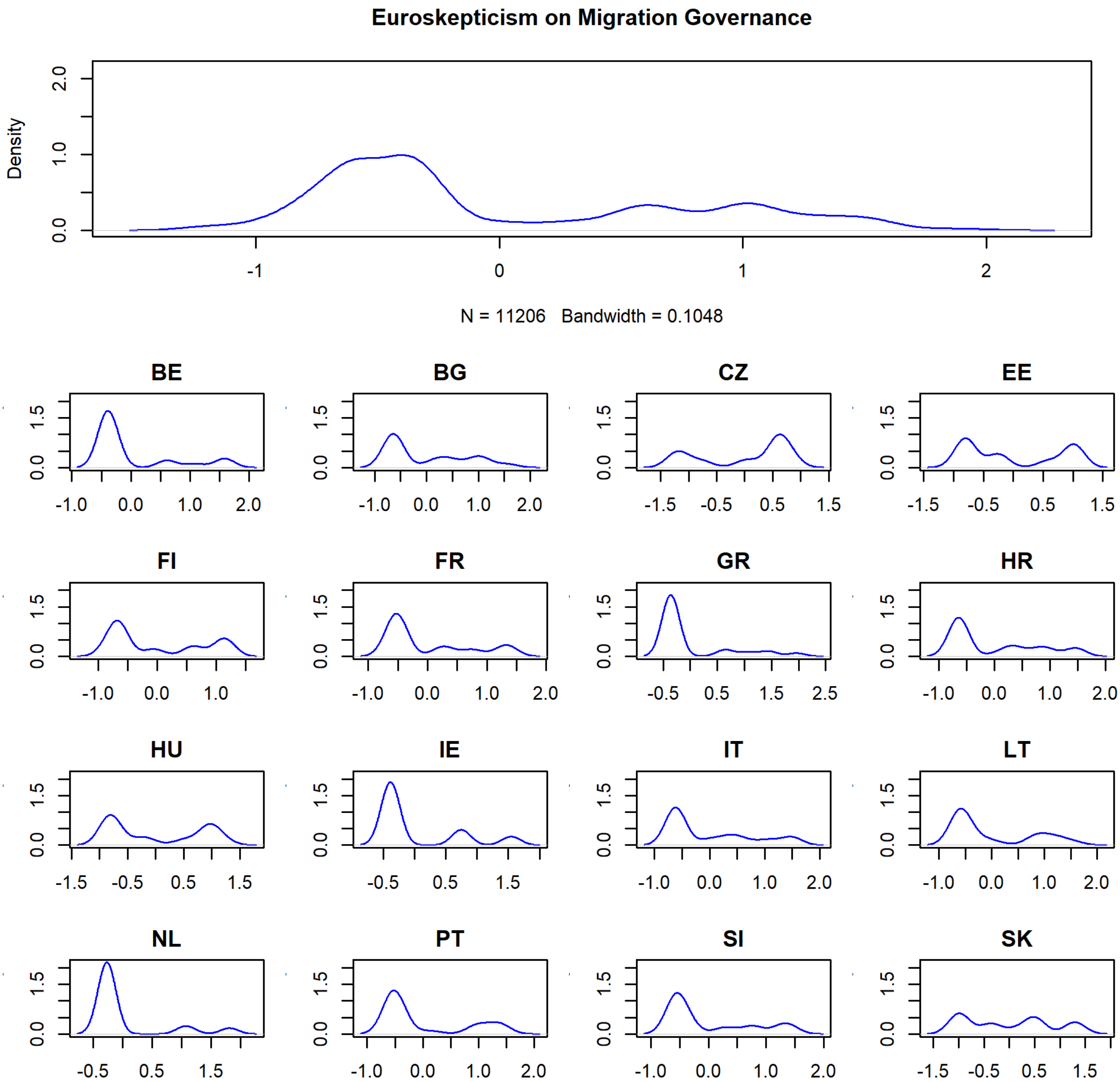

Figure 15: Density plots for the TARGET latent variable “Euroskepticism on Migration Governance” in the Eurobarometer dataset and for each country.

3.5 Control latent variable in the Eurobarometer suvey: Aversion to immigrants

The configural invariance formulation of the multi-group IRT model is also supported in the comparison for estimating the latent trait “Aversion to immigrants” (Table 21).

Table 21: IRT model for “Aversion to immigrants”: model comparison

Model	AIC	BIC	logLik	χ^2	df	p
Strict invariance	95947.2	96064.4	-47957.6			
Scalar Invariance	93351.6	93688.5	-46629.8	2655.6	30	0
Configural invariance	89486.0	91361.0	-44487.0	4285.5	210	0

The configural invariance model results reveal substantial variation in both discrimination coefficients and thresholds across countries and items (Table 22). Discrimination parameters are generally higher for items related to immigration from outside the EU and the perceived contribution of immigrants, indicating that these items are particularly informative in distinguishing levels of aversion. Threshold parameters also vary widely. The variation across both types of parameters confirms the appropriateness of the configural model and highlights the complexity of cross-national comparisons in attitudes toward immigration.

Table 22: IRT model for "Aversion to immigrants": estimates of discrimination parameters and thresholds.

		Immigration from EU	Immigration from outside EU	Immigrants contribution	Help refugees
Discrimination coefficients	BE	2.48	4.51	3.37	2.43
	BG	0.71	2.04	2.15	2.68
	CZ	1.35	1.49	2.63	1.69
	EE	1.60	3.38	3.22	2.99
	FI	1.86	3.58	4.94	2.78
	FR	2.07	3.05	3.25	3.28
	GR	1.00	1.91	2.79	2.24
	HR	1.56	2.09	1.48	1.39
	HU	0.90	2.00	3.91	2.67
	IE	1.92	3.07	2.70	3.14
	IT	2.25	3.06	4.99	3.45
	LT	1.68	1.83	2.39	1.69
	NL	2.34	3.74	1.61	1.31
	PT	2.66	2.69	3.39	2.86
	SI	1.11	1.75	2.37	2.33
	SK	1.87	1.99	4.33	2.76
Trehsholds	BE	0.46	-0.07	-0.08	0.41
	BG	1.41	-0.50	-0.92	-0.57
	CZ	-0.08	-1.20	-1.10	-1.07
	EE	0.38	-1.03	-0.75	-0.44
	FI	0.75	-0.41	0.05	0.27
	FR	0.15	-0.33	-0.08	0.22
	GR	0.36	-0.84	-0.83	0.28
	HR	0.86	0.12	-1.04	0.19
	HU	0.80	-0.77	-0.84	-0.44
	IE	1.60	0.33	0.93	1.09
	IT	-0.01	-0.30	-0.35	-0.06
	LT	1.05	-0.19	-0.27	0.03
	NL	0.52	-0.13	0.36	1.54
	PT	0.95	0.51	0.94	0.92
	SI	0.62	-0.66	-0.63	-0.43
	SK	-0.24	-1.08	-0.96	-0.59

3.6 Latent traits correlation

Table'23 presents the correlations between latent traits derived from the ESS dataset. Specifically, it shows the relationships between Trust in Institutions and two other variables: Immigration Rejection and Perceived Benefits of Immigration. The correlations are reported for the entire dataset as well as for individual countries included in the survey. The correlation between Trust in Institutions and Immigration Rejection is negative, suggesting that higher trust in institutions tends to be associated with lower levels of immigration rejection. On the other hand, the correlation between Trust in Institutions and Perceived Benefits of Immigration is positive, suggesting a more favorable view of immigration benefits in respondents with higher institutional trust. However, and some countries show weaker or even near-zero correlations, indicating more complex or less consistent patterns in those regions.

Table 23: Latent trait correlation in the ESS survey

	Trust in institutions ~ Immigration rejection	Trust in institutions ~ Perceived benefits of immigration
whole dataset	-0.204	0.275
BE	-0.241	0.313
BG	-0.248	0.253
CZ	-0.262	0.339
EE	-0.312	0.360
FI	-0.327	0.403
FR	-0.255	0.305
GR	0.001	0.143
HR	-0.037	0.123
HU	-0.021	0.087
IE	-0.198	0.260
IT	-0.230	0.294
LT	-0.376	0.484
NL	-0.225	0.300
PT	-0.231	0.298
SI	-0.192	0.227
SK	-0.221	0.335

Table 24 displays the correlations between latent traits from the Eurobarometer survey, focusing on Trust in Institutions, Euroskepticism on Migration Governance, and Aversion to Immigrants. The correlation between Trust in Institutions and Euroskepticism on Migration Governance is generally negative across the dataset, with a correlation of -0.253 for the whole dataset. This suggests that higher trust in institutions is associated with lower euroskepticism regarding migration governance. Similarly, the correlation between Trust in Institutions and Aversion to Immigrants is also negative, with a correlation of -0.321 for the whole dataset. This indicates that greater institutional trust tends to align with lower levels of aversion to immigrants. On the other hand, Euroskepticism on Migration Governance and Aversion to Immigrants show a positive correlation for the entire dataset, suggesting that respondents with higher aversion to immigrants also tend to have higher euroskepticism about migration governance.

Table 24: Latent trait correlation in the Eurobarometer survey

	Trust in institutions ∼ Euroskepticism on Migration Governance	Trust in Institutions ∼ Aversion to immigrants	Euroskepticism on Migration Governance ∼ Aversion to immigrants
whole dataset	-0.253	-0.321	0.367
BE	-0.198	-0.362	0.235
BG	-0.175	-0.321	0.199
CZ	-0.293	-0.326	0.324
EE	-0.366	-0.408	0.514
FI	-0.385	-0.514	0.534
FR	-0.216	-0.257	0.394
GR	-0.247	-0.240	0.214
HR	-0.348	-0.229	0.338
HU	-0.027	-0.138	0.335
IE	-0.256	-0.288	0.332
IT	-0.271	-0.386	0.392
LT	-0.183	-0.175	0.305
NL	-0.251	-0.373	0.286
PT	-0.194	-0.255	0.486
SI	-0.240	-0.211	0.277
SK	-0.325	-0.563	0.469

3.7 Dependence of target and control variables on common variables

To test the explanatory power of the common variables with respect to the target variables, we performed a regression analysis of the latent traits“Immigration rejection” and “Perceived benefits of immigration” on the common variables. We also performed a regression analysis for the latent traits derived from the Eurobarometer datasets, “blueticism on Migration Governance” and “Aversion to immigrants”.

We included orthogonal polynomial contrasts (linear, quadratic, and cubic) for ordinal predictors (e.g., education level) to test for potential non-linear trends. The linear contrast tests for a consistent increase or decrease across categories, while the quadratic and cubic contrasts allow for curvilinear relationships (e.g., plateauing or U-shaped effects).

Immigration rejection Table 25 presents the results of the regression analysis predicting the latent trait “Immigration Rejection” e based on the common variables while Figures 16 provides a graphical representation of the direct relattionships. The model identifies several significant predictors. Age and gender show significant associations with immigration rejection, with women expressing lower rejection than men. Socioeconomic status also plays a role: individuals who are unemployed or retired tend to show higher rejection, while those in education exhibit lower levels. Place of residence is relevant, with people living in smaller towns or rural areas more likely to reject immigration compared to those in large cities. Economic difficulties and political orientation, especially leaning toward the right, are strongly associated with higher immigration rejection. Among attitudinal variables, trust in institutions emerges as a key factor, with higher trust linked to lower rejection. The effects of life satisfaction and attachment to country show non-linear trends, suggesting more complex relationships. Similarly, satisfaction with the economy exhibits a significant but curvilinear association with the dependent variable.

Table 25: Regression of "Immigration Rejection" on the common variables in the ESS Survey

Variable	Category / Trend	Code	Estimate	p-value	Signif.
Intercept			-0.594	8E-71	***
Age		Ag	0.006	3E-30	***
Gender (baseline = Man)	Woman	G2	-0.068	4E-08	***
Occupation (baseline = Employed)	Unemployed	O2	0.044	4E-02	*
	Retired	O3	0.086	1E-05	***
	In education	O4	-0.129	9E-06	***
Domicile (baseline = Big city / large town)	Small or mid-sized town	D2	0.100	6E-11	***
	Rural area or village	D3	0.192	3E-40	***
Economic Difficulties		Ed	0.059	9E-08	***
Political Orientation (baseline = Left)	Centre	P2	0.294	2E-76	***
	Right	P3	0.437	4E-103	***
Attachment to Country	Linear trend	AL	0.032	3E-01	
	Quadratic trend	AQ	0.093	9E-05	***
	Cubic trend	AC	-0.013	5E-01	
Life Satisfaction	Linear trend	LL	-0.207	7E-15	***
	Quadratic trend	LQ	0.056	6E-03	**
	Cubic trend	LC	-0.061	1E-05	***
Economy Satisfaction	Linear trend	EL	-0.031	2E-01	
	Quadratic trend	EQ	0.086	2E-05	***
	Cubic trend	EC	-0.013	3E-01	
Trust in Institutions		T	-0.187	1E-132	***

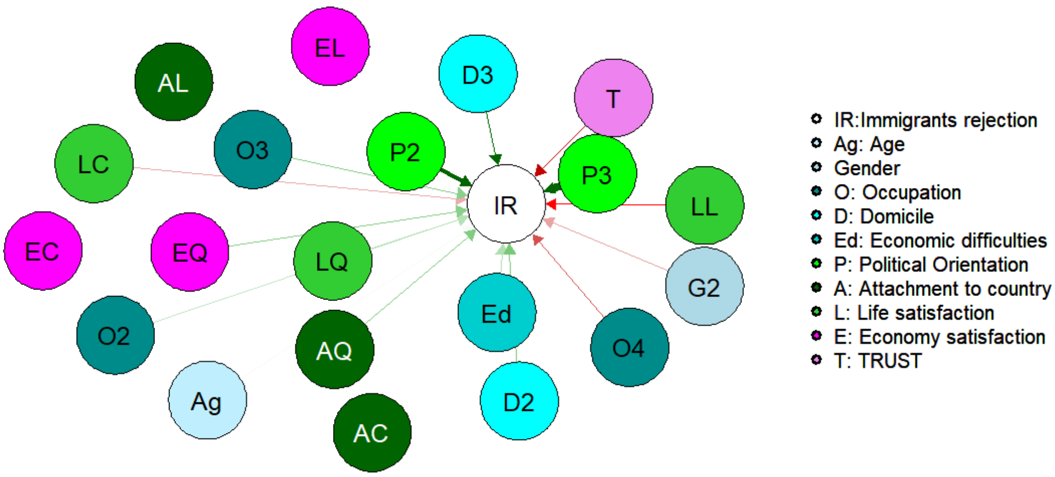

Figure 16: Graphical representation of the regression coefficients for "Immigration rejection" on the common variables in the ESS Survey

Perceived benefits of immigration Table 26 and Figure 17 show the regression results for the latent trait Perceived benefits of immigration, using the same set of common variables previously examined. The pattern of effects confirms and complements the earlier findings, underscoring the consistency of some key predictors across both attitudes. As with rejection, trust in institutions stands out as a crucial attitudinal variable: greater trust is associated with a more positive perception of immigration. Political orientation remains strongly influential—moving from left to right corresponds to a clear decline in perceived benefits, mirroring the increase in rejection observed earlier. Sociodemographic factors show similar directions of effect: younger age, being in education, and living in larger urban areas are associated with more favorable views of immigration. Again, women tend to perceive immigration more positively than men, while individuals reporting economic difficulties or identifying with more conservative political views express less favorable perceptions. Nonlinear trends in life and economic satisfaction, along with attachment to country, further indicate that perceptions of immigration are shaped by complex interplays between personal wellbeing and national identification, as already observed in the regression on immigration rejection.

Table 26: Regression of "Perceived benefits of immigration" on the common variables in the ESS Survey

Variable	Category / Trend	Code	Estimate	p-value	Signif.
Intercept			-0.594	8.00E-71	***
Age		Ag	0.006	3.00E-30	***
Gender (baseline = Man)	Woman	G2	-0.068	4.00E-08	***
Occupation (baseline = Employed)	Unemployed	O2	0.044	4.00E-02	*
	Retired	O3	0.086	1.00E-05	***
	In education	O4	-0.129	9.00E-06	***
Domicile (baseline = Big city / large town)	Small or mid-sized town	D2	0.100	6.00E-11	***
	Rural area or village	D3	0.192	3.00E-40	***
Economic Difficulties		Ed	0.059	9.00E-08	***
Political Orientation (baseline = Left)	Centre	P2	0.294	2.00E-76	***
	Right	P3	0.437	4.00E-103	***
Attachment to Country	Linear trend	AL	0.032	3.00E-01	
	Quadratic trend	AQ	0.093	9.00E-05	***
	Cubic trend	AC	-0.013	5.00E-01	
Life Satisfaction	Linear trend	LL	-0.207	7.00E-15	***
	Quadratic trend	LQ	0.056	6.00E-03	**
	Cubic trend	LC	-0.061	1.00E-05	***
Economy Satisfaction	Linear trend	EL	-0.031	2.00E-01	
	Quadratic trend	EQ	0.086	2.00E-05	***
	Cubic trend	EC	-0.013	3.00E-01	
Trust in Institutions		T	-0.187	1.00E-132	***

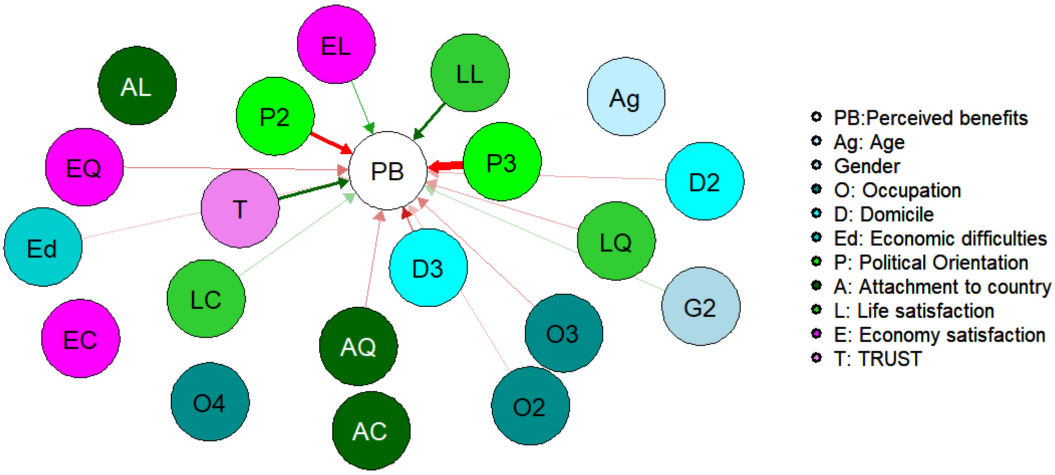

Figure 17: Graphical representation of the regression coefficients for "Perceived benefits of immigration" on the common variables in the ESS Survey

Euroskepticism on Migration Governance Table 27 presents the regression results for Euroskepticism on Migration Governance, represented in Figure 18. The comparison with respect to the regressoin for the target variables to be imputes reveals both continuity and divergence in the underlying drivers of these attitudinal dimensions.

As in the ESS models, trust in institutions once again plays a central role: greater institutional trust is consistently associated with lower skepticism toward a common EU migration policy. This echoes its negative association with immigration rejection and its positive link with perceived benefits, reinforcing the view that institutional confidence sustains more inclusive or pro-integration attitudes. Political orientation remains a strong and consistent predictor: individuals on the right are significantly more skeptical of EU-level migration governance, just as they were more rejecting of immigration and less inclined to perceive its benefits. Similarly, economic difficulties and living in less urbanized areas are linked to more skeptical views, in line with their association with restrictive or negative immigration attitudes in the previous regressions. Some contrasts are notable. While age was significantly related to immigration attitudes in the ESS models, it is not relevant here. Likewise, satisfaction with the economy, which showed nonlinear associations with immigration attitudes, is not significantly related to Euroskepticism in this model. Conversely, attachment to country retains a significant nonlinear influence, suggesting that feelings of national belonging may shape preferences over migration governance more directly than attitudes toward immigrants themselves. Overall, the three regressions reflect a coherent structure of opinion: attitudes toward immigration and EU-level migration policy are shaped by overlapping sociodemographic, ideological, and attitudinal factors, with trust in institutions and political positioning emerging as particularly robust predictors across all dimensions.

Table 27: Regression of "Euroskepticism on Migration Governance" on the common variables in the Eurobarometer Survey

Variable	Category / Trend	Code	Estimate	p-value	Signif.
Intercept			0.051	0.211	
Age		Ag	0.000	0.767	
Gender (baseline = Man)	Woman	G2	-0.033	0.017	*
Occupation (baseline = Employed)	Unemployed	O2	-0.021	0.482	
	Retired	O3	-0.021	0.312	
	In education	O4	-0.083	0.014	*
Domicile (baseline = Big city / large town)	Small or mid-sized town	D2	0.042	0.012	*
	Rural area or village	D3	0.050	0.004	**
Economic Difficulties		Ed	0.056	0.000	***
Political Orientation (baseline = Left)	Centre	P2	0.071	0.000	***
	Right	P3	0.207	0.000	***
Attachment to Country	Linear trend	AL	-0.199	0.000	***
	Quadratic trend	AQ	0.089	0.012	*
	Cubic trend	AC	0.016	0.534	
Life Satisfaction	Linear trend	LL	-0.110	0.000	***
	Quadratic trend	LQ	0.050	0.032	*
	Cubic trend	LC	-0.021	0.212	
Economy Satisfaction	Linear trend	EL	-0.010	0.733	
	Quadratic trend	EQ	-0.011	0.614	
	Cubic trend	EC	0.001	0.955	
Trust in Institutions		T	-0.209	0.000	***

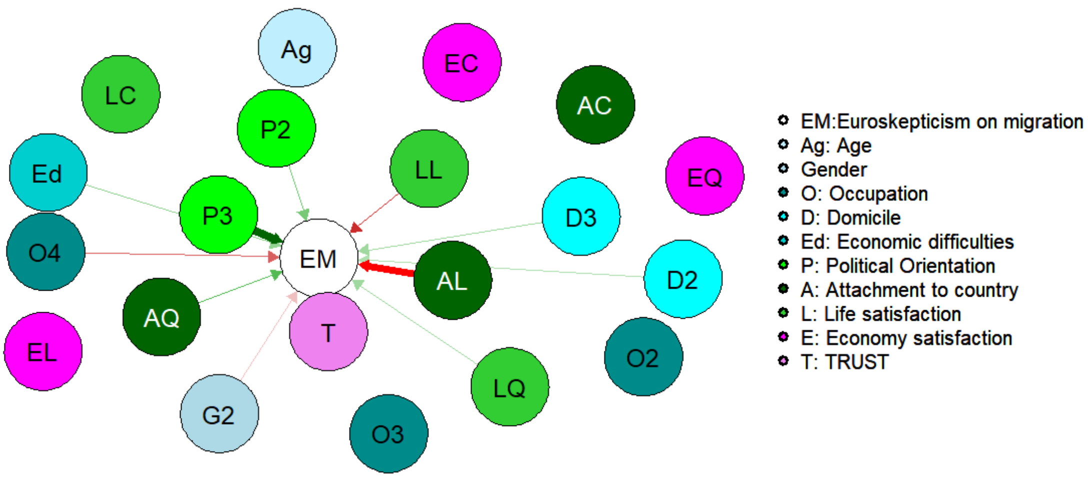

Figure 18: Graphical representation of the regression coefficients for "Euroskepticism on Migration Governance" on the common variables in the Eurobarometer Survey

Aversion to immigrants Compared to previous models, the regression on Aversion to immigrants (Table 28 and Figure 19) further confirms the prominent role of political orientation and institutional trust in shaping attitudes towards migration. As seen earlier, trust in institutions consistently correlates with more inclusive views, while right-leaning orientations predict stronger opposition. Additionally, life satisfaction, economic satisfaction, and type of domicile—already relevant in explaining both rejection of immigration and Euroskepticism—again emerge as significant predictors, underscoring a coherent structure in the socio-demographic and attitudinal drivers of exclusionary sentiments.

Table 28: Regression of "Aversion to immigrants" on the common variables in the Eurobarometer Survey

Variable	Category / Trend	Code	Estimate	p-value	Signif.
Intercept			-0.470	9.8E-24	***
Age		Ag	0.005	6.2E-13	***
Gender (baseline = Man)	Woman	G2	-0.024	1.3E-01	
Occupation (baseline = Employed)	Unemployed	O2	0.026	4.4E-01	
	Retired	O3	-0.007	7.6E-01	
	In education	O4	-0.147	1.5E-04	***
Domicile (baseline = Big city / large town)	Small or mid-sized town	D2	0.071	2.2E-04	***
	Rural area or village	D3	0.142	1.0E-12	***
Economic Difficulties		Ed	0.037	3.5E-03	**
Political Orientation (baseline = Left)	Centre	P2	0.257	3.9E-32	***
	Right	P3	0.492	4.1E-69	***
Attachment to Country	Linear trend	AL	-0.216	1.7E-05	***
	Quadratic trend	AQ	0.175	1.6E-05	***
	Cubic trend	AC	-0.063	2.8E-02	*
Life Satisfaction	Linear trend	LL	-0.228	6.0E-11	***
	Quadratic trend	LQ	0.068	1.1E-02	*
	Cubic trend	LC	-0.033	8.4E-02	
Economy Satisfaction	Linear trend	EL	-0.357	2.1E-25	***
	Quadratic trend	EQ	-0.074	4.3E-03	**
	Cubic trend	EC	-0.042	8.4E-03	**
Trust in Institutions		T	-0.291	2.4E-176	***

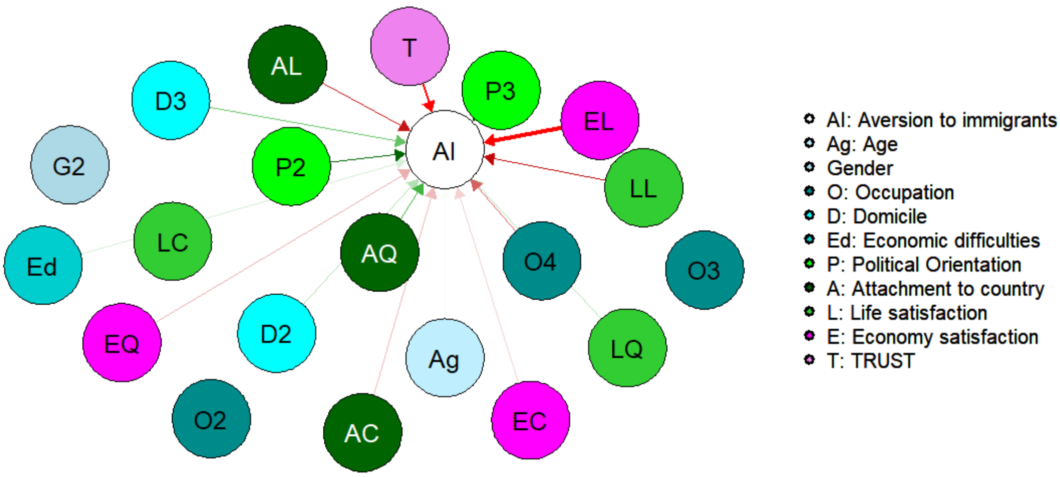

Figure 19: Graphical representation of the regression coefficients for "Aversion to immigrants" on the common variables in the Eurobarometer Survey

4 Statistical Matching for Data integration

Given the two survey sources, we apply Statistical Matching (SM) (D'Orazio et al., 2006; Rässler, 2002) which combines information from two or more datasets that share some common variables but are not directly linked at the unit level. SM enables the integration of data by matching records of units in one dataset with similar units in another, based on shared variables X. Specifically, we adopt a micro-level approach to derive a "synthetic" yet "complete" dataset. Although synthetic in nature, the resulting dataset is considered complete because it consolidates a wide range of variables that were originally collected separately in different sources. This approach allows for the integration of complementary information that would otherwise remain fragmented across distinct datasets.

In general, statistical matching relies on information from a donor dataset to estimate or impute values in a recipient dataset. The goal is to generate a unified microdata file where each unit in the recipient dataset is assigned plausible values for the variables that are only available in the donor.

A detailed discussion of Statistical Matching is presented in the literature review provided in Deliverable D2.1. Here, we synthesize the main features of the different approaches and present the results of data integration on the harmonised ESS and Eurobarometer datasets. The non-parametric imputation procedures were implemented based on the StatMatch package for R (D'Orazio, 2014) approach.

4.1 Non parametric Statistical Matching

In nonparametric micro approaches, a complete dataset can be obtained without considering any specific parametric distribution. Nonparametric imputation procedures are generally referred to as "hot deck imputation methods" and involve replacing missing values of one or more variables for a non-respondent (the recipient) with observed values from a respondent (the donor) that is similar to the non-respondent with respect to characteristics observed by both cases. In SM, the method involves filling in missing variables in one dataset by borrowing observed values from the other dataset based on similarities in shared variables. An attractive feature of the hot deck is that only plausible values can be imputed, since values come from observed responses in the donor pool. In hot deck imputation, the two samples are assigned different roles. One sample assumes the role of the *recipient* or *host* dataset: the missing items of each record of the recipient dataset are imputed using records from the other sample, the *donor* file.

Random Hot Deck In "random hot deck" Random Hot Deck the donor is selected randomly from a set of potential donors (e.g. k=3,5,...). The suitable subset of units in the donor files (e.g. donor pool, donation classes, imputation classes or adjustment cells). In particular, units of both the files are usually grouped into homogeneous subsets according to the common variables (e.g. units in the same countries, individuals with the same socio-demographic characteristics, etc.). Any continuous covariates are categorized before proceeding. Cross-classification by a number of covariates can lead to many adjustment cells. Sparseness of donors can lead to the over-usage of a single donor, so some hot decks limit the number of times any donor is used to impute a recipient (Andridge & Little, 2010).

Distance Hot Deck In "distance hot deck", donor units are selected based on their proximity to the recipient, using a defined similarity or distance metric. The donor is chosen according to a deterministic rule, typically selecting the closest match (k=1). Each record in the recipient dataset is matched with the nearest record in the donor file, based on a distance calculated using the matching variables. If two or more donor records are equally distant from a recipient, one of them is selected at random. In an unconstrained distance hot deck, each record in the donor dataset can be used multiple times. In a constrained approach, each record in the donor file can be used only once and specific constraints must be imposed (D'Orazio et al., 2006).

4.1.1 StatMatch package in R for non parametric SM

For the non-parametric integration of the target latent variables `ALLOW` (rejection of immigration) and `FEELING` (perceived benefits of immigration) from the donor dataset European Social Survey (`ESS10`) to the recipient dataset Eurobarometer 93.1 (`ZA7649`), a k-Nearest Neighbor (k-NN) hot deck approach was implemented.

StatMatch (D'Orazio, 2024) is a comprehensive package that implements most of the commonly used SM techniques.

Hot Deck Imputation: introduction The procedure was applied country by country for the 16 countries common to both surveys. The implemented method used k = 5 nearest neighbors for the random hot deck imputation. The Gower distance matrix (Gower, 1971), quantifying the dissimilarity between donor and recipient records, was computed using the daisy function from the cluster package in R, based on 11 common variables (`Age`, `Gender`, `Occupation`, `Domicile`, `Subjective_income` (i.e. Economic difficulties), `Political_Orientation`, `Attachment_country`, `Life_Satisfaction`, `Economy_Satisfaction`, and `TRUST` (i.e. Trust in Institutions) - see Table 1, Section 3). This calculation was performed for each country after the records with missing values in any of the common variables were removed. The resulting Gower distances informed a nearest-neighbor selection process, based on the `StatMatch` (D'Orazio, 2024) R package approach, to identify suitable donors. For each eligible recipient record, the k=5 donor records with the smallest Gower distances (within the same country) were identified. The donor was then randomly selected from this set and its values for the target variables `ALLOW` and `FEELING` were transferred to the recipient's record. The sequence of steps to perform the imputation analysis is:

1. Calculate Gower distances (using `cluster::daisy`).
2. For each recipient, identify the k=5 nearest donors.
3. From these k donors, randomly select one to be the source of imputation. Each of the k donors has an equal chance.

This procedure was successfully applied to all eligible records in the 16 countries.

Comparison of observed and imputed data To assess the quality and plausibility of the imputations, we compare the summary statistics for the two target variables — `ALLOW` and `FEELING` — between the observed values in the ESS dataset and the imputed values in the Eurobarometer dataset. The statistics include minimum, maximum, median, mean, and quartiles.

Table 29: Descriptive statistics for `ALLOW`: ESS vs Imputed Eurobarometer

Statistic	Observed (ESS)	Imputed (Eurobarometer)
Min	-2.877	-2.688
1st Quartile	-0.491	-0.469
Median	-0.075	-0.074
Mean	-0.005	-0.001
3rd Quartile	0.676	0.674
Max	2.671	2.609

Table 30: Descriptive statistics for `FEELING`: ESS vs Imputed Eurobarometer

Statistic	Observed (ESS)	Imputed (Eurobarometer)
Min	-3.074	-2.890
1st Quartile	-0.576	-0.541
Median	0.051	0.025
Mean	0.003	0.007
3rd Quartile	0.621	0.598
Max	2.608	2.469

The comparison indicates that the imputation procedure generally preserves the distributional properties of the original ESS data. The non-parametric imputation procedure, based on the `StatMatch` framework, succeeds in reproducing the overall shape, central tendency, and dispersion of the target variables. Minor deviations are observed in measures such as the mean and quartiles, particularly for the variable `FEELING`, but the imputed data remains a credible approximation of the donor distributions, supporting the validity of the matching approach.

Distributional Comparison Moreover, we examine the distribution of the imputed values in comparison to the observed data. Figures 20 displays density plots of the original and imputed values for the two main target variables. The alignment between the observed and imputed distributions suggests that the imputations are consistent with the empirical data structure.

To explore the quality of the imputations across countries, Figures 21 and 22 show the same comparison disaggregated by country. These plots allow us to verify whether the imputation procedure respects the between-country heterogeneity, particularly in terms of distributional shape and location.

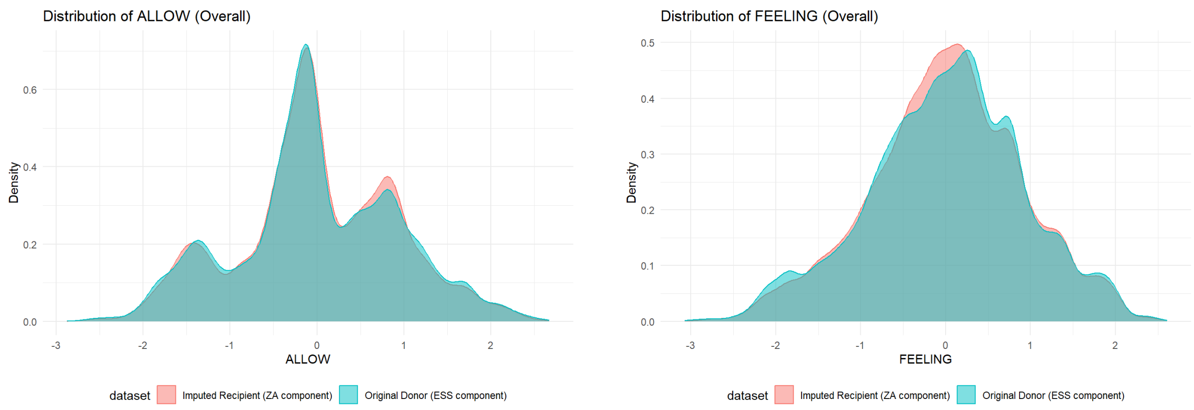

Figure 20: *Hot Deck Imputation*: Density plots for the observed and imputed distribution of the target variables "Immigration rejection" (`ALLOW`) - left - and "Perceived benefits of immigration" (`FEELING`) - right.

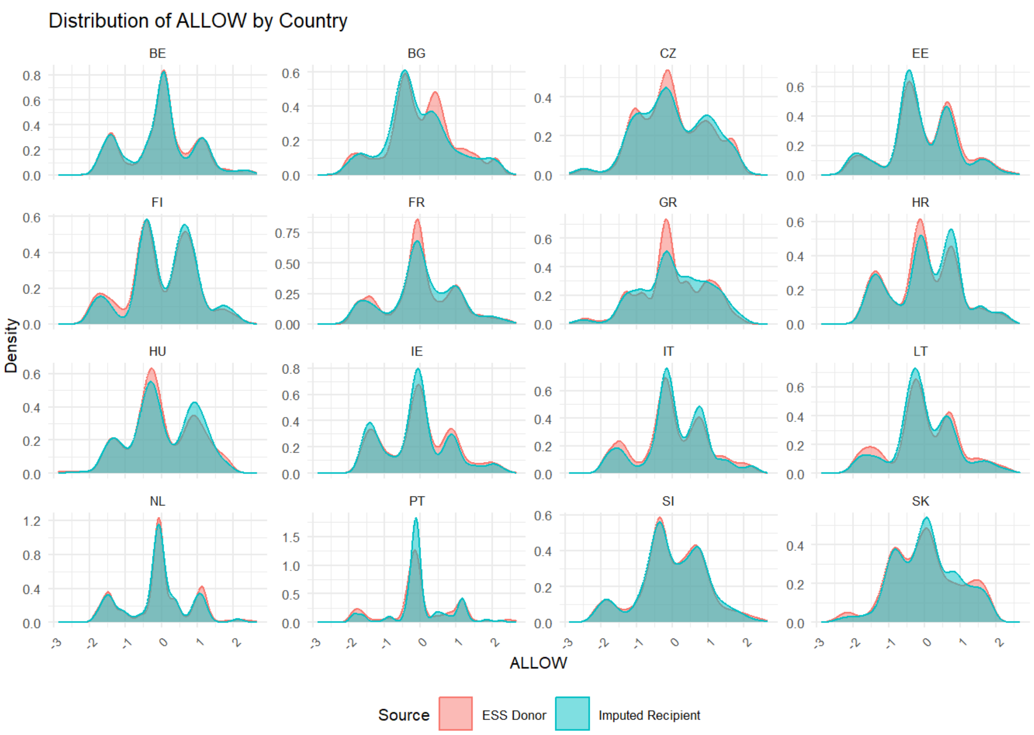

Figure 21: *Hot Deck Imputation*: Density plots for the observed and imputed distribution of the target variable "Immigration rejection" (`ALLOW`) across EU countries.

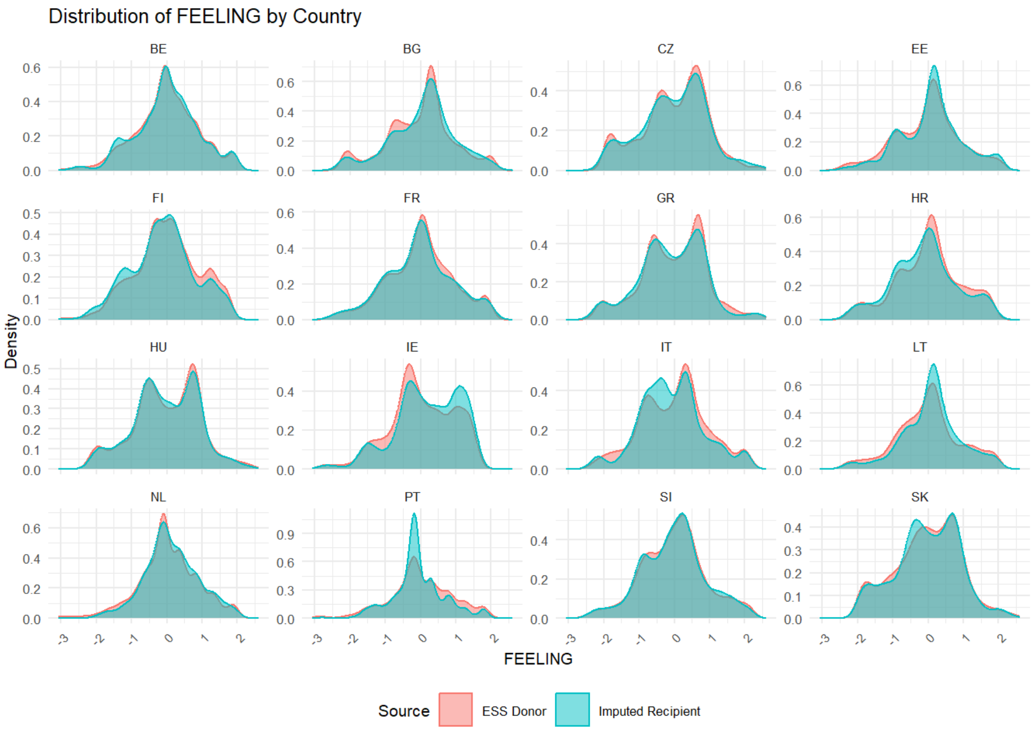

Figure 22: *Hot Deck Imputation*: Density plots for the observed and imputed distribution of the target variable "Perceived benefits of immigration" (`FEELING`) across EU countries.

Similarity Measures To assess the similarity between the distributions of the observed and imputed data, we computed the Hellinger distance (HD) and the Overlap index, discussed in Section 3. These measures quantify the extent to which the imputed distributions deviate from the original (observed) data. Lower values of HD and higher values for Overlap indicate a closer match to the true distribution. Table 31 shows the values of similarity measures for the target variables `ALLOW` and `FEELING`.

Table 31: Similarity measures between the observed and imputed data of the target variables

Target Variable	Overlap Index	Hellinger Distance
`ALLOW`	0.956	0.042
`FEELING`	0.947	0.047

These values indicate a good overall distributional similarity between the original and imputed data.

In particular, a by-country comparison (Cfr. Table 31) exhibit high Overlap Indices (>0.90) and low Hellinger Distances (many <0.10).

Table 32: Distributional similarity measures by Country: best (**bold**) and worst (underline) are emphasized

Country	Overlap Index		Hellinger Distance	
	ALLOW	FEELING	ALLOW	FEELING
BE	**0.949**	0.937	0.062	0.067
BG	0.902	0.931	0.087	0.068
CZ	0.945	0.931	**0.043**	0.068
EE	0.935	0.919	0.061	0.083
FI	0.936	0.932	0.082	0.065
FR	0.934	0.937	0.070	0.062
GR	0.907	0.943	0.073	0.060
HR	0.890	0.904	0.089	0.076
HU	0.928	0.938	0.061	0.066
IE	0.921	0.893	0.066	0.090
IT	0.899	0.890	0.098	0.119
LT	0.897	0.881	0.087	0.097
NL	0.943	**0.949**	0.072	**0.055**
PT	0.862	0.865	0.114	0.079
SI	0.944	0.936	0.066	0.067
SK	0.932	0.914	0.074	0.083

Countries such as Belgium (BE) and Czech Republic (CZ) exhibit the highest overlap values, suggesting a strong match between observed and imputed distributions. Conversely, countries like Portugal (PT) and Croatia (HR) show lower overlap scores, signaling potential mismatches in the distributional shape.

In terms of the Hellinger distance, Czech Republic (CZ) and Greece (GR) show the lowest distances, reflecting a high fidelity of the imputation, while Portugal (PT) and Italy (IT) display higher values, indicating more substantial distributional shifts.

These results highlight the varying effectiveness of the hot deck imputation across countries, potentially reflecting differences in data structures, marginal distributions, or sample sizes within the donor (Eurobarometer) and recipient (ESS) datasets. Nonetheless, the overall magnitude of the metrics remains within acceptable bounds, supporting the credibility of the imputation approach.

Figure 23 and 24 shows the comparison of similarity measures by Country.

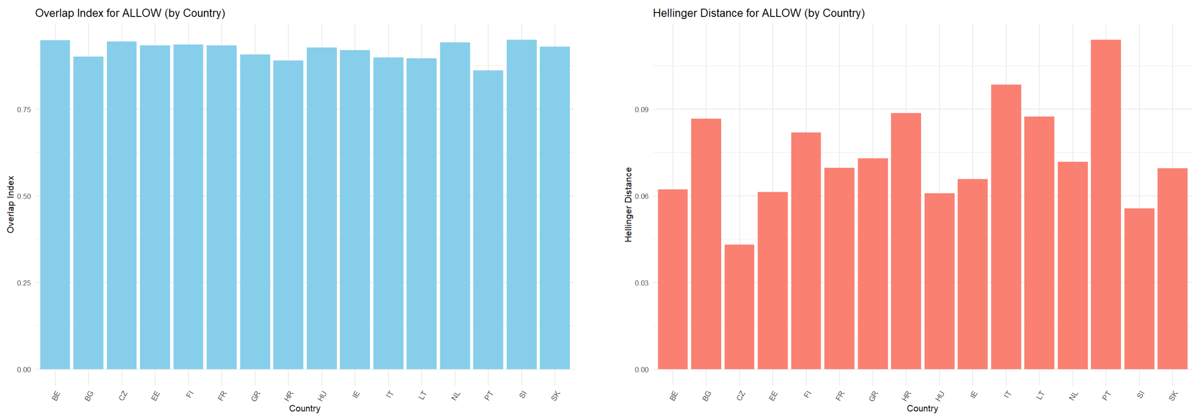

Figure 23: *Hot Deck Imputation*: Comparison of similarity measures by Country for "Immigration rejection" (`ALLOW`): Overlap Index (left) and Hellinger Distance (right).

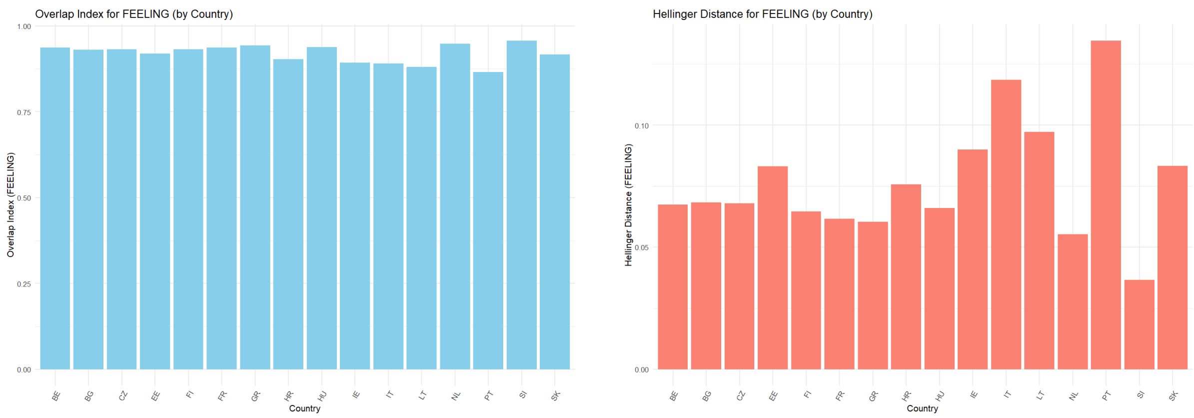

Figure 24: *Hot Deck Imputation*: Comparison of similarity measures by Country for "Perceived benefits of immigration" (`FEELING`): Overlap Index (left) and Hellinger Distance (right).

Conditional Distributional Similarity The analysis of distributional similarity conditioned on the levels of key categorical common variables is useful to understand if the matching quality observed at the aggregate and country level is maintained even in subgroups defined by the levels of the main categorical common variables. Table 33 presents results on analisys which largely indicate robust matching quality across most subgroups. Notably, the best performance is observed among individuals in *small or middle-sized towns*, as well as those who are *not very satisfied with life*, reflecting both high overlap and low divergence.

Conversely, weaker similarity appears in specific subgroups such as individuals *not at all attached to their country*, and those who are *not at all satisfied with life* or rate the *economy as very good*. These groups show lower overlap and higher Hellinger distances, indicating that the imputation procedure may struggle slightly in capturing the distributional characteristics in the extremes of subjective assessments or national attachment.

Nevertheless, the general pattern suggests that the non-parametric hot deck imputation method remains robust across most subpopulations, reinforcing its credibility for use in survey harmonization tasks.

Table 33: Distributional similarity conditional on covariates

Common Variable		Overlap Index		Hellinger Distance	
Variable	**Level Label**	ALLOW	FEELING	ALLOW	FEELING
Gender	Man	0.954	**0.954**	0.046	0.045
	Woman	0.947	0.952	0.045	0.045
Occupation	Employed	0.940	0.935	0.056	0.055
	Unemployed	0.957	0.923	0.054	0.081
	Retired	0.935	0.920	0.062	0.071
	In Education	0.944	0.940	0.054	0.058
Domicile	Big/Large Town	0.923	0.937	0.075	0.055
	Small/Middle Town	0.963	0.953	**0.035**	**0.044**
	Rural/Village	0.935	0.930	0.056	0.068
Subjective income	No	0.941	0.950	0.062	0.045
	Yes	0.928	0.936	0.063	0.060
Political Orientation	Left	0.935	**0.954**	0.066	0.049
	Centre	0.950	0.943	0.051	0.051
	Right	0.939	0.942	0.060	0.051
Attachment country	Not at all attached	0.870	0.877	0.114	0.143
	Not very attached	0.915	0.919	0.097	0.076
	Fairly attached	0.934	0.953	0.057	0.057
	Very attached	0.921	0.923	0.063	0.062
Life Satisfaction	Not at all satisfied	0.892	0.879	0.105	0.097
	Not very satisfied	**0.964**	0.944	0.040	0.059
	Fairly satisfied	0.940	0.935	0.057	0.060
	Very satisfied	0.938	**0.954**	0.054	0.045
Economy Satisfaction	Rather bad	0.944	0.922	0.057	0.070
	Not very good	0.950	0.946	0.051	0.054
	Rather good	0.949	0.949	0.054	0.049
	Very good	0.924	0.926	0.064	0.063

Assessment of Relational Consistency Beyond the similarity of marginal distributions, a crucial aspect of evaluating the quality of statistical imputation is its ability to preserve existing relationships between variables. In this section, we examine the correlation between the two imputed target variables, the relationship between these and the common variables, and finally, we compare the imputed Feeling variable with a similar pre-existing measure in the recipient dataset.

Correlation between `ALLOW` and `FEELING` The relationship between the two imputed target variables, `ALLOW` (rejection of immigration) and `FEELING` (perceived benefits of immigration), was assessed by comparing their pairwise correlation in the donor dataset (ESS) and the imputed dataset (Eurobarometer). At the aggregate level, the correlation observed in the donor data is *-0.765*, while the correlation in the imputed data is remarkably close at *-0.758*, suggesting that the imputation process preserved the global covariance structure of the two constructs.

This strong preservation is further confirmed by a detailed analysis at the country level (Cfr. Table 34). In most countries, the correlation in the imputed data closely mirrors that of the donor dataset. For example, in Czechia and Italy, both datasets exhibit strong negative correlations (e.g., -0.851 vs. -0.875 for CZ; -0.845 vs. -0.848 for IT), highlighting the robustness of the matching process. Even in countries with weaker initial correlations, such as Greece or Croatia, the imputed values remain aligned in direction and magnitude.

Table 34: Correlation between `ALLOW` and `FEELING` by Country

Country	ESS (Observed)	Eurobarometer (Imputed)
BE	-0.780	-0.779
BG	-0.692	-0.689
CZ	-0.851	-0.875
EE	-0.812	-0.792
FI	-0.793	-0.786
FR	-0.783	-0.774
GR	-0.566	-0.548
HR	-0.669	-0.679
HU	-0.791	-0.790
IE	-0.756	-0.733
IT	-0.845	-0.848
LT	-0.778	-0.775
NL	-0.824	-0.818
PT	-0.799	-0.779
SI	-0.782	-0.762
SK	-0.812	-0.819
Aggregate	**-0.765**	**-0.758**

These results demonstrate that the non-parametric hot deck procedure succeeded in maintaining a consistent and substantively meaningful relationship between the two core variables, across both aggregate and disaggregated contexts. This preservation of structural validity supports the credibility of the imputed dataset for subsequent analyses involving attitudinal dimensions of immigration.

Regression Analysis of Target Variables on Common Variables To assess the extent to which the relationship between the target variables (`ALLOW` and `FEELING`) and the common variables is preserved post-imputation, we conducted multiple linear regressions separately on the donor dataset (ESS) and the recipient dataset (Eurobarometer with imputed values). The modeling strategy closely follows that in Section 3.7, with polynomial contrasts applied to ordinal predictors where appropriate.

Regarding the imputation quality, the comparison of models between the donor (ESS) and imputed recipient (Eurobarometer) datasets suggests that the imputation process was generally successful in maintaining the analytical validity of the data. While many key relationships were preserved for both `ALLOW` and `FEELING`, some variations in coefficient magnitudes or significance levels were observed (Cfr.

Table 35 and 36 for donor ESS dataset; Table 37 and 38 for imputed recipient Eurobarometer Data). These findings are crucial for understanding the utility of the imputed dataset for subsequent substantive research.

Table 35: Regression Analysis of `ALLOW` on Common Variables (Donor Data)

Variable	**Category / Trend**	**Estimate**	**Std. Error**	**t-value**	**p-value**	**Signif.**
Intercept	–	-0.646	0.031	-21.125	<0.001	***
Age	–	0.006	0.001	11.445	<0.001	***
Gender	Man (Ref.)					
	Woman	-0.068	0.012	-5.511	<0.001	***
Occupation	Employed (Ref.)					
	Unemployed	0.044	0.021	2.051	0.040	*
	Retired	0.086	0.020	4.359	<0.001	***
	In Education	-0.129	0.029	-4.430	<0.001	***
Domicile	Big / Large Town (Ref.)					
	Small / Middle Town	0.100	0.015	6.550	<0.001	***
	Rural / Village	0.192	0.014	13.304	<0.001	***
Subjective Income	No (Ref.)					
	Yes	0.059	0.011	5.340	<0.001	***
Political Orientation	Left (Ref.)					
	Centre	0.294	0.016	18.585	<0.001	***
	Right	0.437	0.020	21.681	<0.001	***
Attachment to Country	Linear trend	6.165	0.912	6.756	<0.001	***
	Quadratic trend	4.123	0.891	4.629	<0.001	***
	Cubic trend	-0.627	0.879	-0.713	0.476	
Life Satisfaction	Linear trend	-7.298	0.987	-7.391	<0.001	***
	Quadratic trend	0.191	0.903	0.212	0.832	
	Cubic trend	-3.905	0.884	-4.419	<0.001	***
Economy Satisfaction	Linear trend	-3.941	1.009	-3.905	<0.001	***
	Quadratic trend	4.793	0.900	5.328	<0.001	***
	Cubic trend	-0.903	0.883	-1.023	0.306	
TRUST	–	-0.187	0.008	-24.688	<0.001	***

Significance codes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 36: Regression Analysis of FEELING on Common Variables (Donor Data)

Variable	Category / Trend	Estimate	Std. Error	t-value	p-value	Signif.
Intercept	–	0.471	0.030	15.831	<0.001	***
Age	–	-0.003	0.001	-6.066	<0.001	***
Gender	Man (Ref.)					
	Woman	0.059	0.012	4.959	<0.001	***
Occupation	Employed (Ref.)					
	Unemployed	-0.051	0.021	-2.464	0.014	*
	Retired	-0.091	0.019	-4.744	<0.001	***
	In Education	0.037	0.028	1.313	0.189	
Domicile	Big / Large Town (Ref.)					
	Small / Middle Town	-0.061	0.015	-4.111	<0.001	***
	Rural / Village	-0.159	0.014	-11.319	<0.001	***
Subjective Income	No (Ref.)					
	Yes	-0.044	0.011	-4.079	<0.001	***
Political Orientation	Left (Ref.)					
	Centre	-0.269	0.015	-17.497	<0.001	***
	Right	-0.430	0.020	-21.935	<0.001	***
Attachment to Country	Linear trend	-3.828	0.888	-4.313	<0.001	***
	Quadratic trend	-4.189	0.866	-4.835	<0.001	***
	Cubic trend	0.403	0.855	0.471	0.638	
Life Satisfaction	Linear trend	8.166	0.960	8.502	<0.001	***
	Quadratic trend	-0.281	0.878	-0.321	0.749	
	Cubic trend	4.704	0.860	5.472	<0.001	***
Economy Satisfaction	Linear trend	10.760	0.982	10.962	<0.001	***
	Quadratic trend	-5.824	0.875	-6.655	<0.001	***
	Cubic trend	1.600	0.859	1.863	0.062	
TRUST	–	0.240	0.007	32.579	<0.001	***

Significance codes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

For the variable ALLOW, the donor model reveals a number of strong and expected associations: for example, TRUST (Trust in Institution) is positively and significantly related to more permissive attitudes toward immigration, as is greater life satisfaction and confidence in the national economy. Attachment to Country shows a clear non-linear effect, with a strong negative linear trend suggesting that the more one feels attached to their country, the less likely they are to endorse immigration, though the quadratic and cubic components show nuanced curvature in the relationship. Importantly, these same patterns are reflected — albeit with slightly reduced magnitude — in the imputed dataset. The fact that the direction and statistical significance of the key coefficients are preserved suggests that the imputation procedure has not disrupted the core structure of relationships that define public attitudes on immigration.

Table 37: Regression Analysis of ALLOW on Common Variables (Imputed Recipient Data)

Variable	Category / Trend	Estimate	Std. Error	t-value	p-value	Signif.
Intercept	–	-0.474	0.043	-10.991	<0.001	***
Age	–	0.003	0.001	3.566	<0.001	***
Gender	Man (Ref.)					
	Woman	-0.044	0.017	-2.681	0.007	**
Occupation	Employed (Ref.)					
	Unemployed	-0.001	0.035	-0.033	0.974	
	Retired	0.198	0.025	7.803	<0.001	***
	In Education	-0.237	0.041	-5.811	<0.001	***
Domicile	Big / Large Town (Ref.)					
	Small / Middle Town	0.111	0.020	5.451	<0.001	***
	Rural / Village	0.196	0.021	9.355	<0.001	***
Subjective Income	No (Ref.)					
	Yes	0.118	0.013	8.858	<0.001	***
Political Orientation	Left (Ref.)					
	Centre	0.262	0.023	11.478	<0.001	***
	Right	0.388	0.029	13.279	<0.001	***
Attachment to Country	Linear trend	1.270	0.897	1.416	0.157	
	Quadratic trend	0.413	0.876	0.471	0.637	
	Cubic trend	1.161	0.873	1.329	0.184	
Life Satisfaction	Linear trend	-3.379	0.989	-3.418	0.001	***
	Quadratic trend	-1.595	0.890	-1.792	0.073	
	Cubic trend	-0.794	0.878	-0.905	0.366	
Economy Satisfaction	Linear trend	-5.290	0.972	-5.443	<0.001	***
	Quadratic trend	0.461	0.887	0.520	0.603	
	Cubic trend	0.145	0.876	0.165	0.869	
TRUST	–	-0.117	0.011	-10.993	<0.001	***

Significance codes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

Table 38: Regression Analysis of FEELING on Common Variables (Imputed Recipient Data)

Variable	Category / Trend	Estimate	Std. Error	t-value	p-value	Signif.
Intercept	–	0.371	0.042	8.843	<0.001	***
Age	–	-0.001	0.001	-1.761	0.078	
Gender	Man (Ref.)					
	Woman	0.020	0.016	1.263	0.207	
Occupation	Employed (Ref.)					
	Unemployed	-0.017	0.034	-0.482	0.630	
	Retired	-0.113	0.025	-4.575	<0.001	***
	In Education	0.137	0.040	3.460	0.001	***
Domicile	Big / Large Town (Ref.)					
	Small / Middle Town	-0.078	0.020	-3.942	<0.001	***
	Rural / Village	-0.191	0.020	-9.366	<0.001	***
Subjective Income	No (Ref.)					
	Yes	-0.113	0.013	-8.733	<0.001	***
Political Orientation	Left (Ref.)					
	Centre	-0.238	0.022	-10.732	<0.001	***
	Right	-0.367	0.028	-12.892	<0.001	***
Attachment to Country	Linear trend	-0.697	0.872	-0.799	0.424	
	Quadratic trend	-1.922	0.851	-2.258	0.024	*
	Cubic trend	-1.373	0.849	-1.618	0.106	
Life Satisfaction	Linear trend	4.078	0.961	4.244	<0.001	***
	Quadratic trend	1.634	0.865	1.888	0.059	
	Cubic trend	0.225	0.853	0.264	0.792	
Economy Satisfaction	Linear trend	7.583	0.945	8.028	<0.001	***
	Quadratic trend	-2.209	0.862	-2.562	0.010	**
	Cubic trend	0.169	0.852	0.199	0.843	
TRUST	–	0.174	0.010	16.807	<0.001	***

Significance codes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

For FEELING, which measures perceived benefits from immigration, similar patterns emerge. Again, institutional trust, political orientation, and socio-economic satisfaction are significant and directionally consistent drivers of sentiment. The consistency of the regression coefficients between the donor and imputed datasets is particularly reassuring here, as this variable captures a more affective, potentially culturally embedded dimension. Some minor changes in coefficient size are visible, such as a reduction in the effect of life satisfaction or the flattening of non-linear components, but these are in line with expectations from any non-parametric imputation process.

Overall, the regression tables indicate that the imputation retained not only the individual relationships between predictors and outcomes but also the multivariate structure of the data.

The accompanying regression plots in Figure 25 and 26 provide a valuable visual complement to the tables, allowing for a quick and intuitive assessment of model stability across the donor and imputed datasets. These plots show the coefficients of each predictor in the donor model plotted against their counterparts in the imputed model.

What is immediately striking is the tight clustering of most points around the identity line — the line where donor and imputed estimates would be equal. This suggests a high degree of correspondence between the two models. Variables such as `TRUST`, `Age`, and `Political Orientation` show particularly strong alignment, reinforcing their role as stable predictors across datasets. There are, however, a few instances where some divergence is visible. For instance, the coefficients for `Attachment to Country` and `Subjective Income` show slightly more variability, likely reflecting the limitations of donor-recipient matches in capturing more subjective or complex constructs.

Nonetheless, these deviations are small in absolute terms and do not appear to reverse the direction of any relationship. This stability is a strong indicator that the imputed data can be used with a degree of confidence comparable to the original ESS data for analyses that depend on regression structure.

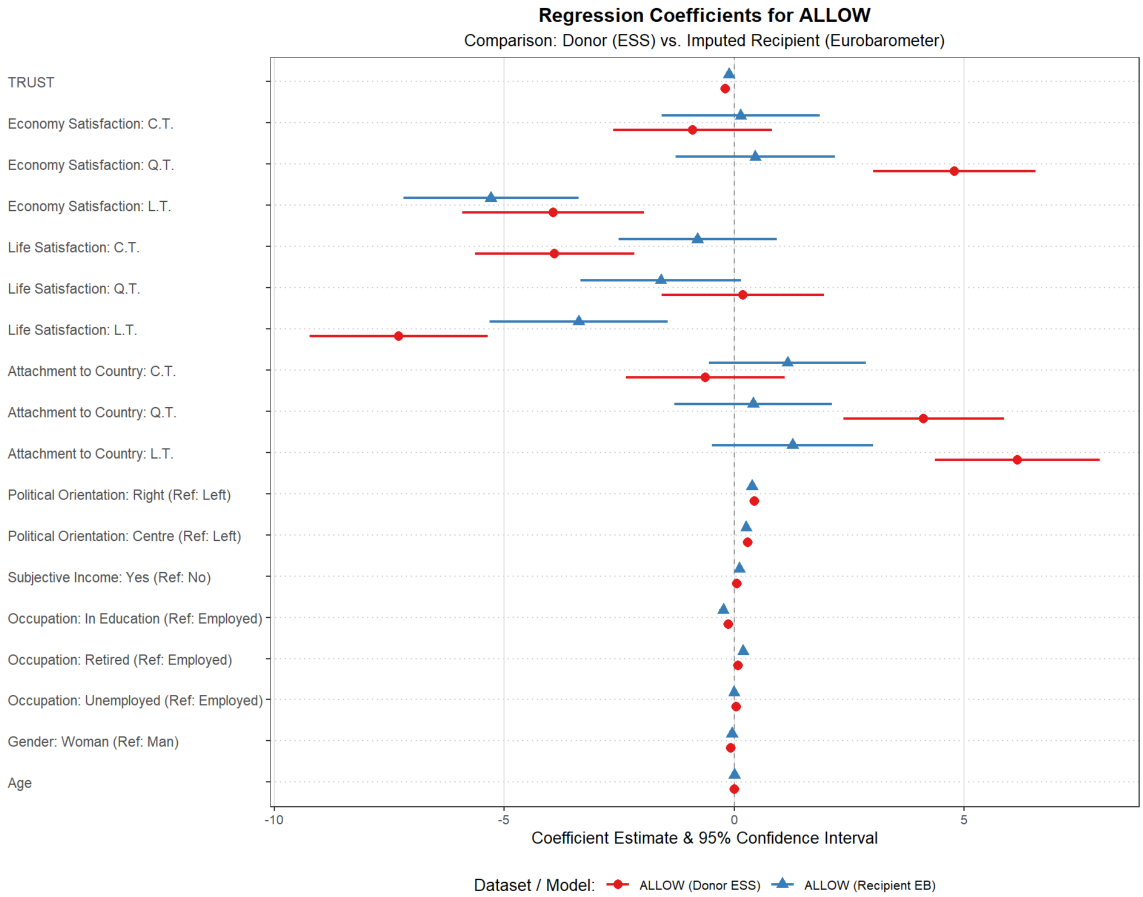

Figure 25: Comparison Of Regression Coefficients for the target variable “Immigration rejection” (`ALLOW`): Donor (ESS) vs. Imputed Recipient (Eurobarometer).

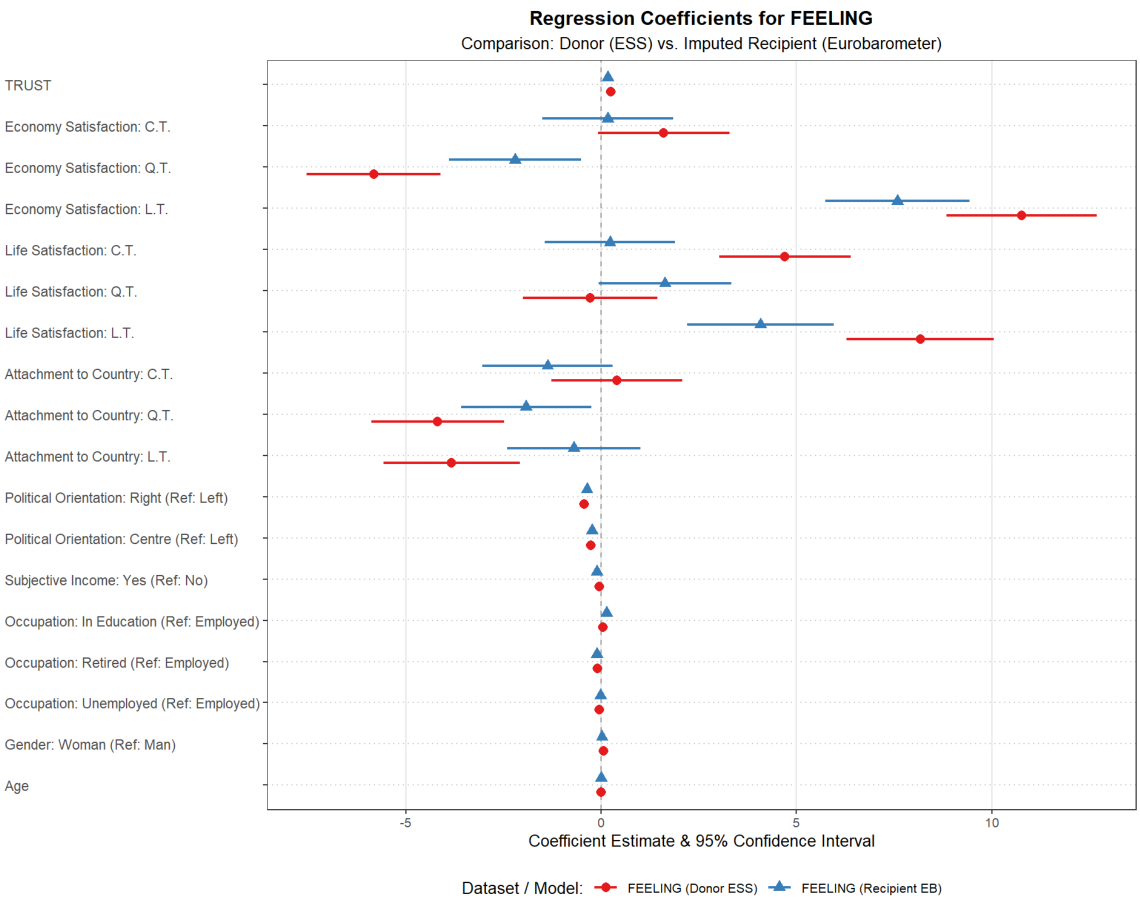

Figure 26: Comparison Of Regression Coefficients for the target variable “perceived benefits of immigration” (`FEELING`): Donor (ESS) vs. Imputed Recipient (Eurobarometer).

The results of the regression analyses offer a compelling validation of the imputation strategy employed. The Hot Deck approach appears to have preserved not only the marginal distributions of key variables, as shown in previous sections, but also the structural relationships that underpin attitudinal dynamics in the data. This is a non-trivial achievement: preserving multivariate regression structure requires that the imputation respect complex interaction patterns and latent associations, something that is often lost in more simplistic matching procedures.

The small differences that do exist are both interpretable and expected. They reflect the known tendency for imputed datasets to exhibit slight attenuation in effect size due to averaging over similar — but not identical — donor profiles. Importantly, no systematic bias or directional distortion is observed.

In sum, the evidence supports the conclusion that the imputed Eurobarometer data remains analytically compatible with the donor ESS structure, enabling meaningful secondary analysis of attitudinal patterns with a high degree of validity.

Convergent Validity Check: Imputed `FEELING` vs. Original Eurobarometer `FEELING_ZA` To assess the convergent validity of the imputed `FEELING` variable, we compare it with the original `FEELING_ZA` variable available in the Eurobarometer (recipient) dataset. This original variable, though potentially measuring a slightly different nuance or using a different scale, serves as a valuable external benchmark.

A moderate to strong positive correlation and similar distributional properties would support the validity of the imputed FEELING.

The convergent validity assessment for the imputed FEELING variable, through comparison with the original FEELING_ZA from the Eurobarometer survey, yields positive results. Descriptive statistics (Cfr. Table 39) and raw distributions (Cfr. Figure 27) reveal striking similarity between the two variables. Quantitative similarity metrics provide further support, with evidence of an high degree of shared distributional mass (Overlap Index of 0.849) and low divergence between the two distributions (Hellinger Distance of 0.140).

Table 39: Descriptive statistics: FEELING (imputed) vs. FEELING_ZA (original)

Statistic	FEELING **(imputed)**	FEELING_ZA **(original)**
Min	-2.89	-2.75
1st Quartile	-0.541	-0.566
Median	0.0025	-0.049
Mean	0.007	0.000
3rd Quartile	0.598	0.619
Max	2.469	2.809
SD	0.891	0.906
N	11206	11206

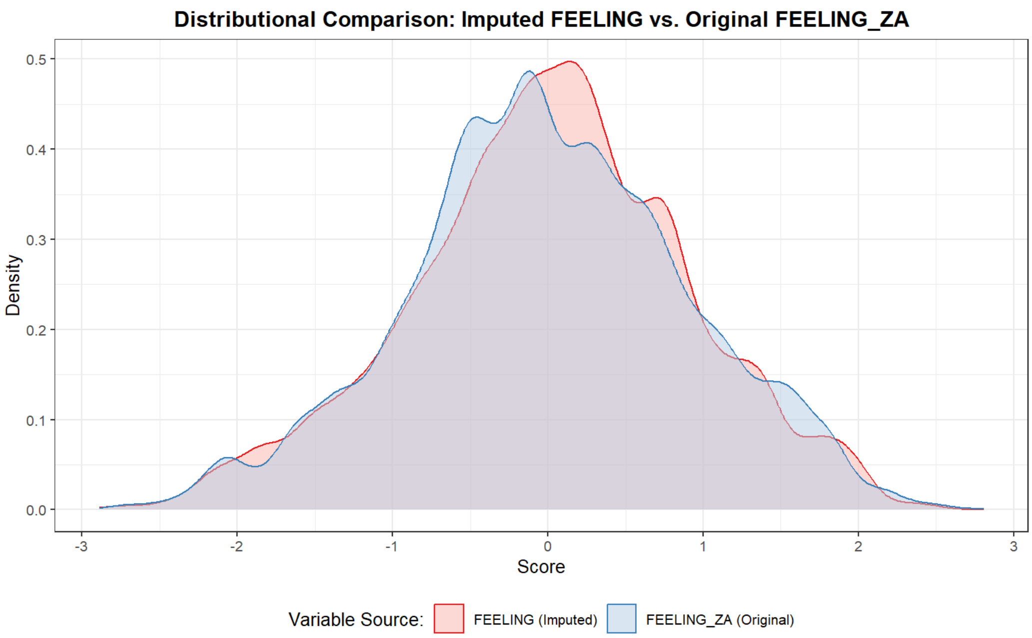

Figure 27: Distributional Comparison: Imputed target variable "perceived benefits of immigration" (FEELING) vs. original (FEELING_ZA).

While the Pearson and Spearman correlations between the imputed and original variables are moderate (approximately -0.135), this is acceptable given potential differences in context and framing between the original and imputed questions. The direction and strength of association suggest a weak but non-trivial consistency between the two measures (Cfr. Figure 28).

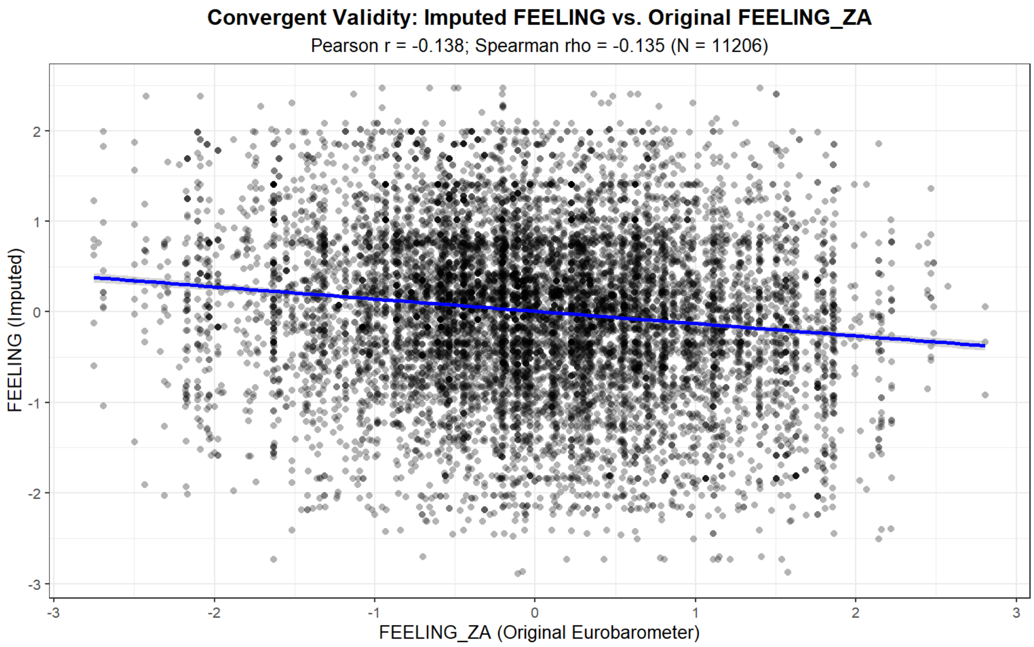

Figure 28: Convergent Validity: Imputed `FEELING` vs. Original `FEELING_ZA`.

The Quantile-Quantile (QQ) plot shows a generally linear relationship along the bisector line, confirming that the distributions of `FEELING` and `FEELING_ZA` are well-aligned across most of their range. Slight deviations in the tails are expected and do not undermine the overall fidelity (Cfr. Figure 29).

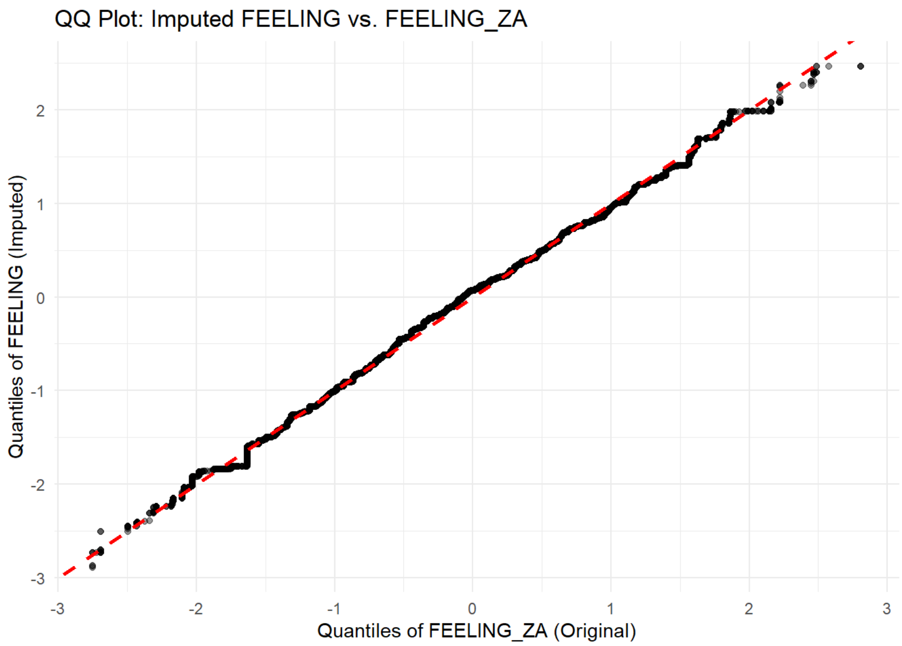

Figure 29: QQ plot: Imputed `FEELING` vs. Original `FEELING_ZA`.

The results suggests that the imputed `FEELING` can be used with reasonable confidence in analyses aiming to explore attitudes similar to those covered by the original Eurobarometer item, bearing in mind the scaling differences observed.

4.2 Data integration in multilevel data using parametric Statistical Matching approaches

Considering the hierarchical structure of the ESS and Eurobarometer surveys, where respondents are nested within countries, a suitable approach to address the data integration process of target variables from the ESS dataset to the Eurobarometer one is the use of multilevel models within a parametric Statistical Matching (SM) framework (D'Orazio et al., 2006; Rässler, 2002).

Parametric SM methods Parametric methods are model-based imputation techniques that rely on an assumed underlying parametric distribution. In the context of SM, parametric methods typically involve specifying a statistical model that captures the relationships between the target variables and the common variables. Once the model is defined, its parameters are estimated using the ESS (donor) dataset through either frequentist or Bayesian approaches. Based on the estimated model, a synthetic dataset with completed records can be generated by imputing the missing items in the Eurobarometer (recipient) dataset with values drawn from the conditional distribution of the target variables, given the observed variables.

Two widely used parametric micro-level methods in SM are conditional mean matching and draws from the predictive distribution.

Conditional Mean Matching is a parametric imputation technique that fills in missing data using the conditional expectation of the missing variable. When the target variables are assumed to follow a normal distribution, this approach corresponds to regression imputation. The method is straightforward and computationally efficient: each missing value is replaced by a single predicted value, thereby simplifying the imputation process. However, because it imputes deterministic values, this method tends to underestimate variability and can lead to biased variance estimates.

Draws from the Conditional Predictive Distribution, by contrast, is a parametric imputation approach that preserves variability by sampling imputed values from the predictive distribution of the missing variable. In this case, missing values in the Eurobarometer dataset are replaced with random draws from their respective conditional predictive distributions, given the common variables. When the target variables follow a multivariate normal distribution, this approach is commonly referred to as stochastic regression imputation.

It is important to note that both methods typically result in a single imputed dataset, which may underestimate the uncertainty and variability associated with the missing data.

Multiple Imputation (MI) procedures are often preferred, as they generate multiple datasets and allow for valid inferences by incorporating imputation uncertainty. MI involves generating multiple plausible values for each missing entry by drawing from the conditional predictive distribution. Each of these imputations reflects the inherent uncertainty in the imputation process, creating multiple completed datasets that can be analyzed separately. The results from these analyses are then pooled to provide final estimates that incorporate both within-imputation and between-imputation variability. Transferring MI procedures from the general missing data situation to the statistical matching task was proposed by Rubin (1986, 1987). The Bayesian approach is the usual framework for multiple imputation (D'Orazio et al., 2006). A Bayesian proper form of multiple imputation uses the method of chained equations.

The MI process consists of the following steps:

1. **Specifying an imputation model:** A probability distribution is specified for the data, representing the assumed data-generating mechanism. This model forms the basis for imputing missing values.

2. **Generating m complete datasets:** Using the imputation model, each missing value is replaced by m plausible values, leading to m complete versions of the dataset.

3. **Performing statistical analysis:** The same analysis (e.g., regression, hypothesis testing) is applied independently to each of the m completed datasets. This yields m sets of parameter estimates and standard errors.

4. **Pooling the results:** The m sets of estimates are combined using **Rubin's rules** (Rubin, 1987) detailed below. The pooled estimate is calculated as the average of the m individual estimates, while the total variance accounts for both:

   - the *within-imputation variance* (the average of the variances from each dataset), and
   - the *between-imputation variance* (the variance of the parameter estimates across datasets),

   appropriately adjusted for the number of imputations.

5. Assess whether imputations are plausible. Imputations should be values that could have been obtained had they not been missing. Imputations should be close to the data. Data values that are clearly impossible should not occur in the imputed data. Imputations should respect relations between variables and reflect the appropriate amount of uncertainty about their 'true' values.

Rubin's Rules for Pooling Estimates.
Let m denote the number of imputed datasets. For each dataset $i = 1, \dots, m$, let $\hat{Q}_i$ be the estimate of the quantity of interest (e.g., a regression coefficient), and let U_i be the associated variance estimate.

- *Pooled estimate (mean across imputations)*: $\bar{Q} = \frac{1}{m}\sum_{i=1}^{m}\hat{Q}_i$
- *Within-imputation variance*: $\bar{U} = \frac{1}{m}\sum_{i=1}^{m}U_i$
- *Between-imputation variance*: $B = \frac{1}{m-1}\sum_{i=1}^{m}(\hat{Q}_i - \bar{Q})^2$
- *Total variance*: $T = \bar{U} + \left(1 + \frac{1}{m}\right)B$

The pooled estimate $\bar{Q}$ can be used as the point estimate of the parameter of interest, and T represents its total variance, accounting for both within- and between-imputation uncertainty.

Multiple Imputation of Multivariate Missing Data When dealing with multivariate missing data, two main approaches are commonly used for imputation: *Joint Modelling* (JM) and *Fully Conditional Specification* (FCS).

In the **Joint Modelling** (JM) approach (Schafer, 1997), a single statistical model is used to impute all incomplete variables simultaneously. JM assumes that the data follow a **multivariate distribution**, and imputations are generated as draws from the corresponding conditional distributions using Markov Chain Monte Carlo (MCMC) techniques.

JM uses the following imputation scheme (van Buuren, 2018):

- Imputing missing values given current estimates of the parameters.

$$Y_{\text{mis}}^{(t)} \sim P\left(Y_{\text{mis}} \mid Y_{\text{obs}}, X, \theta^{(t-1)}\right)$$

- Updating the parameter estimates based on the completed data.

$$\theta^{(t)} \sim P\left(\theta \mid Y_{\text{obs}}, Y_{\text{mis}}^{(t)}, X\right)$$

In the **Fully Conditional Specification** (FCS) approach, also known as *chained equations* or *sequential regression*, is a widely used method for the multiple imputation of multivariate missing data (Van Buuren et al., 2006). Unlike Joint Modelling, FCS imputes missing values on a variable-by-variable basis. Specifically, it requires the specification of a **univariate imputation model** for each variable with missing data. These models are then used in an iterative procedure, where each incomplete variable is imputed conditionally on all other variables in the dataset.

Formally, the FCS approach defines the joint distribution $P(Y, X, R \mid \theta)$ through a set of conditional densities, one for each incomplete variable Y_j, such that

$$P(Y_j \mid X, Y_{-j}, R, \varphi_j),$$

where Y_{-j} denotes all variables except Y_j, X includes covariates, and R indicates the missingness pattern (van Buuren, 2018). These conditional distributions are then used to sequentially update and impute the missing values in Y_j given the observed data.

Compared to JM, FCS offers greater flexibility in practical applications, as it allows each univariate imputation model to be tailored to the specific type and distribution of the corresponding variable (e.g., linear regression for continuous variables, logistic regression for binary variables, or ordinal models). This modularity makes FCS particularly attractive in settings where the data include variables of different types, or where specifying a coherent multivariate distribution is challenging. However, unlike JM, FCS does not guarantee that the set of conditional models corresponds to a valid joint distribution, which may raise theoretical concerns in some contexts.

Multiple Imputation of Multilevel Multivariate Missing Data Given the hierarchical nature of the ESS and Eurobarometer data, with respondents nested within countries, it is crucial to account for this multilevel structure during the imputation process.

When dealing with multilevel data—where lower-level units (e.g., individuals or respondents) are nested within higher-level units (e.g., schools, countries)—it is essential that the imputation model reflects the hierarchical structure of the data. In general, the imputation model must be at least as general as the analysis model to avoid biased estimates and invalid inference. This implies that multilevel dependencies must be explicitly incorporated into the imputation procedure.

Both JM and FCS approaches can be extended to multilevel settings by including random effects in the imputation models:

- The `pan` package for R (Grund et al., 2016) implements a JM approach based on multivariate linear mixed models and is designed to handle continuous multilevel data. It also serves as the backend for the `mitml` package (Grund et al., 2023), which provides a user-friendly interface and tools for the analysis and pooling of multiply imputed multilevel datasets.
- The `mice` package (van Buuren & Groothuis-Oudshoorn, 2011) supports FCS for multilevel data through specialized methods, such as `2l.pan`, which allows for imputing level-1 variables with random intercepts at level-2. This extension enables variable-by-variable imputation while preserving the hierarchical structure in the data.

Accounting for the multilevel structure in the imputation model ensures that between- and within-cluster variability are properly captured, leading to more reliable imputations and valid statistical inference in multilevel analyses.

In our, study we implement the FCS approach through the `mice` package (van Buuren, 2024) for R and the JM approach using the `mitml` (Grund et al., 2023) package for R.

4.2.1 Multiple Imputation for Multilevel Multivariate Data Using the `mice` and `mitml` Packages

We applied multiple imputation using both the **Fully Conditional Specification (FCS)** and **Joint Modelling (JM)** approaches, tailored to single-level and multilevel data structures.

- **FCS via the `mice` package** (van Buuren & Groothuis-Oudshoorn, 2011):
  - *Single-level model (FCSsl)*: Standard univariate regression imputation using the method `norm`.
  - ***Multilevel models***:
    - *Random intercept only (FCSri)*: Imputation with random intercepts using `2l.pan`.
    - *Random intercept and slope (FCSrs)*: A more flexible multilevel model with both random intercepts and slopes, also implemented via `2l.pan`.
- **JM via the `mitml` package** (Grund et al., 2023):
  - *Country-wise imputation (JMsep)*: Separate imputations performed within each group using `jomo.impute`.
  - ***Multilevel models***:
    - *Random intercept only (JMri)*: Multivariate linear mixed model with random intercepts, implemented via `pan.impute`.
    - *Random intercept and slope (JMrs)*: Full multilevel imputation model with both random intercepts and slopes, also using `pan.impute`.

All methods were implemented in R, generating $m = 10$ imputed datasets for each scenario.

In the following, we provide a synthesis of the results obtained using the different imputation methods.

Comparison of observed and imputed data Figure 30 displays density plots to compare imputed and reference distributions under different multiple imputation strategies. Each panel compares the density of the two target variables — *Immigration rejection* (left) and *Perceived benefits of immigration* (right) — using different imputation models. The blue line represents the original distribution in the ESS donor dataset, while the red line represents the distribution in the Eurobarometer recipient dataset after statistical matching via multiple imputation. Model complexity increases from top to bottom: from single-level imputation (FCSsl, JMsep) to multilevel with random intercepts (FCSri, JMri) and random slopes (FCSrs, JMrs).

Distribution comparison through Hellinger distance and Overlap is discussed in Section ???? where we compare the results of the previous approaches with the ones obtained through the integrated model presented in Section ??.

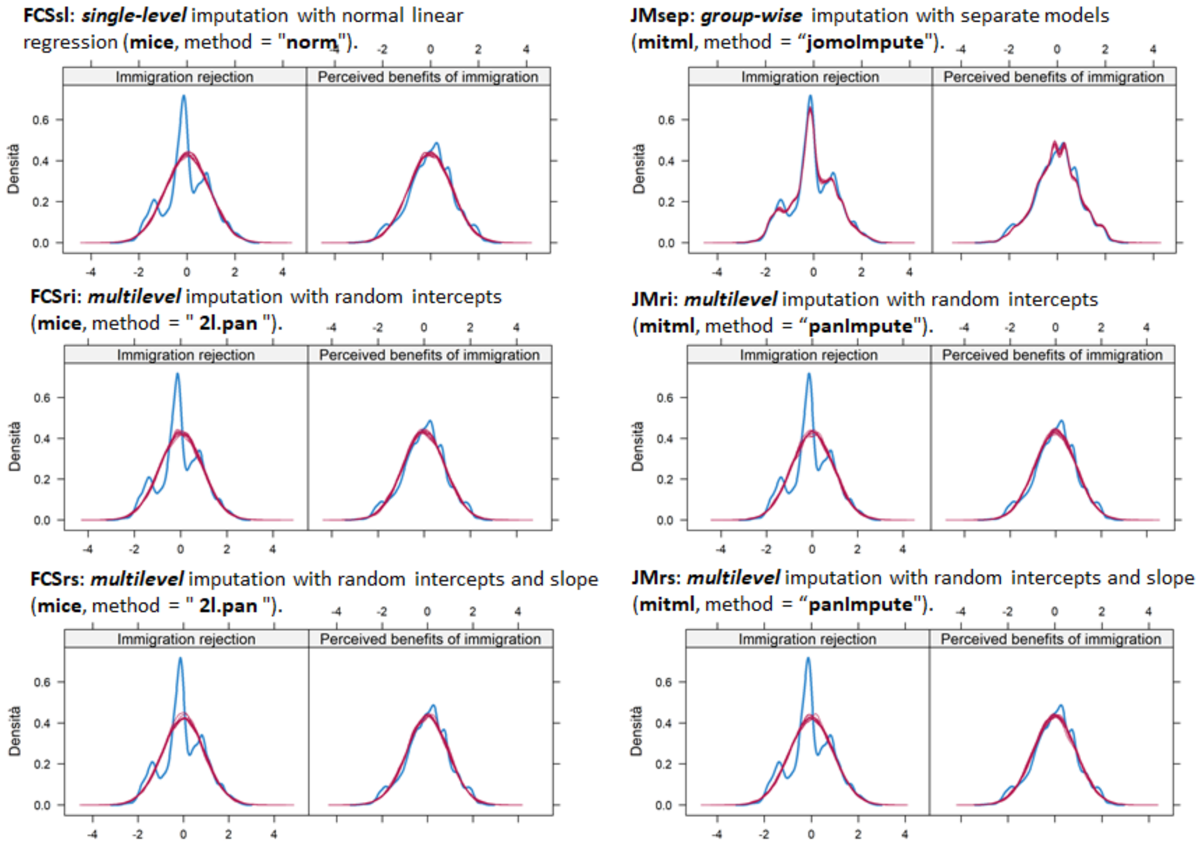

Figure 30: Density plots for the observed (blue) and imputed (red) distribution of the target variables

Figures 31 to 42 show the same comparison disaggregated by country. The alignment between the observed and imputed distributions suggests that the imputations are consistent with the empirical data structure at the overall level and for each country.

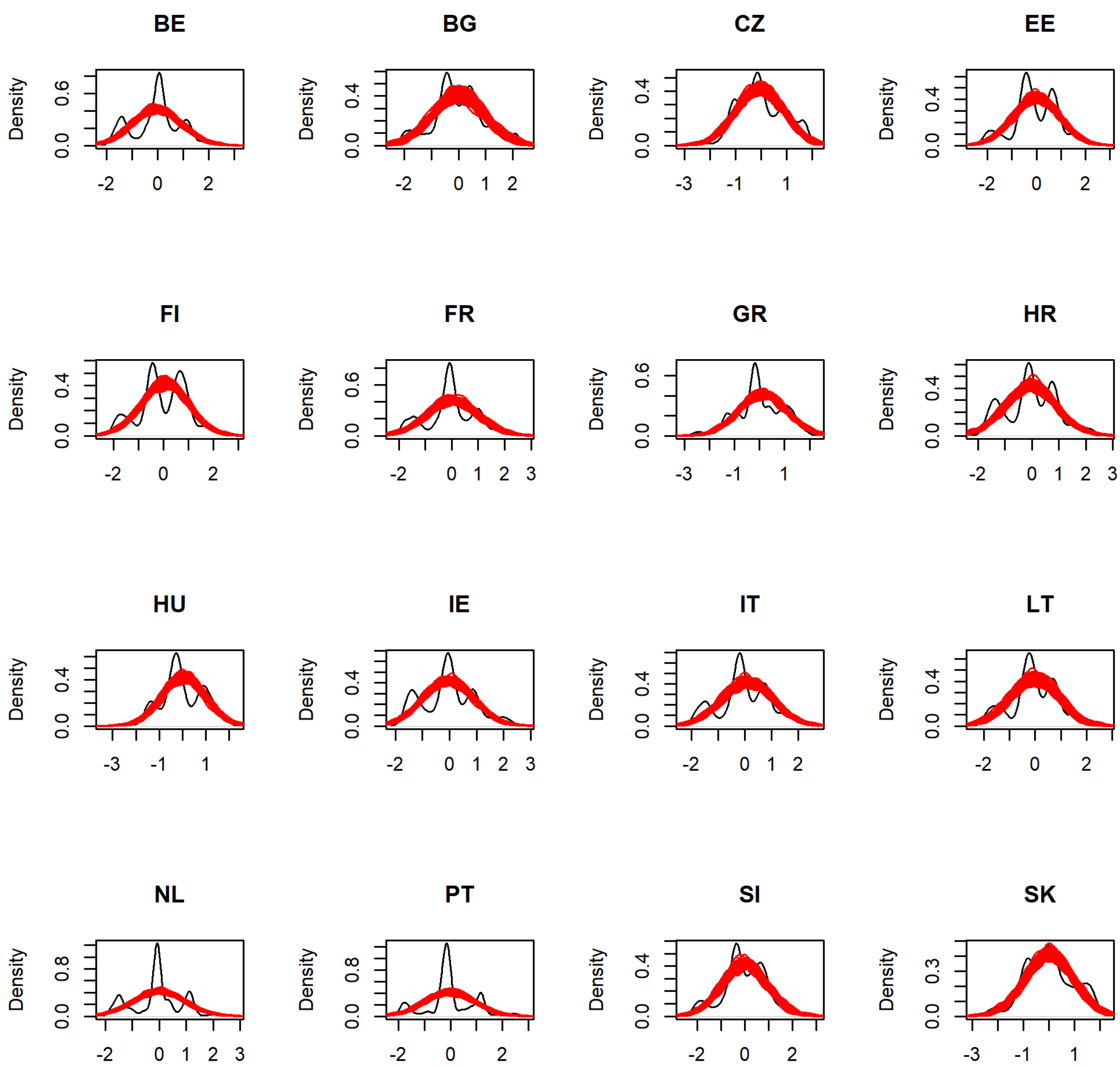

Figure 31: *FCSsl- single level imputation with normal lienar regression*: Density plots for the observed (black) and imputed (red) distribution of the target variable “Immigration rejection” across the EU countries

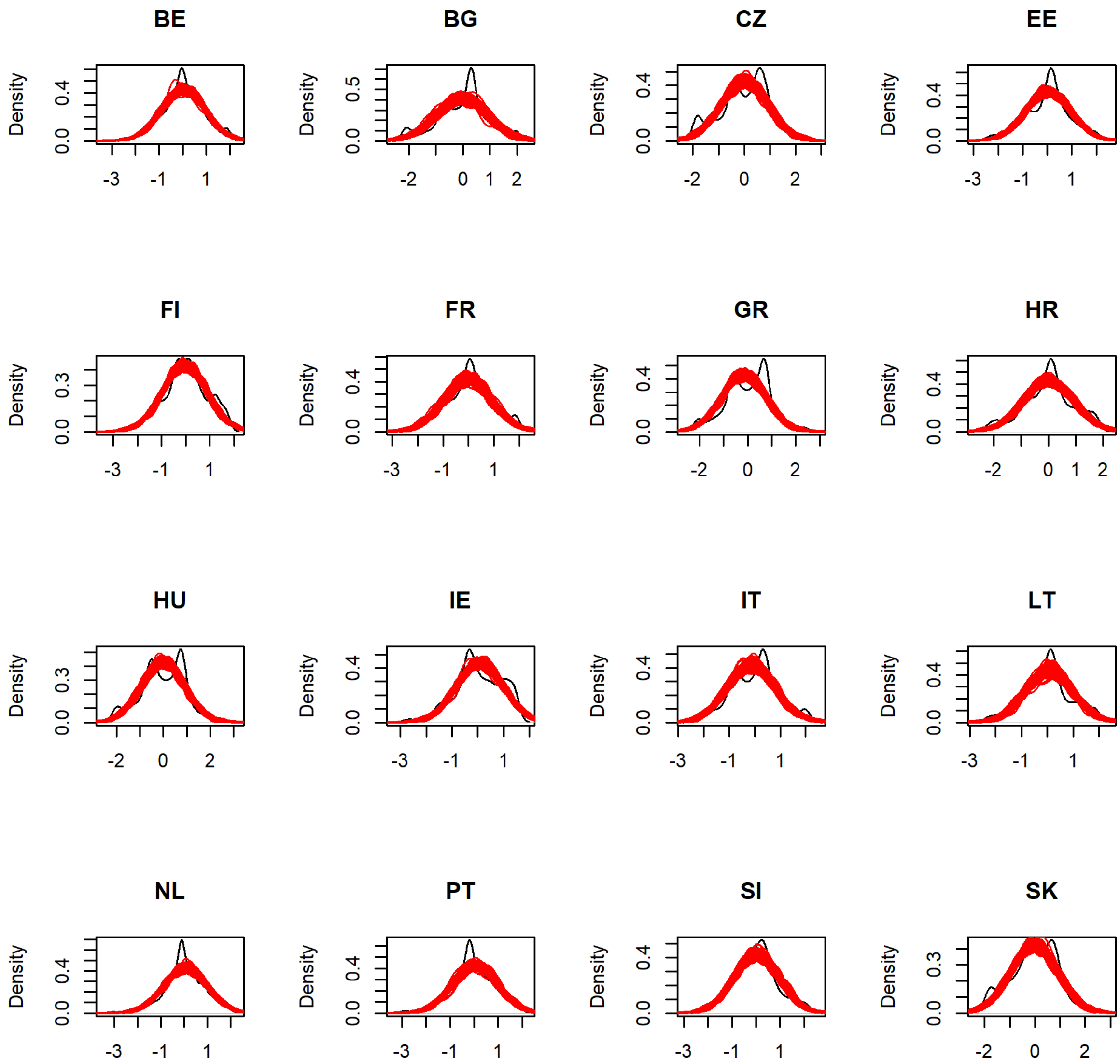

Figure 32: *FCSsl- single level imputation with normal lienar regression*: Density plots for the observed (black) and imputed (red) distribution of the target variable "Perceived benefits of immigration" across the EU countries

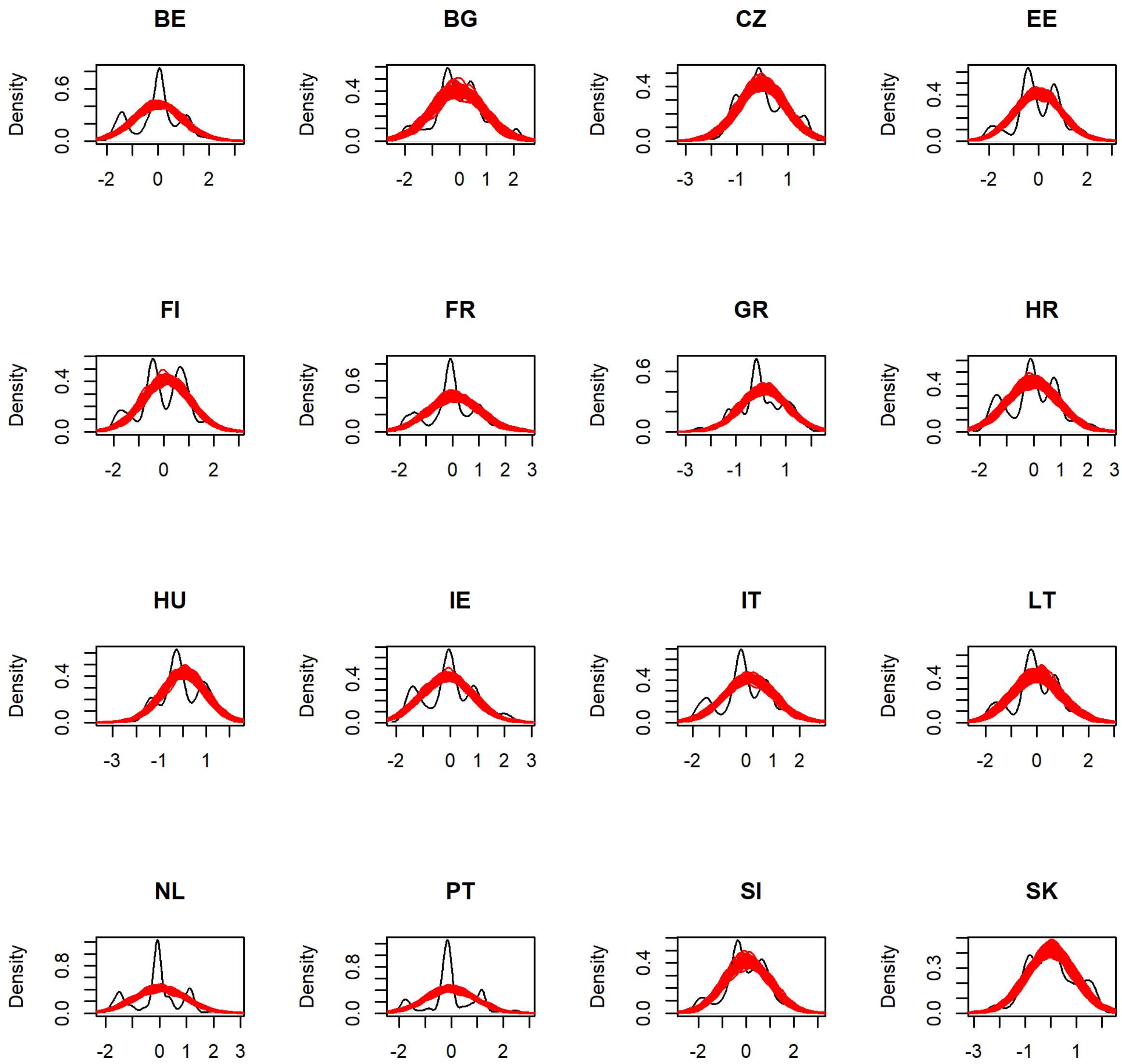

Figure 33: *FCSri- multilevel imputation with random intercept.* Density plots for the observed (black) and imputed (red) distribution of the target variable "Immigration rejection" across the EU countries

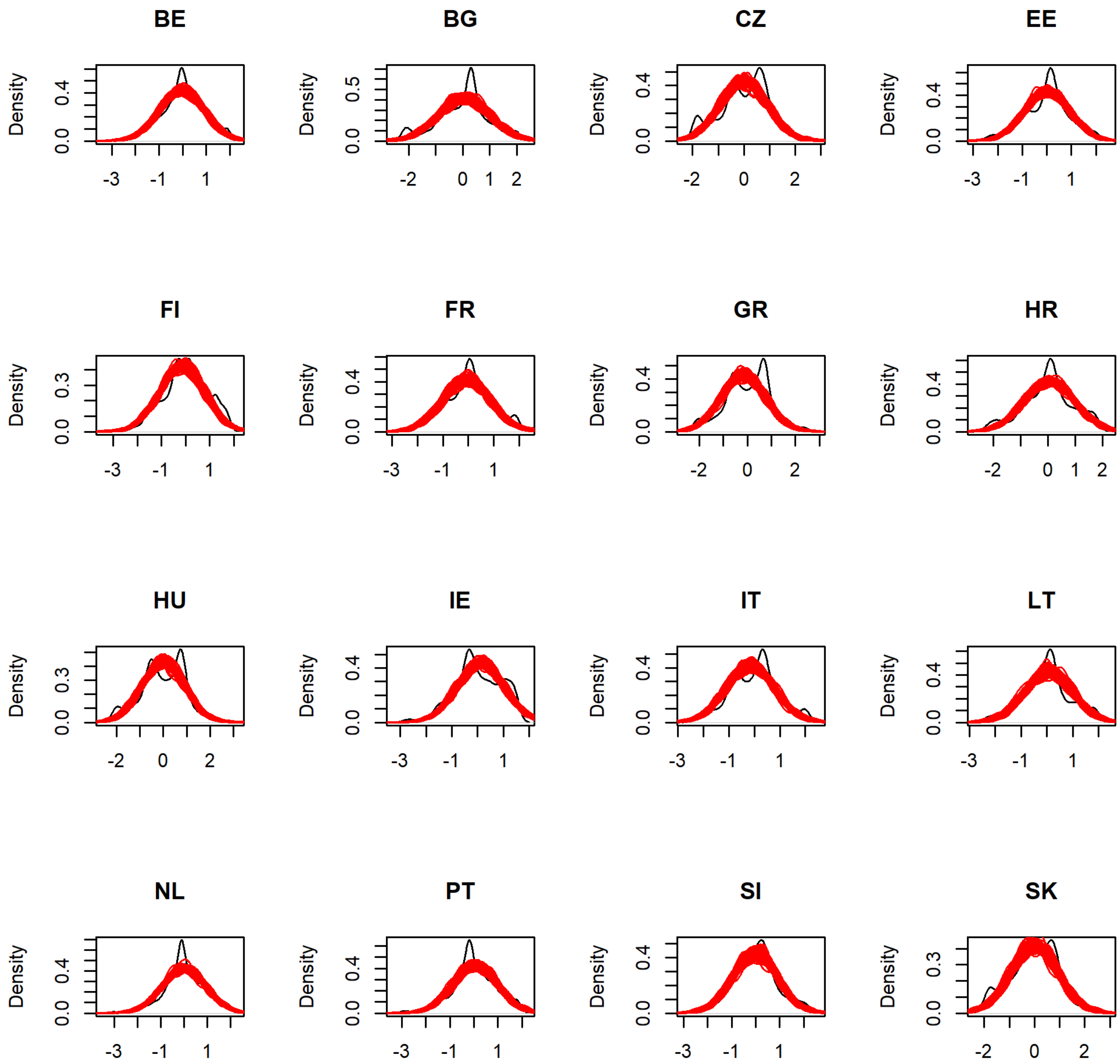

Figure 34: *FCSri- multilevel imputation with random intercept.* Density plots for the observed (black) and imputed (red) distribution of the target variable “Perceived benefits of immigration” across the EU countries

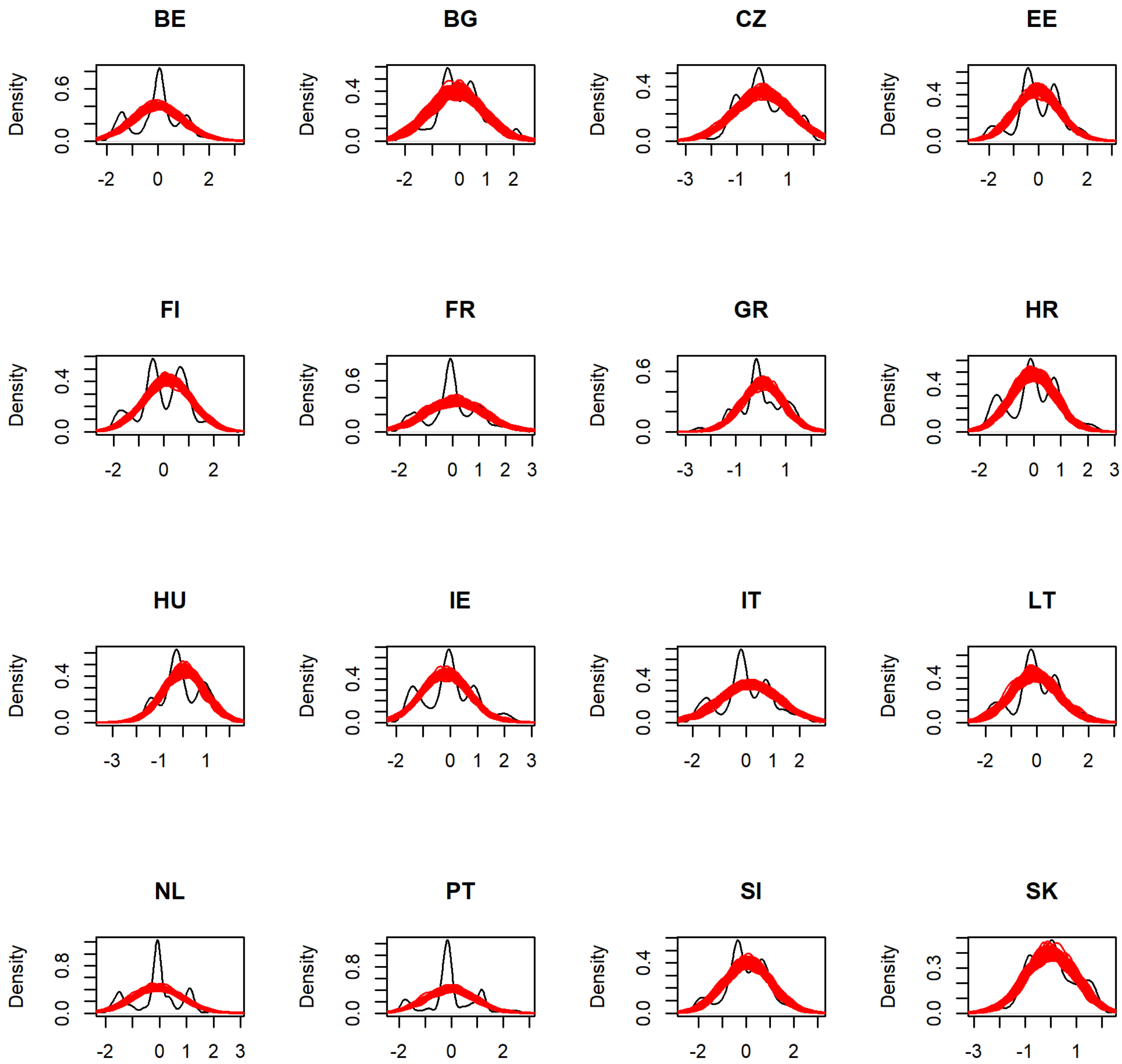

Figure 35: *FCSrs- multilevel imputation with random intercept and slope*: Density plots for the observed (black) and imputed (red) distribution of the target variable “Immigration rejection” across the EU countries

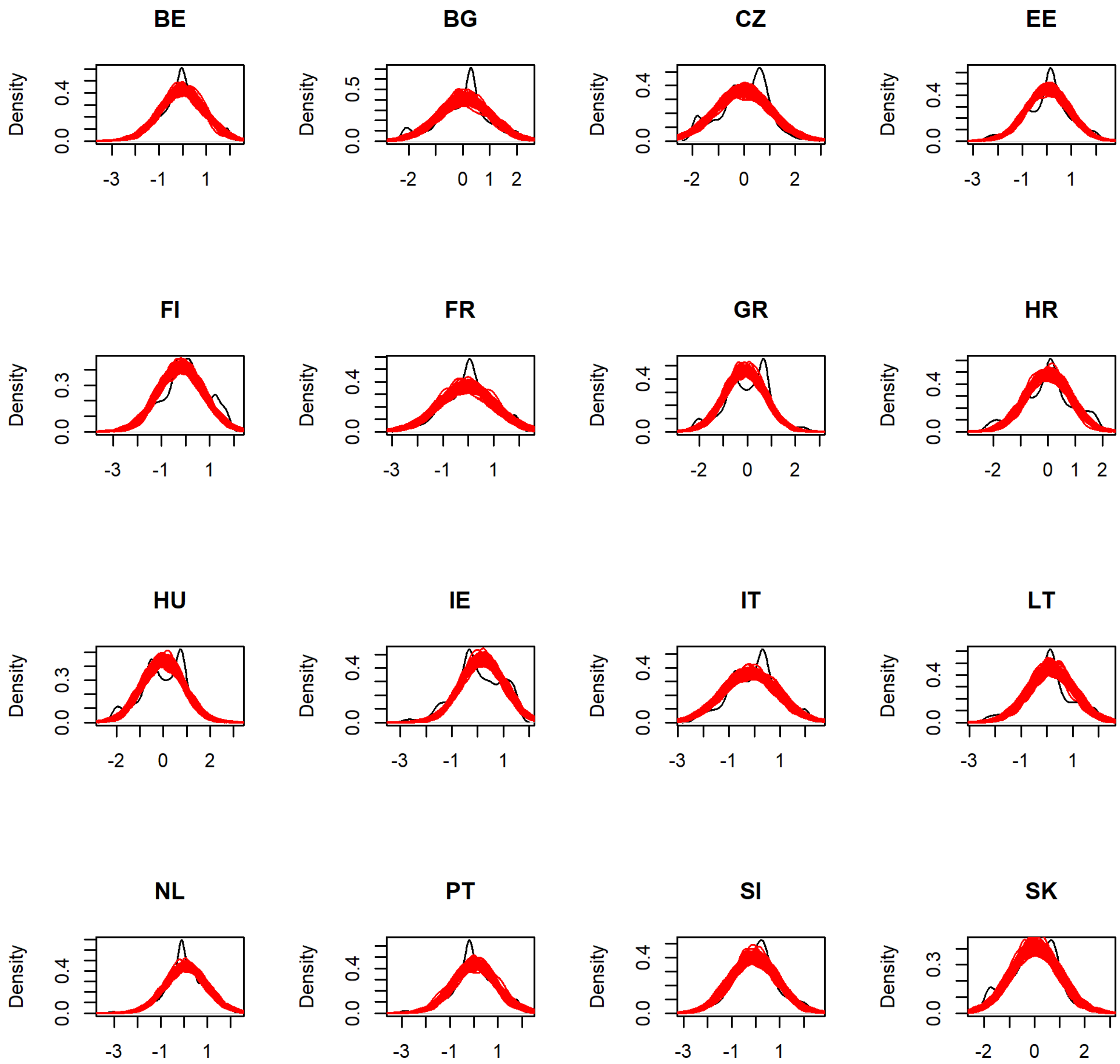

Figure 36: *FCSrs- multilevel imputation with random intercept and slope*: Density plots for the observed (black) and imputed (red) distribution of the target variable “Perceived benefits of immigration” across the EU countries

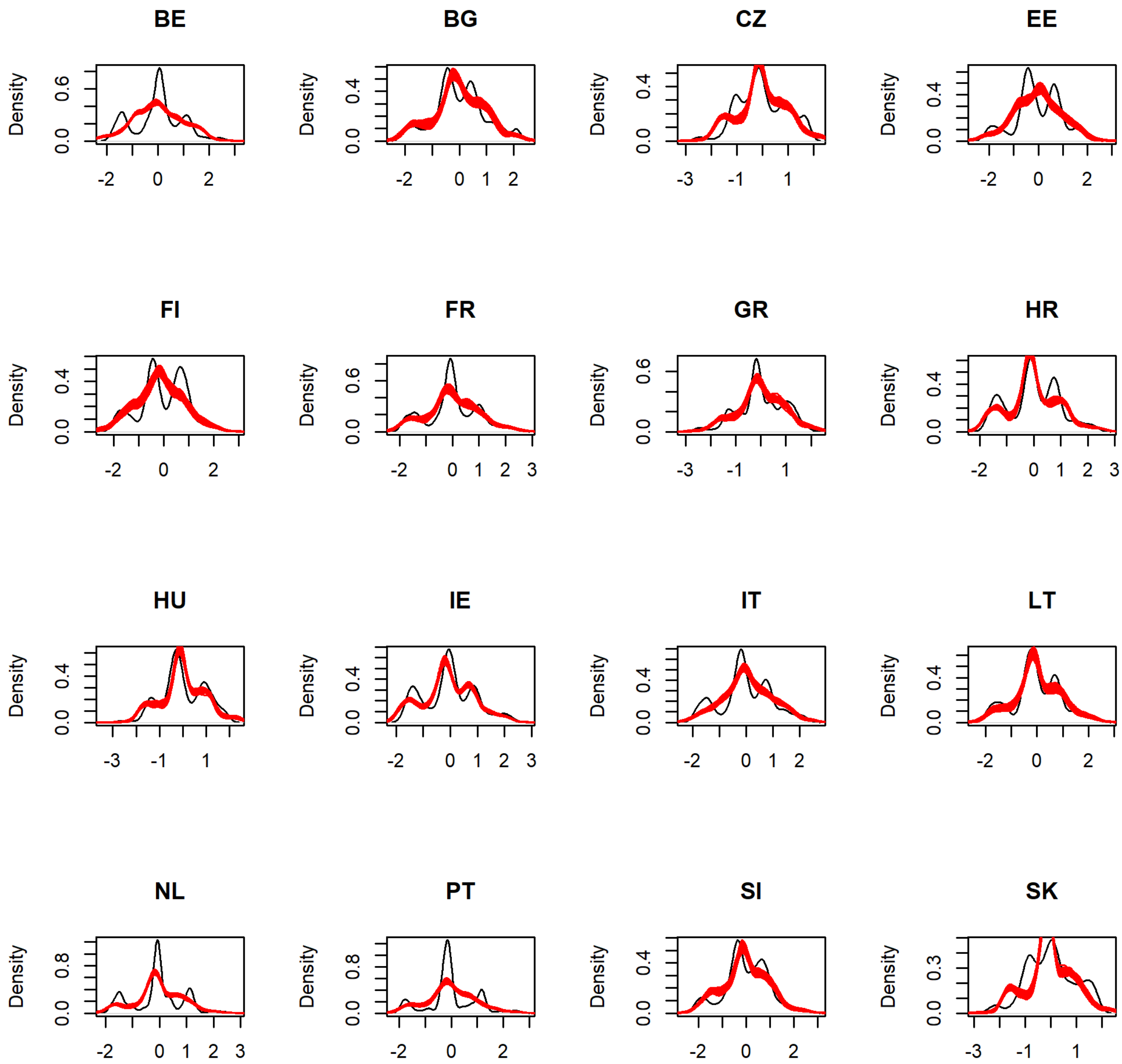

Figure 37: *JMsep- country wise imputation*: Density plots for the observed (black) and imputed (red) distribution of the target variable “Immigration rejection” across the EU countries

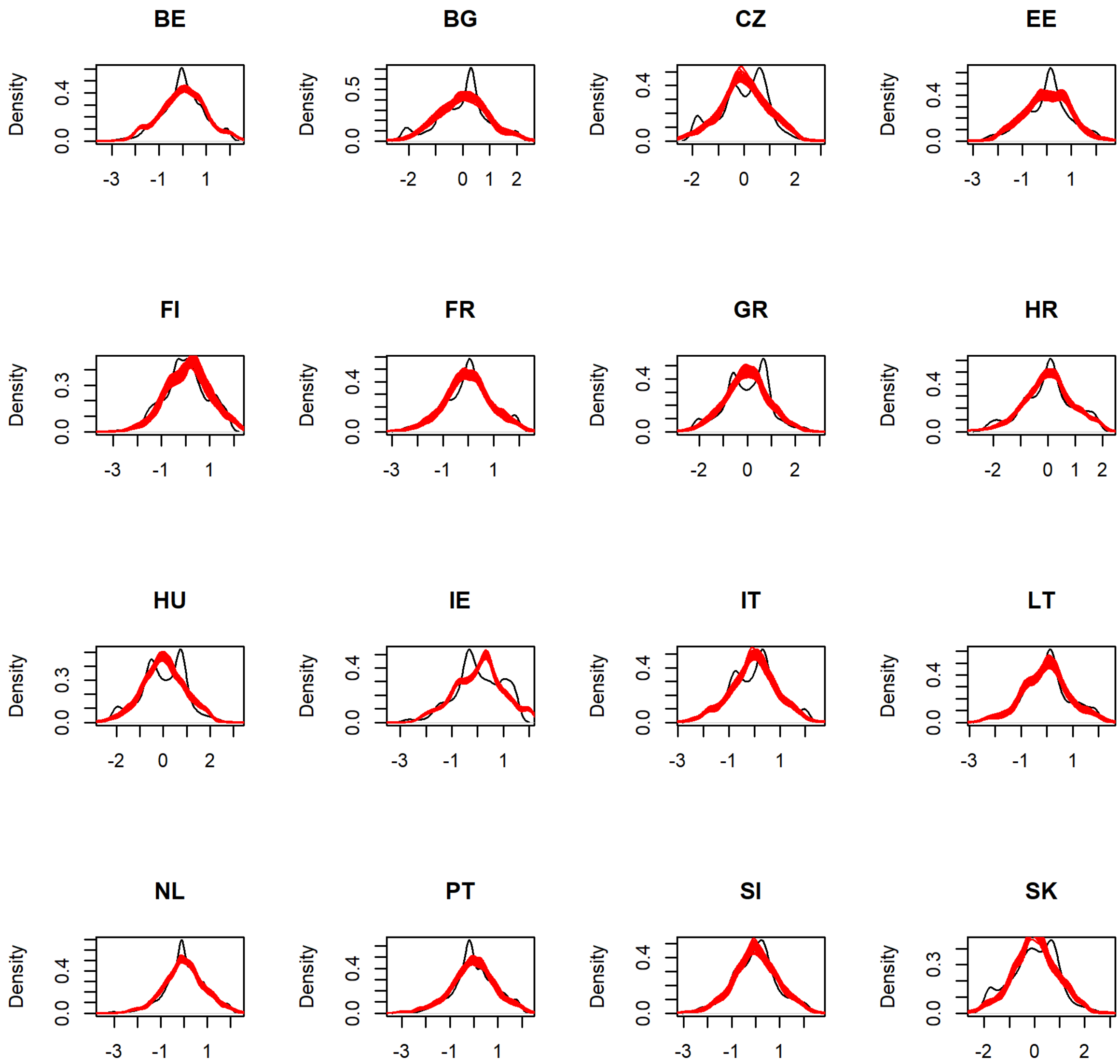

Figure 38: *FJMsep- country wise imputation*: Density plots for the observed (black) and imputed (red) distribution of the target variable "Perceived benefits of immigration" across the EU countries

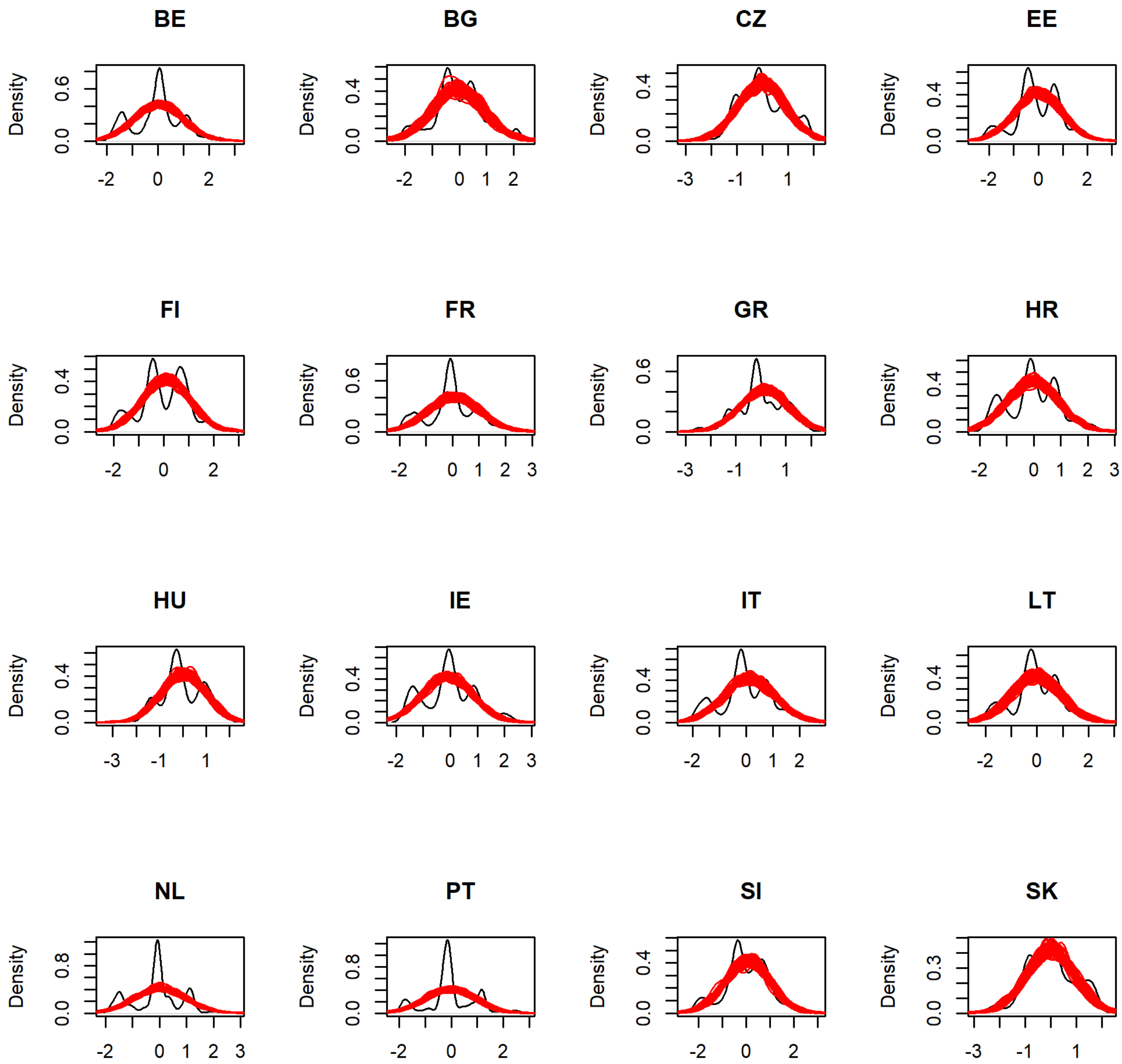

Figure 39: *JMri- imputation with random intercept*. Density plots for the observed (black) and imputed (red) distribution of the target variable "Immigration rejection" across the EU countries

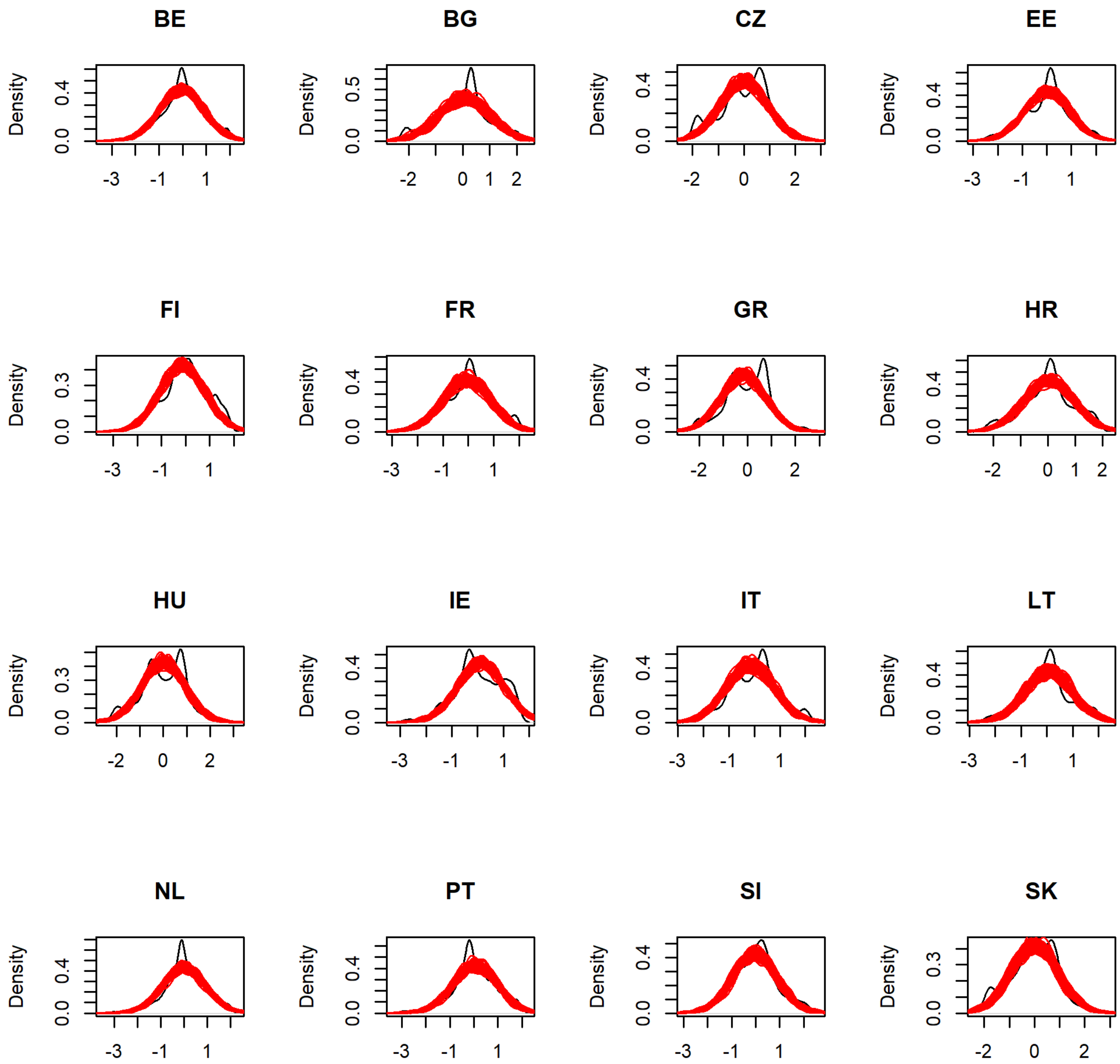

Figure 40: *JMri- imputation with random intercept*: Density plots for the observed (black) and imputed (red) distribution of the target variable "Perceived benefits of immigration" across the EU countries

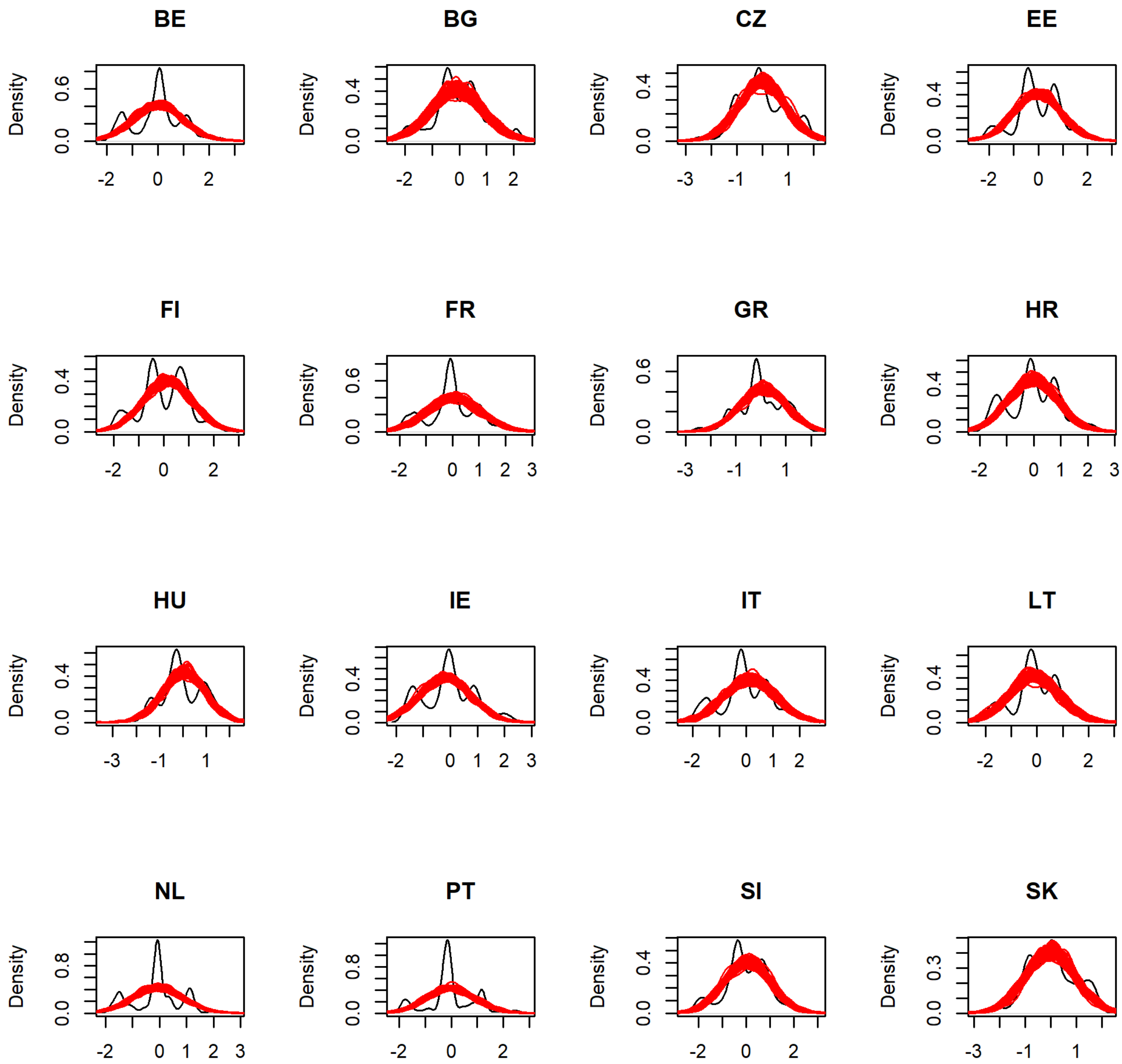

Figure 41: *JMrs- imputation with random intercept and slope*: Density plots for the observed (black) and imputed (red) distribution of the target variable “Immigration rejection” across the EU countries

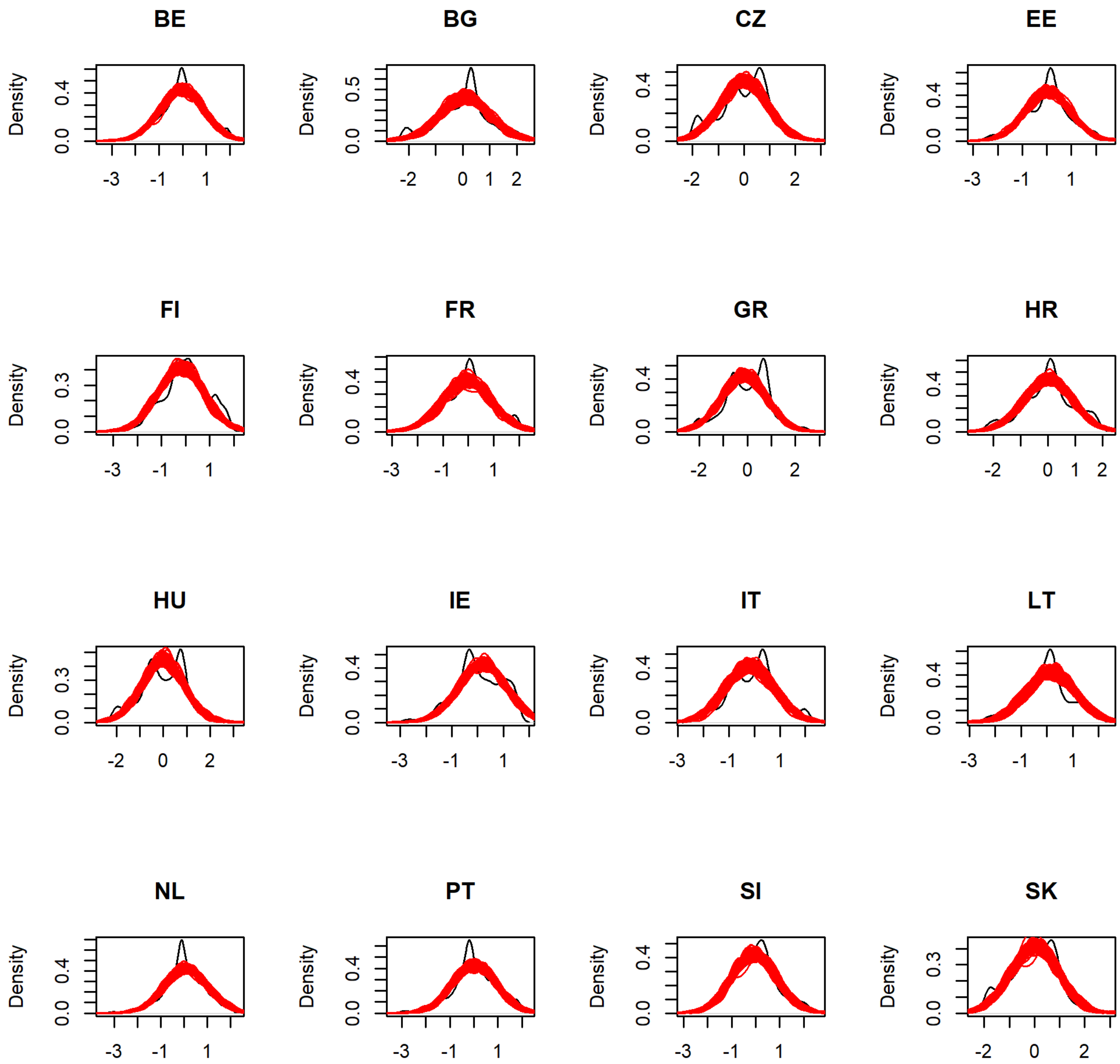

Figure 42: *JMrs- imputation with random intercept and slope*: Density plots for the observed (black) and imputed (red) distribution of the target variable “Perceived benefits of immigration” across the EU countries

4.3 A Fully Integrated Bayesian Approach to parametric Statistical Matching with Latent Variables in Multilevel Data

One of the main limitations of the data integration procedure discussed in the previous sections is that, once the latent trait scores for the various latent variables—defined according to the research design presented in Section 1—are estimated, they are subsequently treated as fixed, thereby neglecting the uncertainty inherent in their estimation. To address this limitation and to fully account for all sources of variability in the data integration process, following a Joint modeling approach, we propose a fully integrated Bayesian approach (*Jmint*) in which item and person parameters for each latent trait are estimated jointly with the regression model used for data imputation within the Markov Chain Monte Carlo (MCMC) framework. This allows us to propagate uncertainty throughout the entire data integration process. Furthermore, to account for the hierarchical structure of the data, with individuals nested within countries, we adopt a multilevel modeling strategy.

4.3.1 Methodology

Considering the model detailed in Equation (4) for the generic latent traits $\boldsymbol{\theta}$

$$P(Y_{ijk}=c|\boldsymbol{\theta}_{ij},\boldsymbol{\alpha}_{kj},\gamma_{kj})=\Phi\left(\boldsymbol{\alpha}'_{kj}\boldsymbol{\theta}_{ij}-\gamma_{kj,c-1}\right)-\Phi\left(\boldsymbol{\alpha}'_{kj}\boldsymbol{\theta}_{ij}-\gamma_{kj,c}\right)=$$

we assume a multi-unidimensional model, where each of the M correlated constructs is being measured by its own set Ω_m containing K_m items. This assumption can be written as $\alpha_{kj,m}\neq 0$ if $k\in\Omega_m$, $\alpha_{kj,m}=0$ if $k\notin\Omega_m$ and the matrix of group specific discrimination parameters, $\boldsymbol{A}_j$, has a block structure common to all groups (i.e., configurational invariance).
Following de Jong et al. (2007), Fontanella et al. (2016), and Fontanella et al. (2018), we link the item parameters in a hierarchical way imposing a common prior. For the discrimination parameters, we assume that each nonzero element of the matrix $\boldsymbol{A}_j$ is independently truncated normal

$$\alpha_{kj,m}\sim\mathcal{N}(\alpha_{k,m},\sigma^2_{\alpha,m(k)})I(\alpha_{kj,m}>0)\ if\ k\in\Omega_m$$

where $m(k)$ is the construct that item k measures and $I(\cdot)$ represents the indicator function. Analogously, the distribution of the ordered thresholds is normal

$$\gamma_{kj,c}\sim\mathcal{N}(\gamma_{k,c},\sigma^2_{\gamma,m(k)}),\ c=1,\ldots,C-1,\ \gamma_{kj,1}\leq\cdots\leq\gamma_{kj,C-1},\ \forall k\in\Omega_m.$$

At the second level of the hierarchy, we assume that all free discrimination parameters are positive $\alpha_{k,m}\propto I(\alpha_{k,m}>0)$, if $k\in\Omega_m$, and assign a uniform prior to the ordered thresholds $\gamma_{k,c}\sim uniform, c=1,\ldots,C-1, \gamma_{k,1}\leq\cdots\leq\gamma_{k,C-1}$, $\forall k$. The univariate variance parameters are given inverse gamma priors.
With regard to the person parameters, we assume a multivariate normal model

$$\boldsymbol{\theta}_{i,j}\sim\mathcal{N}_M(\boldsymbol{\mu}_{\theta_{i,j}},\boldsymbol{\Sigma}_{\theta_j})$$

where the prior for the mean is specified considering the following hierarchical model

$$\boldsymbol{\theta}_{ij}\sim\mathcal{N}_M(\boldsymbol{B}_j\boldsymbol{d}_{ij},\boldsymbol{\Sigma}_{\theta_j}),\quad \boldsymbol{B}_j\sim\mathcal{MN}_{M,p+1}\left(\mathbf{0}_{M,p+1},,\boldsymbol{\Sigma}_B^{(r)},\boldsymbol{\Sigma}_B^{(c)}\right).$$

The prior for the inverse-covariance matrix at the first level, $\boldsymbol{\Sigma}^{-1}_{\theta_j}$, is Wishart.

For the latent traits measuring "Trust in Institutions", "Euroskepticism on Migration Governance", and "Aversion to Immigrants", we impose $\boldsymbol{d}_{ij}=\mathbf{1}$ to allow for a random intercept across countries. In contrast, for the target variables "Immigration Rejection" and "Perceived Benefits of Immigration", $\boldsymbol{d}_{ij}=(\mathbf{1},\boldsymbol{x}_{ij})'$ where $\boldsymbol{x}_{ij}$ is the p-dimensional vector of common variables for subject i in country j. This specification capture the dependence of the target latent variables on these common predictors.

Identifiability issues The multidimensional graded response models need identification restrictions since they are over-parameterized. The nature of the rating scale implies that scale restrictions have to be imposed because the observed outcomes do not change for different combinations of parameters. The locations of the latent variables are influenced by the mean of the latent traits and the threshold parameters. Analogously, the variances and covariances of the latent traits are determined both by the latent trait covariance matrix and by the discrimination parameters. To fix the location indeterminacy, following de Jong and Steenkamp (2010), for a chosen category c, we consider the constraints $\sum_{k\in\Omega_m}\gamma_{kj,c}=0$. To solve the scale indeterminacy, we impose that across the items of each dimension, the product of the discrimination parameters is equal to 1: $\prod_{k\in\Omega_m}\alpha_{kj,m}=1$. These constraints are applied for each dimension $m=1,\dots,M$ and each country $j=1,\dots,J$.

Estimation To draw samples from the conditional distribution of the parameters it is convenient to use data augmentation technique (Tanner & Wong, 1987).
For each observed polytomous item, as described in Section 2, we assume that a continuous variable Z underlies the observed ordinal measure and that there is a linear relationships between item and person parameters and the underlying variable, such that $Z_{ij,k}=\boldsymbol{\alpha}'_{kj}\boldsymbol{\theta}_{ij}+e_{ij,k}$, with $e_{ij,k}\sim\mathcal{N}(0,1)$.

The relation between the observed item and the underlying variable is expressed by the threshold model The relation between the observed items and the underlying variables is given by the threshold model

$$Y_{ij,k}=c\quad if\ \gamma_{kj,c-1}\le Z_{ij,k}\le\gamma_{kj,c},\ c=1,\dots,C;\ \gamma_{kj,0}=-\infty,\gamma_{kj,C}=\infty$$

The full conditional of most parameters can be specified in closed form which allows for a Gibbs sampler although Metropolis-Hastings steps are required to sample the threshold parameters. In particular to draw the thresholds we consider the Cowles' algorithm (Cowles, 1996).

4.3.2 Latent traits estimation results

In this section, we present the results of the estimation of the latent traits described in Section 1 .

Common Latent trait: Trust in Institutions Table 40 presents the posterior estimates of the factor loadings for the latent trait measuring trust in institutions, along with the estimated common thresholds. The country-specific thresholds exhibit very low variability compared to the common threshold level, due to the constraints applied at the country level.

The results indicate that Parliament, Police, Political Parties, and the EU are the most influential institutions in shaping the latent trait under study, with substantial cross-country variability. Countries like Finland, Netherlands, and Hungary show particularly sharp divides, suggesting that political institutions are critical markers of public sentiment. Meanwhile, international organizations like the UN exhibit lower discrimination, hinting at more stable or less polarized views. These insights underscore the deep political and institutional fragmentation that characterizes public attitudes across different European contexts.

Table 40: Bayesian IRT model for Trust: posterior estimates of discrimination parameters and common thresholds.

		Parliament	Legal system	Police	Political parties	EU	UN
Discrimination coefficients	**Overall**	**1.35**	**1.09**	**1.30**	**1.23**	**1.29**	**1.11**
	BE	1.12	0.76	0.76	1.09	1.46	0.99
	BG	0.91	1.61	2.21	0.68	0.65	0.71
	CZ	0.99	0.68	0.90	1.28	1.17	1.11
	EE	0.92	0.77	0.86	0.84	1.62	1.24
	FI	3.63	0.80	0.44	1.59	0.71	0.72
	FR	1.03	0.88	0.95	0.73	1.77	0.93
	GR	1.14	0.40	0.92	1.12	1.72	1.27
	HR	0.96	1.38	1.47	0.78	0.78	0.85
	HU	1.19	1.25	1.95	1.43	0.47	0.52
	IE	1.07	0.95	1.06	1.10	1.11	0.77
	IT	1.08	0.91	0.84	0.85	1.49	0.96
	LT	0.61	0.78	1.10	0.87	1.61	1.40
	NL	1.89	0.88	0.59	2.57	0.66	0.62
	PT	1.19	0.81	1.00	0.90	1.30	0.90
	SI	0.80	0.95	1.14	0.78	1.24	1.23
	SK	0.87	0.94	1.68	0.95	0.90	0.87
Thresholds		0.42	-0.10	-1.37	1.36	-0.06	-0.25

Figure 43 and 44 compare the distribution of the scores on the latent trait for respondents from the ESS and the Eurobarometer survey. The two distributions appear to be broadly comparable, although trust levels are generally higher in the Eurobarometer compared to the ESS.

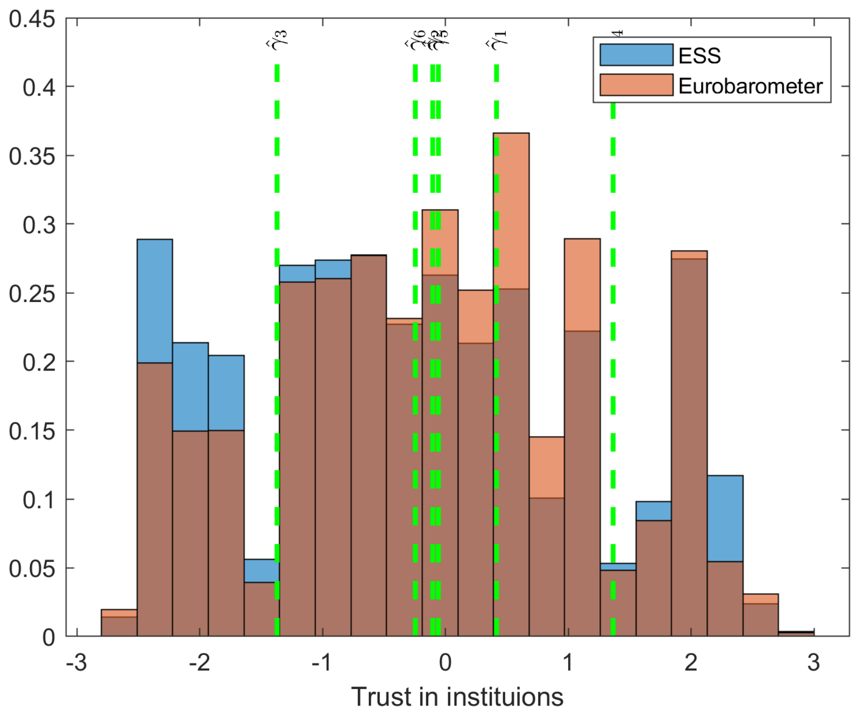

Figure 43: Bayesian IRT model for Trust: distributions of latent trait scores across the ESS and the Eurobarometer survey. The green lines represent the estimated thresholds for the items in the trust scale.

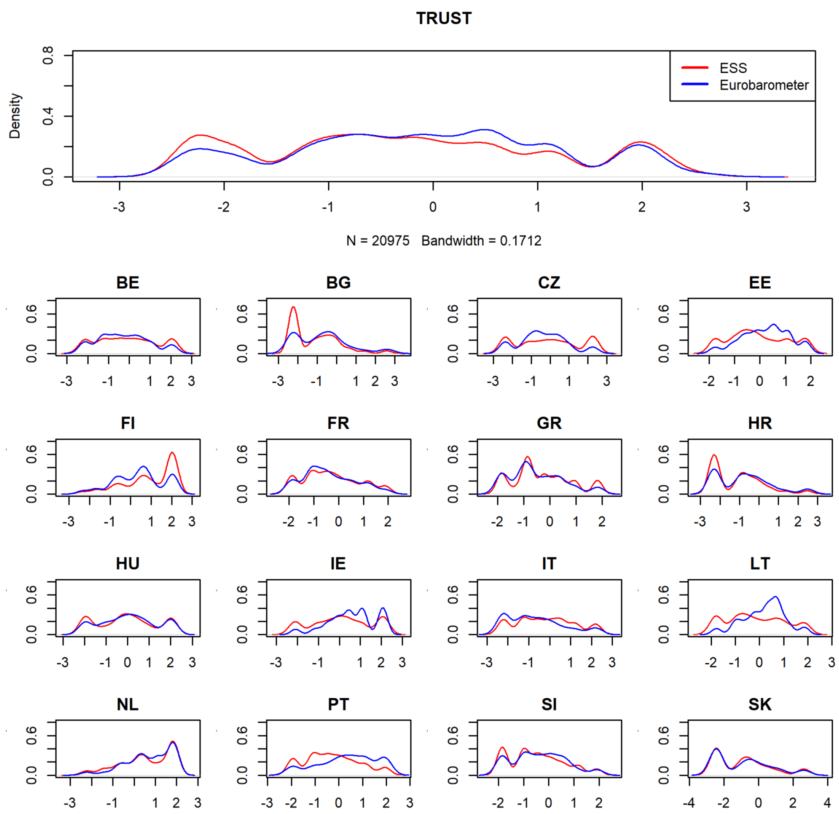

Figure 44: Bayesian IRT model for Trust: distributions of latent trait scores across the ESS and the Eurobarometer survey for each country.

Figure 45 presents the distribution of latent trait scores for trust in institutions across countries, based on respondents from both the ESS and Eurobarometer surveys. The figure highlights substantial cross-country variability in institutional trust. Northern European countries such as Finland, Ireland, and the Netherlands exhibit predominantly positive latent trait scores, indicating stronger public confidence in institutions. In contrast, Eastern and some Southern European countries like Bulgaria, Croatia, and Slovakia display largely negative scores, highlighting widespread skepticism towards institutional effectiveness. The variability within countries, suggests that institutional trust is not uniformly distributed, with some segments of the population maintaining confidence despite the broader climate of skepticism.

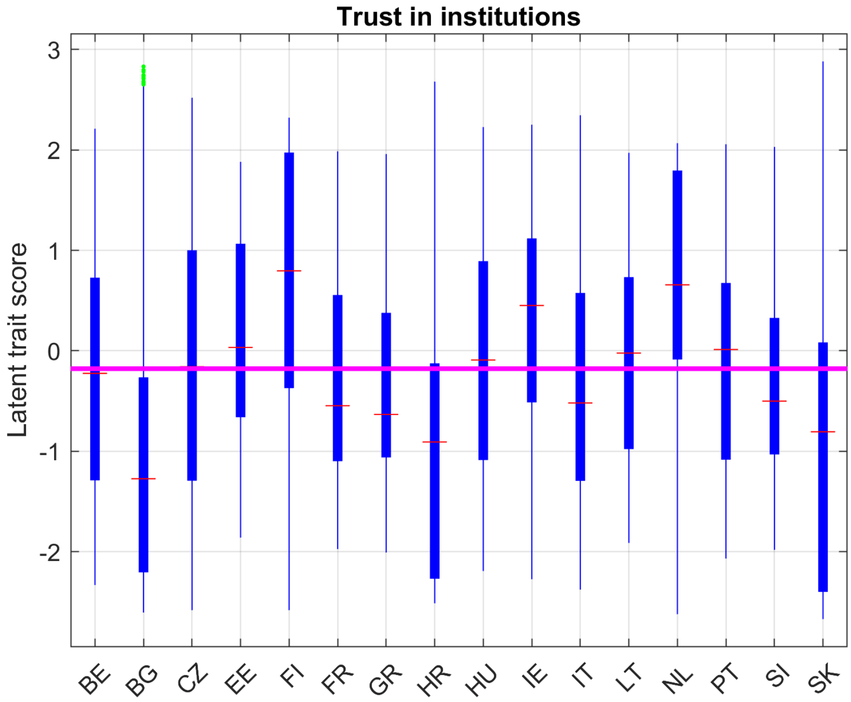

Figure 45: Bayesian IRT model for Trust: distributions of latent trait scores across the EU countries. The pink line represents the mean level across all the countries.

Immigration rejection and Perceived benefits of immigration Table 41 presents the posterior estimates of the factor loadings for the latent traits measuring Immigration rejection and Perceived benefits of immigration, along with the estimated common thresholds. The factor loadings for the latent trait Immigration rejection indicate that, across countries, the items "Allow different race" and "Allow from poor countries" consistently show higher discriminative power than "Allow same race." For perceived benefits, the item concerning immigration's impact on the economy is the most discriminative. This pattern holds quite consistently across countries.

Table 41: Bayesian IRT model for Immigration rejection and Perceived benefits of immigration: posterior estimates of discrimination parameters and common thresholds.

		Immigration rejection			Perceived benefits of immigration		
		Allow same race	Allow different race	Allow poor countries	Impact on economy	Impact on cultural life	Impact on the country
	Overall	**0.96**	**1.18**	**1.27**	**1.40**	**0.97**	**0.85**
Discrimination coefficients	*BE*	0.79	1.02	1.30	1.17	1.10	0.80
	BG	0.93	0.98	1.12	1.49	0.87	0.78
	CZ	0.97	1.13	0.93	1.59	0.80	0.80
	EE	0.81	1.07	1.19	1.42	0.88	0.82
	FI	0.84	1.09	1.13	1.14	1.26	0.71
	FR	0.75	1.09	1.27	1.26	1.06	0.76
	GR	0.56	1.49	1.28	1.40	0.90	0.81
	HR	0.87	1.06	1.11	1.26	0.94	0.86
	HU	0.91	1.15	0.99	1.57	0.90	0.72
	IE	0.88	1.05	1.11	1.20	0.89	0.95
	IT	0.83	1.05	1.18	1.43	0.98	0.72
	LT	1.12	0.99	0.93	1.47	0.78	0.89
	NL	0.64	1.21	1.40	1.16	1.12	0.79
	PT	0.51	1.31	1.95	1.53	0.91	0.73
	SI	0.80	1.03	1.27	1.46	0.87	0.80
	SK	1.07	1.01	0.95	1.62	0.84	0.75
Thresholds	$\gamma 1$	-0.54	-1.09	-1.29	-1.61	-0.80	-0.69
	$\gamma 2$	0.52	-0.01	-0.51	0.04	-0.17	0.12
	$\gamma 3$	1.58	0.92	0.75	1.65	1.05	1.12
	mean	0.52	-0.06	-0.35	0.03	0.03	0.18

Figure 46 provides a representation of the distribution for the two latent traits.

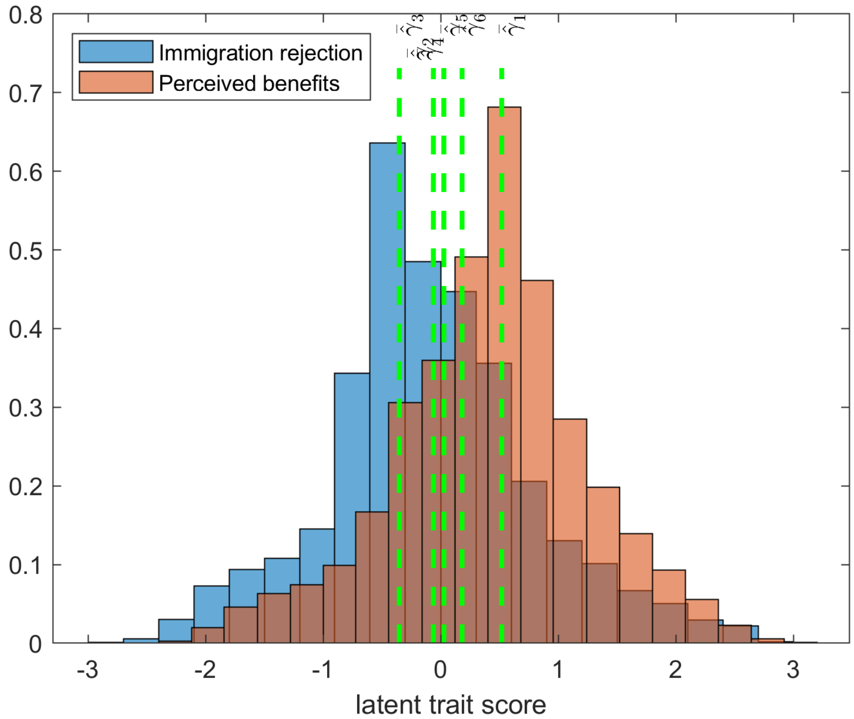

Figure 46: Bayesian IRT model for Immigration rejection and Perceived benefits of immigration: distributions of latent trait scores. The green lines represent the estimated thresholds for the items in the trust scale.

Figure 47 presents the distribution of the two latent traits across countries, suggesting significant cross-country variation in the rejection of immigration and the perception of benfits. Countries in Eastern Europe exhibit the highest levels of rejection, reflected in their positive latent trait scores. These same countries also report the lowest perceptions of immigration benefits, indicating that immigrants are not widely seen as contributing positively to the economy, culture, or societal well-being. In contrast, Western and Southern European nations, particularly Netherlands, Portugal, and Ireland, display more favorable attitudes, with lower rejection scores and stronger perceptions of benefits. The compact distribution of scores in countries like Portugal suggests a broader societal consensus on immigration's positive impact. Meanwhile, the presence of outliers in both dimensions—especially in Hungary for rejection and Netherlands for perceived benefits—highlights segments of the population with particularly extreme views.

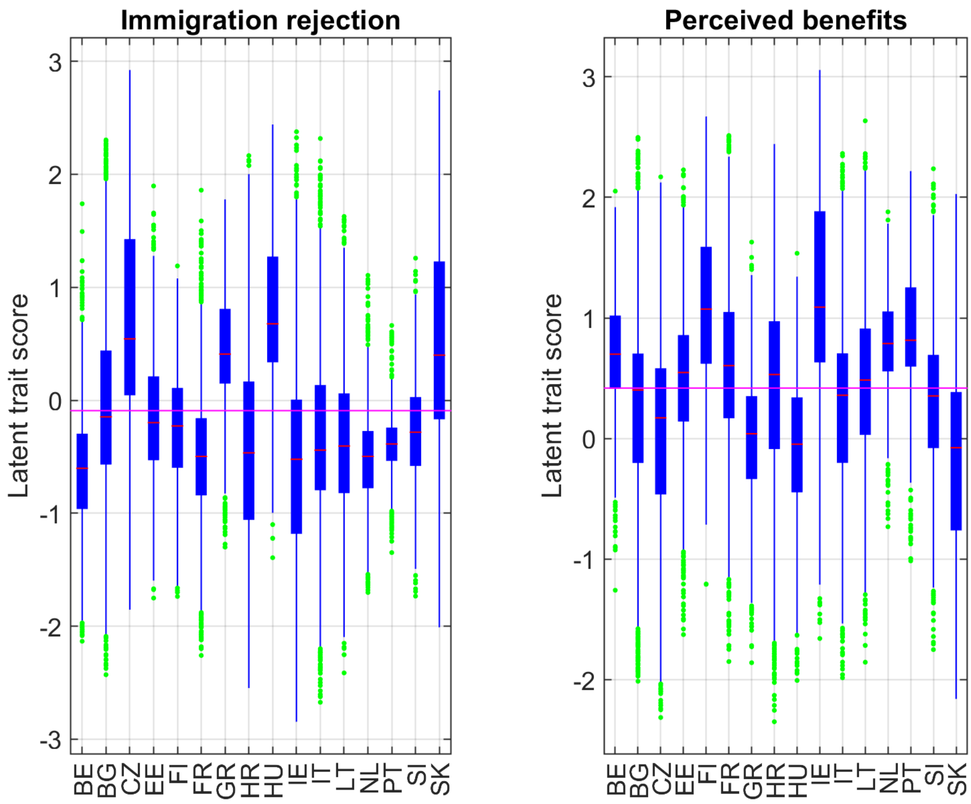

Figure 47: Bayesian IRT model for Immigration rejection and Perceived benefits of immigration: distributions of latent trait scores across the EU countries. The pink line represents the mean level across all the countries.

The correlation between the two latent traits (see Table 42) is relatively high and stable across the analyzed countries.

Table 42: Correlation between "Immigration rejection" and "Perceived benefits of immigration"

Country	Posterior mean	95% CI	
BE	-0.62	-0.68	-0.55
BG	-0.69	-0.72	-0.65
CZ	-0.68	-0.72	-0.65
EE	-0.61	-0.67	-0.55
FI	-0.63	-0.68	-0.57
FR	-0.68	-0.72	-0.63
GR	-0.60	-0.64	-0.55
HR	-0.60	-0.65	-0.55
HU	-0.65	-0.70	-0.59
IE	-0.59	-0.64	-0.52
IT	-0.71	-0.74	-0.67
LT	-0.57	-0.65	-0.49
NL	-0.56	-0.64	-0.47
PT	-0.63	-0.69	-0.55
SI	-0.65	-0.71	-0.58
SK	-0.64	-0.69	-0.58

Euroskepticism on Common Migration Policy Table 43 presents the posterior estimates of the factor loadings for the latent trait measuring Euroskepticism on Common Migration Policy, along with the estimated common thresholds. The analysis reveals that asylum policies are the most divisive aspect of immigration governance across Europe, with stark differences in public sentiment, particularly in Finland, Slovenia, and Hungary. Common Policy is moderately polarizing, especially in Estonia and the Netherlands, while External Border management is the least contentious, reflecting broader alignment or less public focus. These patterns suggest that debates over refugee handling are the primary driver of migration-related polarization in Europe, followed by differences in support for EU-wide policy coordination.

Table 43: Bayesian IRT model for Euroskepticism on Common Migration Policy: posterior estimates of discrimination parameters and common thresholds.

		Common policy	Asylum system	External border
	Overall	**1.15**	**2.32**	**0.79**
Discrimination coefficients	*BE*	1.86	4.30	0.13
	BG	0.68	4.45	0.37
	CZ	2.04	2.73	0.19
	EE	3.00	2.73	0.15
	FI	1.03	8.74	0.11
	FR	1.71	4.46	0.14
	GR	0.79	2.76	0.47
	HR	0.72	3.50	0.41
	HU	1.04	5.34	0.20
	IE	2.06	4.81	0.11
	IT	0.88	3.11	0.39
	LT	2.39	1.60	0.37
	NL	2.77	4.13	0.11
	PT	1.47	2.89	0.26
	SI	0.88	7.78	0.15
	SK	0.68	3.47	0.45
Thresholds		**-0.15**	**-0.42**	**0.57**

Figure 48 provides a representation of the distribution for the latent trait.

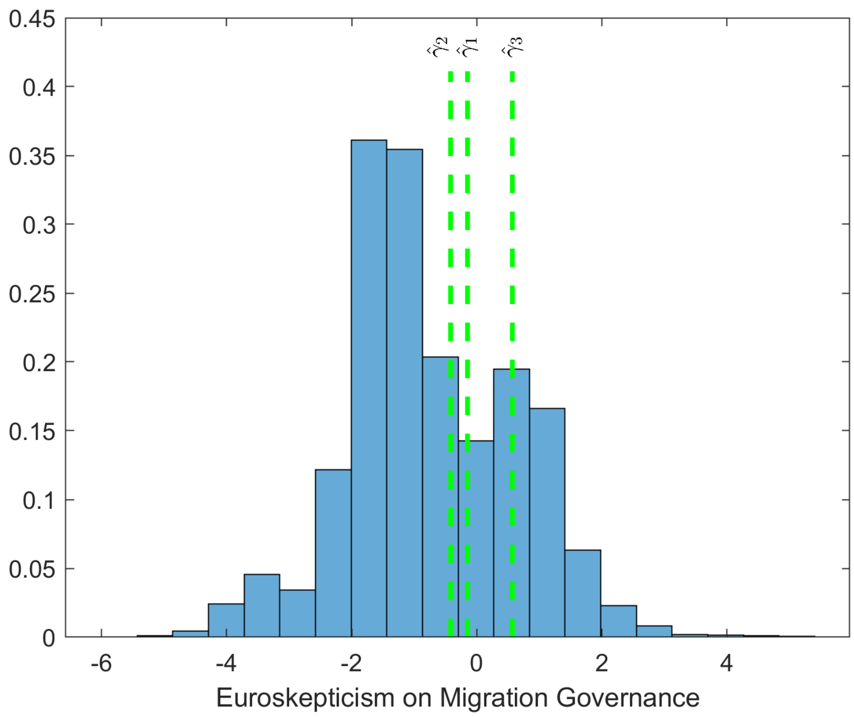

Figure 48: Bayesian IRT model for Euroskepticism on Common Migration Policy: distributions of latent trait scores. The green lines represent the estimated thresholds for the items in the trust scale.

Figure 49 presents the distribution of the latent trait across countries. Greece emerges as the strongest supporter of collective EU governance on migration, reflected in its markedly low skepticism scores. In contrast, Hungary and Slovakia display the highest levels of skepticism, indicating firm resistance to ceding migration control to European institutions. Countries like Croatia and Belgium also show relatively supportive attitudes, although less pronounced than Greece, suggesting a broader acceptance of EU policies in managing migration flows. The Netherlands and Portugal, with their tightly clustered and neutral scores, reveal a more moderate stance, reflecting internal consensus. Estonia and the Czech Republic occupy a middle ground, neither strongly opposing nor fully endorsing centralized policies, indicating a more cautious or pragmatic approach.

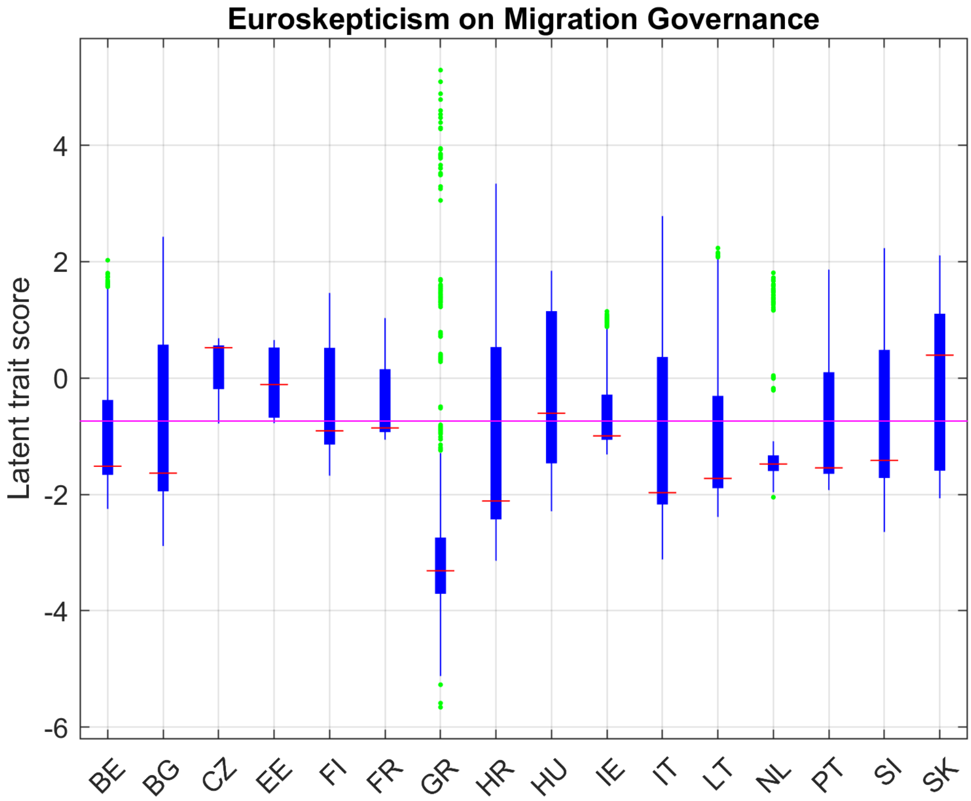

Figure 49: Bayesian IRT model for Euroskepticism on Common Migration Policy: distributions of latent trait scores across the EU countries. The pink line represents the mean level across all the countries.

Aversion to immigrants Table 44 presents the posterior estimates of the factor loadings for the latent trait measuring aversion to immigrants, along with the estimated common thresholds. The discrimiantion coefficients shows that skepticism or resistance towards providing help to refugees is a strong indicator of generalized anti-immigrant sentiment. Following this, Immigrants' Contribution also shows a strong association. Immigration from outside the EU has a substantial factor loading , highlighting that non-EU migration is a critical driver of anti-immigrant sentiment. In contrast, Immigration from the EU displays the lowest factor loading, indicating that intra-European mobility is less associated with aversion. The variation of the estimates across countries indicate that the sensitivity to different aspects of immigration is not uniform across dimensions for individual countries.

Table 44: Bayesian IRT model for Aversion to immigrants: posterior estimates of discrimination parameters and common thresholds.

		Immigration from EU	Immigration from outside EU	Immigrants contribution	Help refugees
Discrimination coefficients	**Overal**	**0.91**	**1.02**	**1.24**	**1.59**
	BE	0.86	1.05	0.95	1.22
	BG	0.30	0.93	1.99	2.36
	CZ	0.66	0.66	1.35	1.85
	EE	0.51	1.07	1.19	1.63
	FI	0.82	0.92	1.09	1.27
	FR	0.85	0.83	1.03	1.40
	GR	0.83	1.05	1.08	1.14
	HR	1.30	1.10	0.69	1.30
	HU	0.39	0.87	1.61	1.99
	IE	0.96	0.75	1.08	1.34
	IT	0.89	0.80	1.02	1.41
	LT	1.01	0.96	0.92	1.24
	NL	0.83	0.80	0.99	1.63
	PT	0.90	0.93	1.18	1.09
	SI	0.72	0.89	1.11	1.52
	SK	0.86	0.75	1.18	1.38
Thresholds	$\gamma 1$	-1.04	-1.32	-1.09	-0.98
	$\gamma 2$	0.18	-0.23	0.02	0.02
	$\gamma 3$	1.60	0.58	0.82	1.67
	mean	0.25	-0.32	-0.08	0.24

Figure 50 provides a representation of the distribution for the latent trait.

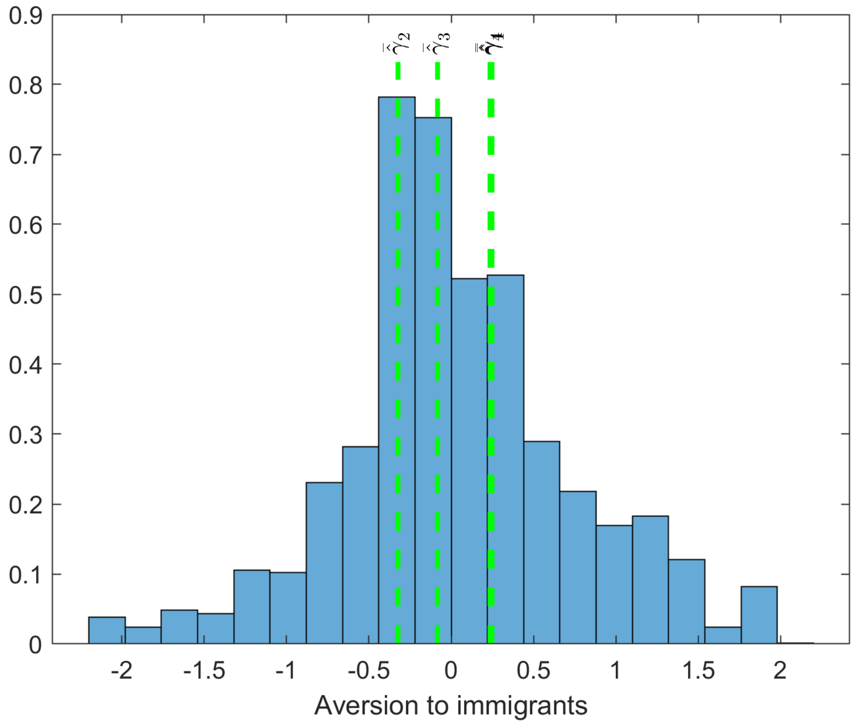

Figure 50: Bayesian IRT model for Aversion to immigrants: distributions of latent trais scores. The green lines represent the estimated thresholds for the items in the trust scale.

Figure 51 presents the distribution of the latent trait across countries. Eastern European nations, such as Hungary, Slovakia, and Bulgaria, display higher trait scores, signaling a stronger overall resistance to immigration. This aversion is not only prevalent but also widely spread within these populations, indicating both a high degree of skepticism and significant internal variability. In contrast, Southern and Northern European countries, including Portugal, Finland, and Slovenia, demonstrate predominantly negative trait scores, reflecting more accepting or neutral attitudes towards immigrants. The respondents from these countries populations tend to be more cohesive in their perspectives, with fewer extreme deviations.

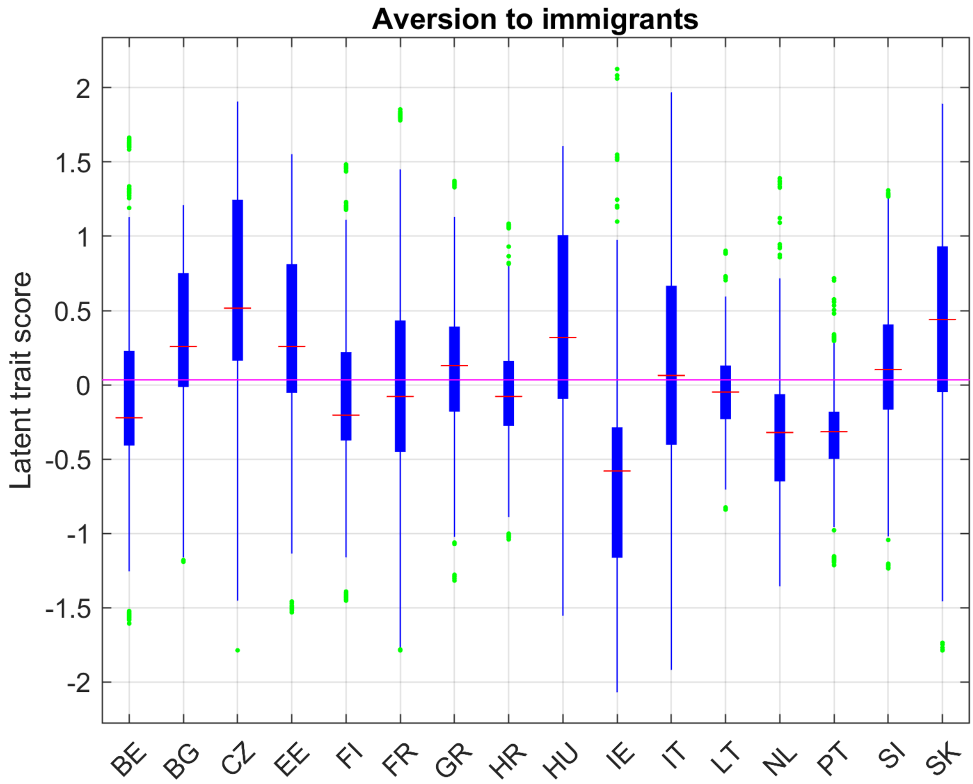

Figure 51: Bayesian IRT model for Aversion to immigrants: distributions of latent trais scores across the EU countries. The pink line represents the mean level across all the countries.

Dependence of target latent variables on common variables Table 45 presents the posterior estimates of the regression coefficients showing the dependence of the latent trait Immigration Rejection on common individual-level variables. The shaded coefficients are statistically significant, as their 95% credible intervals do not include zero. The cross-country analysis identifies key predictors of immigration rejection across Europe, with right-wing political orientation standing out as the strongest and most consistent driver—particularly in France, Hungary, Ireland, Italy, and Slovakia. Age is another significant factor, with older individuals generally expressing stronger rejection, especially in Estonia, Finland, and Ireland. Residing in rural areas or villages is consistently associated with higher levels of immigration rejection. Gender is a significant predictor in 6 out of the 16 countries, as is satisfaction with life and the economy. Trust in institutions is associated with more positive views towards immigrants in 14 countries.

Table 45: Bayesian IRT model for Immigration Rejection: posterior estimates of the regression coefficients for the common variables across countries. The shaded coefficients are statistically significant, as their 95% credible intervals do not include zero.

Variable	level/trend	BE	BG	CZ	EE	FI	FR	GR	HR	HU	IE	IT	LT	NL	PT	SI	SK
(Intercept)		**-0.98**	**-0.48**	**0.62**	-0.26	**-0.60**	**-1.09**	0.06	**-0.68**	0.24	**-1.34**	**-0.88**	**-0.60**	**-0.82**	**-0.46**	**-0.62**	0.33
Age		**0.14**	0.08	0.04	**0.25**	**0.15**	**0.14**	**0.14**	**0.16**	0.00	**0.16**	**0.16**	0.09	0.04	**0.07**	**0.13**	0.06
Gender (baseline Man)	*Woman*	-0.04	**-0.13**	-0.05	**-0.12**	**-0.20**	-0.08	-0.01	**-0.16**	0.02	-0.09	-0.05	0.03	-0.07	0.03	**-0.11**	**-0.15**
Occupation	*Unemployed*	-0.01	-0.10	-0.03	0.12	0.14	0.00	-0.04	0.05	-0.13	0.19	**0.19**	0.16	-0.03	0.04	0.00	-0.21
(baseline	*Retired*	0.08	0.14	0.09	0.07	0.07	0.04	-0.02	-0.03	0.04	0.22	**0.19**	0.11	-0.05	-0.10	0.07	0.14
Employed)	*In Education*	-0.16	-0.17	-0.17	0.04	**-0.17**	-0.13	-0.08	-0.10	-0.09	-0.08	**-0.31**	**-0.49**	-0.06	-0.19	-0.16	-0.44
Domicile	*Small middle town*	0.00	**0.26**	0.04	-0.02	**0.19**	0.10	0.03	-0.07	0.06	**0.23**	-0.12	0.07	**0.12**	0.03	0.11	0.06
(baseline A big city	*Rural Area or village*	0.13	**0.26**	**0.31**	**0.16**	**0.16**	**0.17**	**0.10**	-0.01	0.14	**0.51**	0.03	0.04	**0.18**	-0.01	**0.19**	0.10
or large town)	*Economic difficulties*	**0.21**	0.06	**0.25**	0.12	0.07	0.10	0.05	0.10	0.02	**0.35**	0.05	0.16	-0.05	0.08	0.09	**0.24**
Political	*Centre*	**0.46**	-0.03	-0.02	0.15	**0.34**	**0.62**	**0.34**	**0.43**	**0.27**	**0.45**	**0.53**	-0.05	**0.45**	**0.11**	**0.30**	-0.15
Orientation	*Right*	**0.70**	-0.01	-0.01	0.20	**0.37**	**0.99**	**0.41**	**0.68**	**0.53**	**0.61**	**0.76**	-0.03	**0.66**	**0.18**	**0.60**	-0.14
Attachment	*Linear trend*	0.17	0.12	-0.16	-0.07	-0.17	-0.04	-0.20	-0.03	-0.36	0.06	-0.06	0.13	-0.01	-0.09	-0.26	0.21
country	*Quadratic trend*	-0.08	0.01	**0.15**	-0.07	0.11	-0.04	0.15	0.15	**0.44**	-0.02	0.13	-0.12	-0.02	0.02	0.02	0.15
	Cubic trend	-0.06	-0.05	-0.08	-0.08	0.03	-0.04	-0.02	0.09	**0.26**	**0.20**	-0.05	-0.01	-0.05	0.02	-0.04	0.00
Life Satisfaction	*Linear trend*	**0.51**	0.09	0.23	0.16	0.21	**0.41**	**0.24**	0.02	**0.43**	0.20	**0.50**	0.22	-0.02	**0.22**	0.11	0.20
	Quadratic trend	-0.09	-0.08	0.02	-0.05	0.01	-0.03	**-0.13**	-0.06	-0.02	**-0.40**	-0.07	-0.16	**-0.24**	-0.03	-0.08	**-0.24**
	Cubic trend	-0.11	-0.01	**-0.13**	-0.09	-0.03	-0.04	0.01	-0.03	0.08	0.09	-0.07	0.02	-0.10	-0.03	0.03	0.11
Economy	*Linear trend*	0.06	**0.35**	0.07	**0.26**	0.15	0.12	**-0.20**	-0.02	**0.24**	-0.18	0.23	**0.36**	0.15	-0.05	0.01	**0.55**
Satisfaction	*Quadratic trend*	0.21	-0.01	0.04	0.00	**-0.23**	0.09	0.04	0.31	0.11	0.24	0.04	-0.22	0.13	0.12	0.12	0.06
	Cubic trend	-0.06	-0.01	-0.03	**-0.10**	-0.04	-0.11	0.02	-0.18	0.03	0.07	-0.09	-0.11	-0.04	-0.05	-0.09	**-0.27**
Trust in istitution		**-0.07**	**-0.13**	**-0.11**	**-0.09**	**-0.10**	**-0.09**	**-0.03**	-0.01	**-0.05**	**-0.14**	**-0.09**	**-0.12**	**-0.05**	**-0.07**	**-0.08**	-0.04

Table 46 presents the posterior estimates of the regression coefficients indicating the relationship between the latent trait Perceived Benefits of Immigration and common individual-level variables. Across nearly all countries, trust in institutions is positively associated with more favorable attitudes toward immigration. Political orientation and residence in rural areas or villages are significantly correlated with lower support for immigration in many countries. Economic satisfaction also plays an important role, with higher levels of satisfaction consistently linked to more positive views on immigration in several national contexts.

Table 46: Bayesian IRT model for Perceived benefits of immigration: posterior estimates of the regression coefficients for the common variables across countries. The shaded coefficients are statistically significant, as their 95% credible intervals do not include zero.

		BE	BG	CZ	EE	FI	FR	GR	HR	HU	IE	IT	LT	NL	PT	SI	SK
(Intercept)		**1.39**	**0.50**	-0.06	**0.75**	**1.49**	**1.43**	**0.28**	**0.81**	**0.31**	**1.74**	**0.93**	**0.92**	**1.27**	**1.19**	**0.87**	0.16
Age		0.05	0.01	-0.04	**-0.12**	**0.10**	-0.01	**-0.13**	-0.01	-0.04	-0.07	**-0.11**	-0.01	**0.06**	0.00	0.06	-0.04
Gender (baseline Man)	*Woman*	-0.01	**0.11**	0.04	**0.14**	**0.18**	0.01	0.03	0.10	-0.02	-0.05	0.07	-0.07	0.00	-0.04	0.11	0.03
Occupation	*Unemployed*	-0.14	0.10	0.03	-0.01	-0.11	0.02	-0.06	0.03	0.08	-0.15	**-0.24**	-0.16	0.01	-0.07	-0.04	0.02
(baseline	*Retired*	**-0.25**	-0.02	-0.09	-0.16	**-0.17**	-0.14	-0.06	0.05	0.11	-0.20	**-0.19**	-0.02	-0.11	0.02	-0.08	-0.17
Employed)	*In Education*	-0.07	0.17	0.16	-0.15	0.11	-0.04	0.02	0.03	-0.09	0.13	0.15	**0.30**	0.04	0.10	0.17	0.03
Domicile	*Small middle town*	-0.15	**-0.14**	-0.05	-0.04	**-0.17**	-0.11	**0.24**	0.01	0.02	-0.17	0.07	**-0.21**	-0.10	-0.05	-0.12	-0.13
(baseline A big city	*Rural Area or village*	**-0.21**	**-0.24**	**-0.16**	**-0.14**	**-0.31**	**-0.23**	**0.11**	-0.02	-0.11	**-0.36**	-0.03	**-0.34**	**-0.19**	**-0.15**	**-0.22**	-0.01
or large town)	*Economic difficulties*	-0.13	0.03	**-0.23**	-0.08	-0.02	-0.03	0.03	-0.12	-0.04	**-0.27**	-0.08	**-0.23**	0.04	-0.09	**-0.30**	**-0.18**
Political	*Centre*	**-0.39**	**0.15**	0.04	-0.17	**-0.37**	**-0.63**	**-0.27**	**-0.31**	**-0.35**	**-0.27**	**-0.45**	0.01	**-0.46**	**-0.19**	**-0.38**	0.08
Orientation	*Right*	**-0.64**	0.11	**0.20**	-0.19	**-0.44**	**-1.15**	**-0.69**	**-0.54**	**-0.61**	-0.19	**-0.61**	0.03	**-0.74**	**-0.23**	**-0.73**	0.09
Attachment	*Linear trend*	-0.06	-0.10	-0.15	0.15	-0.05	-0.31	-0.50	-0.08	-0.18	-0.31	0.05	**-0.51**	-0.03	0.23	0.06	-0.20
country	*Quadratic trend*	0.07	-0.01	-0.07	-0.07	**-0.25**	0.02	-0.14	**-0.19**	**-0.30**	**0.27**	-0.13	-0.06	0.04	0.01	-0.11	-0.11
	Cubic trend	0.00	0.03	**0.18**	0.01	-0.17	0.09	**0.17**	0.06	-0.07	0.07	0.05	0.10	0.06	-0.05	0.03	0.00
Life Satisfaction	*Linear trend*	-0.16	**-0.31**	**-0.36**	0.07	-0.03	**-0.36**	-0.21	**-0.51**	**-0.59**	-0.06	**-0.38**	**-0.31**	0.06	**-0.41**	-0.17	-0.07
	Quadratic trend	0.07	0.09	-0.06	0.07	0.07	0.11	-0.04	0.04	0.14	**0.37**	0.12	**0.25**	**0.21**	**0.17**	0.13	**0.19**
	Cubic trend	-0.02	0.02	**0.24**	0.01	-0.06	0.02	-0.02	0.11	0.06	-0.05	-0.02	0.00	0.05	0.08	0.06	-0.10
Economy	*Linear trend*	**-0.29**	**-0.34**	**-0.40**	**-0.54**	**-0.32**	**-0.37**	**-0.35**	**-0.32**	**-0.18**	-0.17	**-0.43**	**-0.66**	**-0.32**	0.04	**-0.29**	**-0.64**
Satisfaction	*Quadratic trend*	0.10	-0.05	-0.05	**0.18**	**0.37**	0.16	0.02	-0.04	-0.10	0.08	0.26	**0.28**	0.11	-0.05	0.10	0.01
	Cubic trend	0.10	**0.20**	**0.16**	**0.14**	**0.15**	**0.15**	**0.12**	0.17	-0.03	0.07	0.02	0.10	0.03	0.16	**0.14**	0.15
Trust in istitution		**0.10**	**0.12**	**0.12**	**0.14**	**0.17**	**0.12**	**0.08**	0.05	**0.07**	**0.14**	**0.12**	**0.17**	**0.08**	**0.13**	**0.12**	**0.09**

4.3.3 Data integration

At each iteration of the MCMC sampling procedure, the predictive distribution of the latent variables *Immigration Rejection* and *Perceived Benefits of Immigration* is computed conditional on the regression coefficients $B_j,\ j = 1, \ldots, J$, which are sampled according to the hierarchical regression model delineated in Section 4.3.1. These conditional samples are subsequently employed to impute the latent trait values for the Eurobarometer respondents, leveraging the structure of the underlying probabilistic model. The imputed latent traits are then accumulated across MCMC iterations to construct their posterior predictive distributions.

In the following, we present a quality assessment of the imputed latent traits in the Eurobarometer survey (recipient), benchmarking them against the corresponding distribution observed in the ESS dataset (donor). This benchmarking exercise evaluates the consistency and reliability of the statistical matching process, with a particular focus on how well the imputed traits in the recipient reflect the distributional properties captured in the donor dataset. Furthermore, we provide a concise discussion of the outcomes derived from a multiple imputation strategy, highlighting its role in enhancing data integration robustness and mitigating imputation uncertainty within the recipient-donor framework.

Comparison of observed and imputed data Figures 52 and 53 represent the observed and imputed distribution of the two target variables. The blue histogram and density curve represent the original distribution from the ESS (donor), while the red histogram and density curve correspond to the imputed distribution in the Eurobarometer survey (recipient). Overall, the matching process appears to have successfully transferred the latent trait's central structure, but with some loss of detail in the extremes.

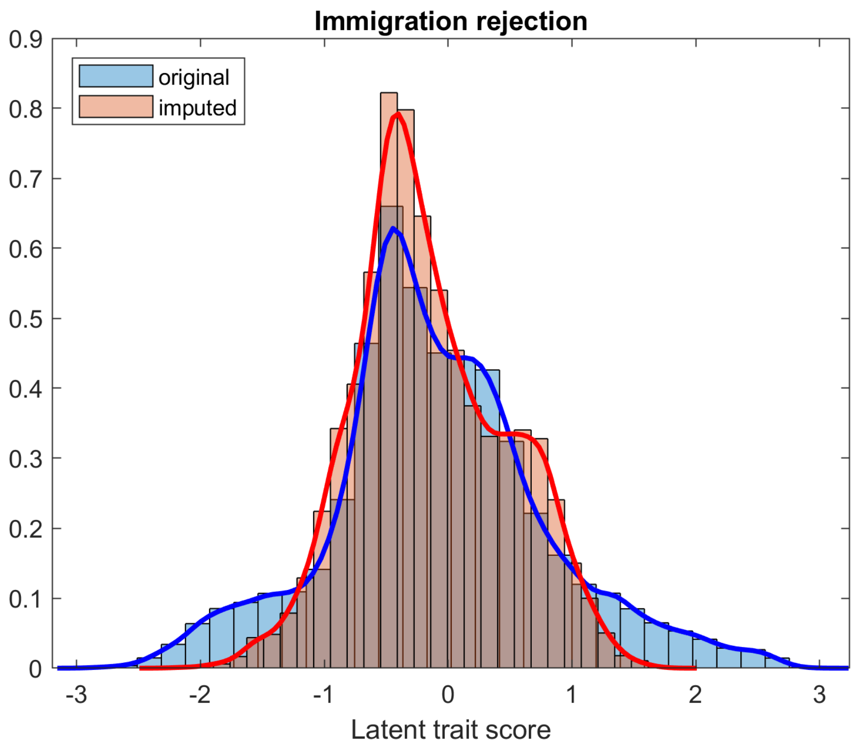

Figure 52: *JMint*: observed and imputed distributions of the target variable "Immigration rejection".

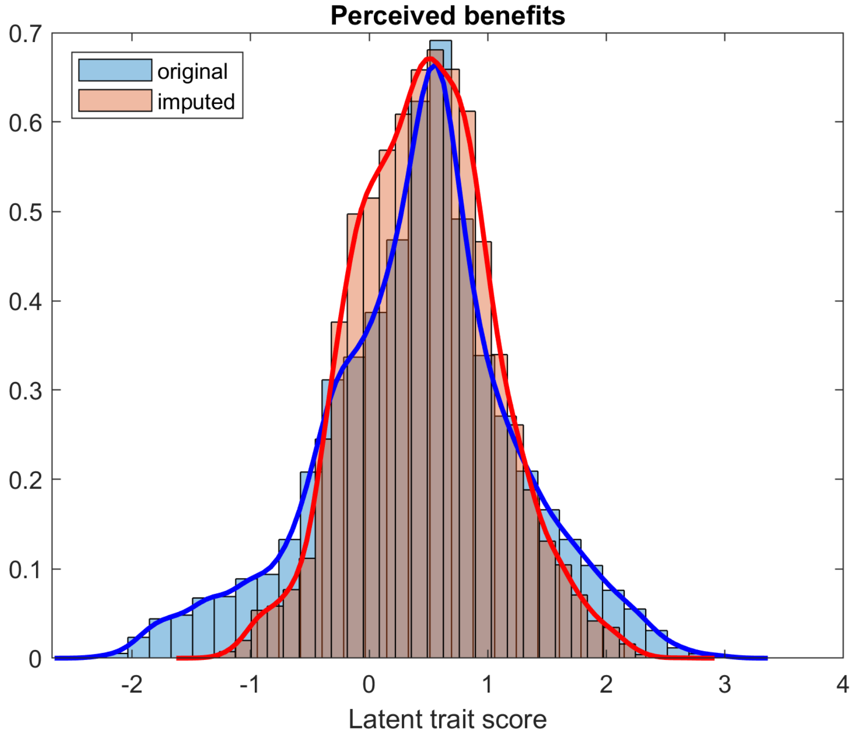

Figure 53: *JMint*: observed and imputed distributions of the target variable "Perceived benefits of immigration".

Figures 54 and 55 represent the observed and imputed distribution of the two target variables by countries. The comparison between the original (ESS) and imputed (Eurobarometer) distributions for the latent traits "Immigration Rejection" and "Perceived Benefits of Immigration" reveals distinct patterns across European countries. For both traits, the imputed distributions generally exhibit higher central concentration and reduced variability in the tails compared to the original ESS data. This effect is particularly pronounced in countries such as Bulgaria, Czech Republic, and Hungary, where the imputation process appears to have oversmoothed the latent trait distributions. In contrast, alignment is more consistent in France and Netherlands, suggesting better model performance in these settings. These discrepancies suggest that while the integrated Bayesian statistical matching procedure effectively captures central tendencies, it may underestimate tail behavior, potentially overlooking regional heterogeneity.

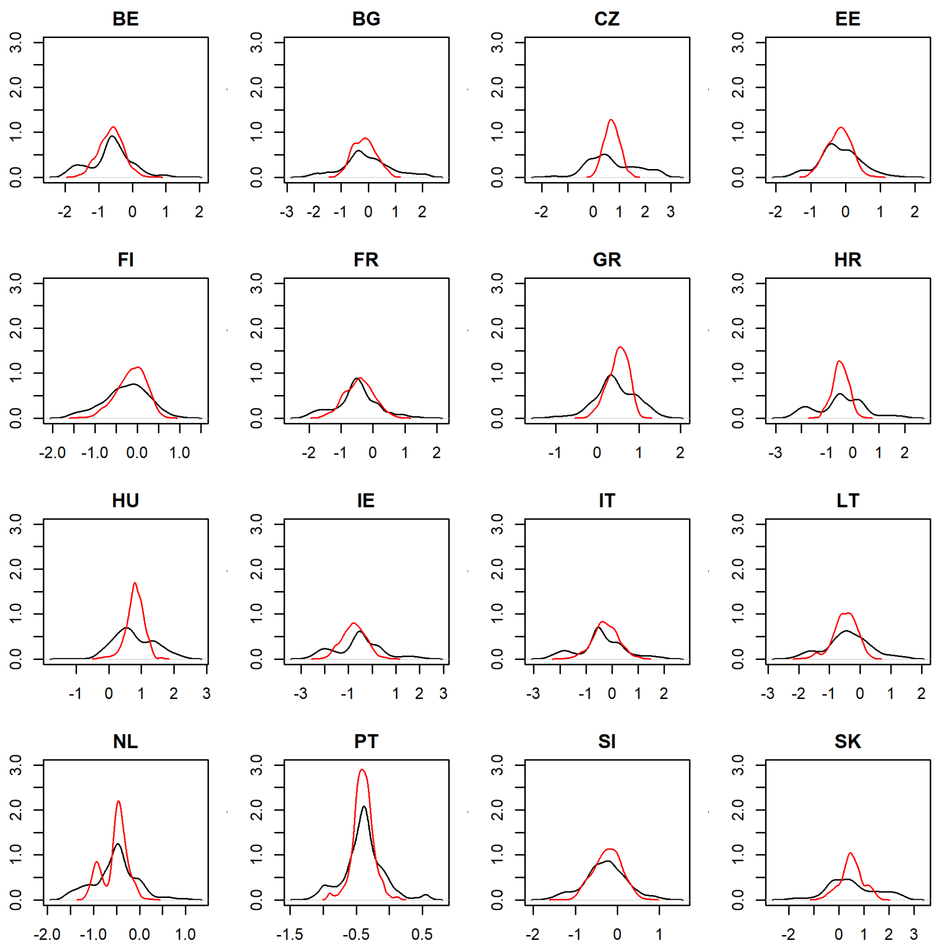

Figure 54: JMint: observed (black) and imputed (red) distributions of the target variable “Immigration rejection” across countries.

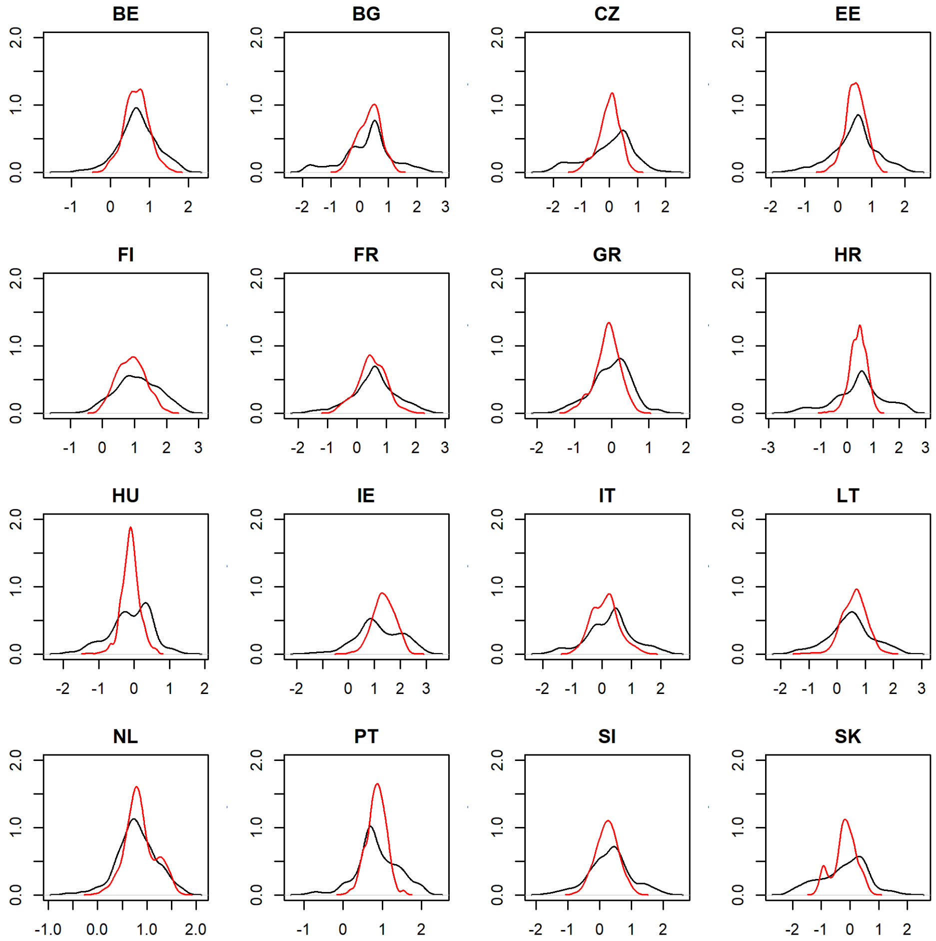

Figure 55: JMint: observed (black) and imputed (red) distributions of the target variable “Perceived benefits of immigration” across countries.

Distributional Fit across countries Table 47 provides the Overlap Coefficient and the Hellinger Distance across European countries. The overall overlap values of 0.875 for Immigration Rejection and 0.880 for Perceived Benefits of Immigration indicate a high degree of shared probability mass between the original (ESS) and imputed (Eurobarometer) distributions. Correspondingly, the Hellinger distances of 0.160 and 0.143 suggest moderate divergence, implying that the imputed distributions generally approximate the original ones with reasonable fidelity.

At the country level, the overlap and Hellinger distances exhibit substantial variability. Countries such as France, Italy, and Slovenia demonstrate strong alignment, signifying high-quality imputation. In contrast, Czech Republic, Croatia, and Hungary report significantly lower overlap and elevated Hellinger distances, indicating marked discrepancies between the imputed and original distributions. These results suggest that the imputation model captured central tendencies effectively in certain regions but struggled to preserve distributional properties in others, likely reflecting regional heterogeneity not fully accounted for during the matching process.

Moreover, the imputation of Perceived Benefits of Immigration consistently shows higher overlap and lower Hellinger distances relative to Immigration Rejection, indicating a more accurate reconstruction of distributional features for this trait. This may suggest that the underlying model assumptions align more closely with the structural characteristics of perceived benefits compared to immigration rejection sentiments.

Table 47: Overlap coefficient and Hellinger distance between the observed and imputed distributions of the target variables "'Immigration rejection" and "Perceived benefits of immigration" across countries.

	Immigration rejection		**Perceived benefits**	
country	***Overlap***	***Hellinger***	***Overlap***	***Hellinger***
Overall	0.875	0.160	0.880	0.143
BE	0.787	0.245	0.840	0.170
BG	0.744	0.320	0.790	0.305
CZ	0.490	0.529	0.631	0.396
EE	0.798	0.249	0.788	0.241
FI	0.797	0.231	0.753	0.294
FR	0.831	0.193	0.832	0.190
GR	0.667	0.360	0.758	0.239
HR	0.623	0.389	0.689	0.341
HU	0.535	0.412	0.583	0.369
IE	0.648	0.351	0.607	0.373
IT	0.806	0.222	0.738	0.265
LT	0.757	0.276	0.762	0.264
NL	0.696	0.320	0.849	0.148
PT	0.817	0.191	0.685	0.340
SI	0.841	0.220	0.788	0.252
SK	0.645	0.347	0.652	0.370

Distributional Fit conditional on common variables Table 48 presents the Overlap Coefficient and Hellinger Distance for the latent traits "Immigration Rejection" and "Perceived Benefits of Immigration", disaggregated by socio-demographic and socio-economic factors. These indicators assess the similarity between the original (ESS) and imputed (Eurobarometer) distributions across various subgroups. The analysis suggests that the statistical matching process performs well in capturing central tendencies across most subgroups. However, there are slightly higher discrepancies for individuals with high satisfaction levels, strong national attachment, and those in education.

Table 48: Overlap coefficient and Hellinger distance between the observed and imputed distributions of the target variables "'Immigration rejection" and "Perceived benefits of immigration" conditional on common variable levels.

		Immigration rejection		Perceived benefits	
		Overlap	*Hellinger*	*Overlap*	*Hellinger*
Gender	Man	0.843	0.191	0.864	0.158
	Woman	0.892	0.140	0.889	0.131
Occupation	Employed	0.835	0.195	0.846	0.190
	Unemployed	0.872	0.162	0.883	0.127
	Retired	0.860	0.178	0.857	0.185
	In Education	0.799	0.214	0.833	0.174
Domicile	A big city or large town	0.858	0.175	0.876	0.153
	Small middle town	0.880	0.165	0.894	0.144
	Rural Area or village	0.865	0.179	0.864	0.147
Economic difficulties	No	0.877	0.158	0.886	0.135
	Yes	0.804	0.228	0.830	0.201
Political Orientation	Left	0.860	0.170	0.881	0.132
	Centre	0.777	0.245	0.810	0.203
	Right	0.808	0.214	0.814	0.221
Attachment country	Not at all attached	0.866	0.208	0.837	0.175
	Not very attached	0.878	0.153	0.883	0.122
	Fairly attached	0.864	0.174	0.865	0.175
	Very attached	0.741	0.313	0.787	0.303
Life Satisfaction	Not at all satisfied	0.868	0.177	0.876	0.142
	Not very satisfied	0.829	0.176	0.879	0.153
	Fairly satisfied	0.828	0.226	0.828	0.191
	Very satisfied	0.682	0.328	0.612	0.399
Economy Satisfaction	Very bad	0.860	0.176	0.880	0.166
	Rather bad	0.851	0.160	0.900	0.121
	Rather good	0.838	0.224	0.706	0.313
	Very good	0.745	0.278	0.773	0.313

Correlation between the imputed data and the Eurobaromenter latent traits "Euroskepticism on Common Migration Policy" and "Aversion to immigrants"
The correlation analysis presented in Table 49 reveals a consistent relationship in the Eurobarometer between Aversion to Immigrants and the two imputed latent traits: Immigration Rejection and Perceived Benefits of Immigration. Specifically, the correlation with Immigration Rejection is positive and statistically significant across all countries, with an overall correlation of 0.48. This suggests that stronger aversion to immigrants is systematically associated with higher levels of immigration rejection. Conversely, the correlation with Perceived Benefits of Immigration is negative, with an overall value of -0.53, indicating that individuals with greater aversion tend to perceive fewer benefits from immigration. The strength of these associations varies by country, with the highest correlations observed in Slovakia (SK) and Finland (FI), while weaker relationships are detected in Croatia (HR) and Hungary (HU).

Table 49: Correlation between "Aversion to immigrants", "Immigration rejection" and "Perceived benefits of immigration"

	Aversion to migrants			
	Immigration rejection		Pereceived benefits	
Overall	0.48	***	-0.53	***
BE	0.38	***	-0.39	***
BG	0.37	***	-0.43	***
CZ	0.25	***	-0.33	***
EE	0.39	***	-0.42	***
FI	0.43	***	-0.53	***
FR	0.44	***	-0.45	***
GR	0.14	***	-0.27	***
HR	0.08	**	-0.17	***
HU	0.12	***	-0.17	***
IE	0.32	***	-0.33	***
IT	0.40	***	-0.45	***
LT	0.21	***	-0.18	***
NL	0.37	***	-0.42	***
PT	0.33	***	-0.34	***
SI	0.30	***	-0.37	***
SK	0.49	***	-0.53	***

The correlation analysis presented in Table 50 provides insights into the relationship between Euroskepticism on Common Migration Policy and the two latent imputed traits: Immigration Rejection and Perceived Benefits of Immigration, again in the Eruobarometer dataset . Compared to the stronger correlations observed with Aversion to Immigrants (Table 49), the associations here are slightly weaker, reflecting a more nuanced or indirect link between Euroskeptic attitudes and perceptions of immigration.

Table 50: Correlation between "Euroskepticism on Common Migration Policy", "Immigration rejection" and "Perceived benefits of immigration"

	Euroskepticism			
	Immigration rejection		Pereceived benefits	
Overall	0.11	***	-0.08	***
BE	0.11	***	-0.19	***
BG	0.18	***	-0.17	***
CZ	0.19	***	-0.24	***
EE	0.24	***	-0.27	***
FI	0.22	***	-0.38	***
FR	0.27	***	-0.30	***
GR	0.01		-0.11	***
HR	-0.03		-0.13	***
HU	0.10	**	-0.13	***
IE	0.12	***	-0.15	***
IT	0.24	***	-0.25	***
LT	0.11	**	-0.07	
NL	0.16	***	-0.22	***
PT	0.26	***	-0.27	***
SI	0.05		-0.17	***
SK	0.21	***	-0.21	***

4.3.4 Consistency of the findings across multiple imputations

To assess the robustness of the results, we conducted an analysis following the principles of the multiple imputation framework. Specifically, we ran the fully integrated Bayesian approach ten times, thereby generating ten completed datasets. In the following sections, we present the results pertaining to the estimation of latent traits and the subsequent data integration phase.

Estimation of latent traits across imputations The density plots presented in Figure 56 illustrate the distribution of the estimated latent traits across the ten repetition of the fully integrated Bayesian approach. The results demonstrate a high degree of stability in the estimated densities, indicating robustness in the estimation process.

For Trust in Institutions (both in the ESS and Eurobarometer datasets), the density curves are notably consistent across the ten imputations, preserving the characteristic bimodal structure observed in the original data. This consistency suggests that the Bayesian sampling effectively captures the latent distribution of institutional trust, with minimal sensitivity to imputation variability.

Similarly, the estimated latent traits for Immigration Rejection and Perceived Benefits of Immigration in the ESS maintain their general distributional shapes across imputations, although with slight variations in density height and spread. These minor discrepancies reflect the natural variability expected in multiple imputation but do not significantly alter the interpretation of the latent constructs.

In the Eurobarometer dataset, the distributions for Euroskepticism and Aversion to Immigrants also exhibit strong alignment across iterations. The density estimates are stable, with well-defined peaks that align closely with those observed in the ESS data, indicating successful statistical matching and coherent integration of latent traits.

Overall, the stability of the density plots across the ten multiple imputation runs provides evidence of the robustness of the fully integrated Bayesian approach. The method effectively maintains the structural characteristics of the latent traits, supporting its reliability for the statistical matching and data integration phase.

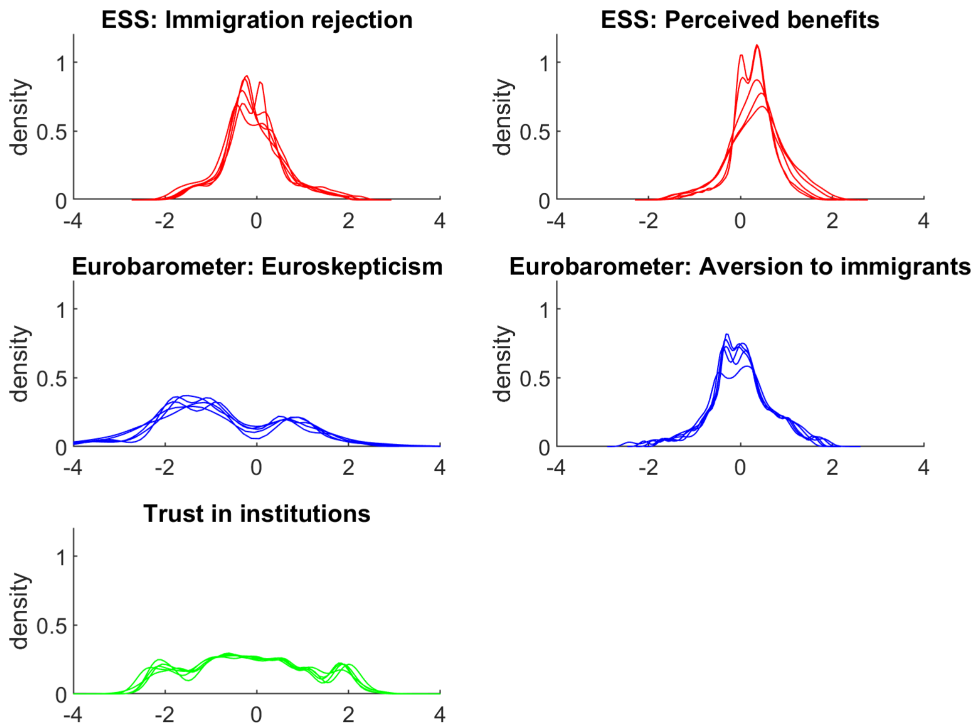

Figure 56: *Jmint*: density plot for the estimated latent traits across repetitions.

Data Integration across multiple imputations The density plots in Figures 57 and 58 illustrate the distributions of the latent traits, comparing the original estimates from the ESS dataset (donor)—represented by the blue curves—with the imputed estimates for the Eurobarometer dataset (recipient)—represented by the red curves. The results demonstrate relative consistency across imputations.

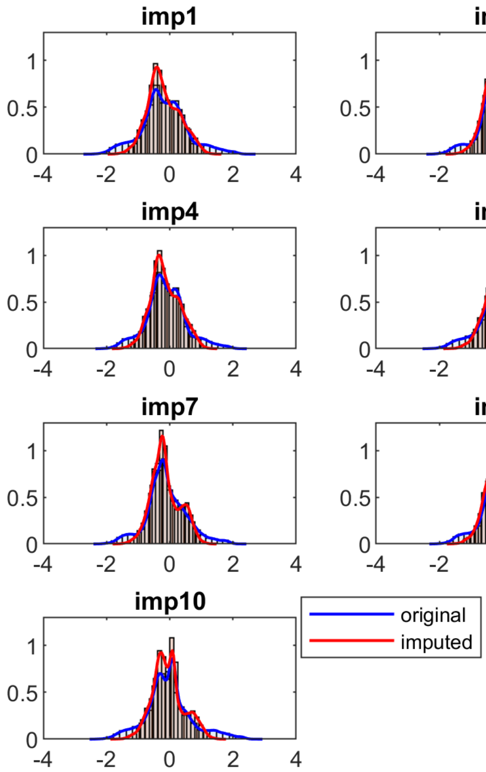

Figure 57: *JMint*: observed (black) and imputed (red) distributions of the target variable "Immigration Rejection" across repetitions.

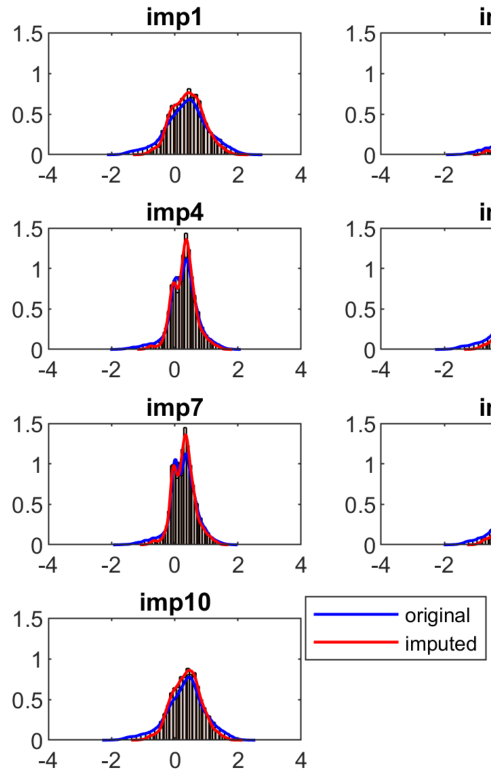

Figure 58: *JMint*: observed (black) and imputed (red) distributions of the target variable “Benefits of Immigration” across repetitions.

4.4 Comparison of parametric SM approaches

In the following, we compare the distributional properties of the latent traits originally estimated in the ESS with those imputed in the Eurobarometer, and evaluate the external validity of the imputation results based on available auxiliary information.

Distributional Fit: Hellinger Distance and Overlap Measures To evaluate the quality of the imputations obtained through different multiple imputation (MI) strategies, we assess the distributional similarity between the estimated latent traits in the ESS and the imputed traits in the Eurobarometer dataset. Specifically, we use :Hellinger Distance, which quantifies the dissimilarity between two probability distributions (lower values indicate better fit), and Overlap , which captures the degree of shared support between two distributions (higher values indicate better fit). Hellinger distance (HD) and the Overlap index are discussed in greater detail in Section 3

Both measures are computed using the `comp.cont` function from the `StatMatch` R package (D'Orazio, 2015). The metrics are reported for the two target latent variables: *Immigration rejection* and *Perceived benefits of immigration*, across six imputation strategies including both Fully Conditional Specification (FCS) and Joint Modelling (JM), under single-level and multilevel configurations. We also include the results for the Bayesian integrated approach.

The results are represented in Figures 59 and 60.

Hellinger distance across imputation methods

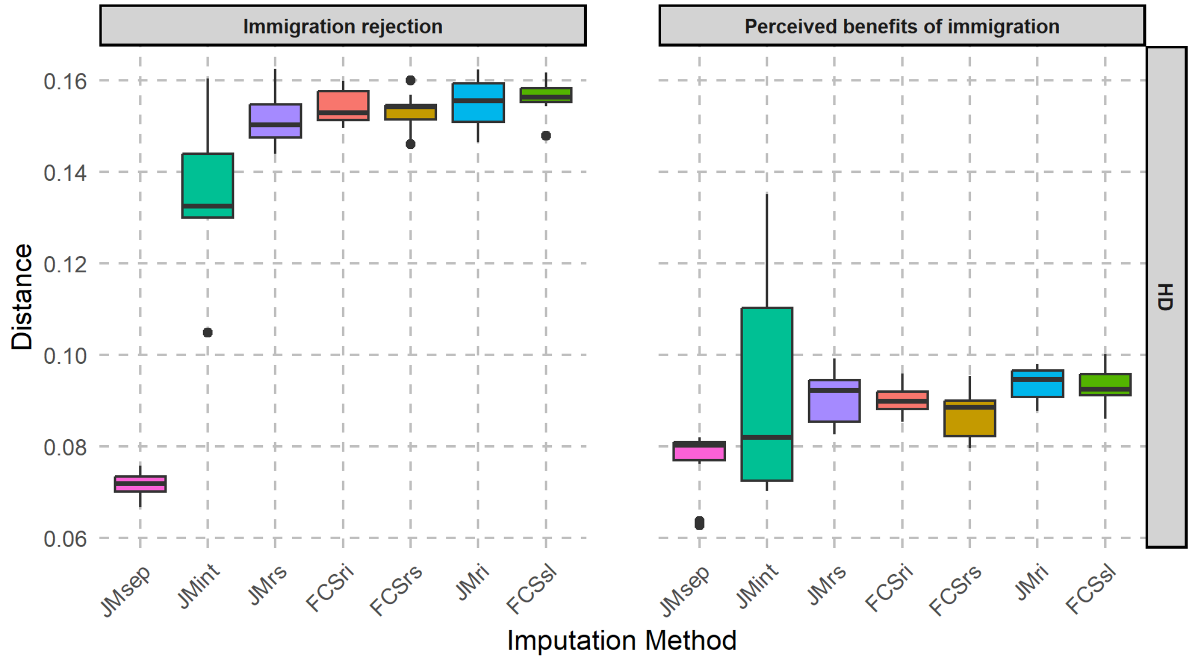

Figure 59: Hellinger distance (HD) between the observed and imputed distributions of the target variables across the m replications and the imputation approaches.

Overlap measure across imputation methods

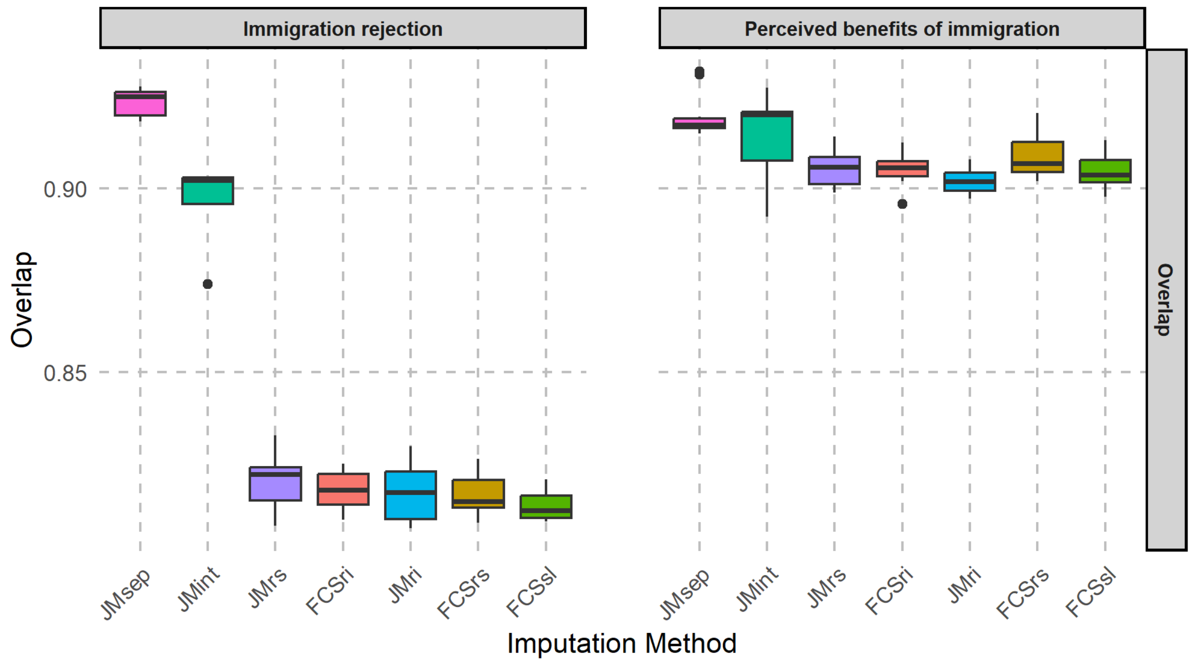

Figure 60: Overlap measure between the observed and imputed distributions of the target variables across the m replications and the imputation approaches.

Figures 59 and 60 clearly illustrates that the choice of imputation strategy has a significant impact on the quality of the reconstructed latent trait distributions. The single-level method (FCSsl) and group-wise imputation (JMsep) yield relatively low Hellinger distances and high overlap scores for *Immigration rejection*, suggesting a good fit.

However, for the more complex trait *Perceived benefits of immigration*, these methods show increased divergence from the ESS reference distribution. In contrast, multilevel imputation methods—especially those accounting for random slopes (FCSrs and JMrs)—achieve more consistent performance across both metrics and variables. This confirms the importance of modeling hierarchical structure and allowing for within-group heterogeneity in data integration tasks involving latent constructs.

Overall, the combination of multilevel modeling and parametric imputation appears to provide the most reliable reproduction of latent trait distributions when transferring information from the ESS to the Eurobarometer.

Distributional Fit Across Countries When comparing the distributional distances between observed and imputed data across countries (Tables 51 and 52) it is possible to appreciate that the imputation process is generally robust across most countries, with better alignment for Perceived Benefits of Immigration than for Immigration Rejection. This might suggest that respondents' attitudes toward perceived benefits are more uniformly captured in the statistical matching procedure compared to rejection sentiments .

Table 51: Means of the Hellinger distance between the observed and imputed distributions of the target variables "Immigration rejection" and "Perceived benefits of immigration" for the 10 replications across countries.

	Immigration rejection							Perceived benefits of immigration						
	FCSsl	*FCSri*	*FCSrs*	*JMsep*	*JMri*	*JMrs*	*Jmint*	*FCSsl*	*FCSri*	*FCSrs*	*JMsep*	*JMri*	*JMrs*	*Jmint*
All countries	**0.156**	**0.154**	**0.153**	**0.072**	**0.155**	**0.152**	**0.134**	**0.093**	**0.090**	**0.087**	**0.077**	**0.094**	**0.091**	**0.094**
BE	0.30	0.30	0.30	0.31	0.30	0.29	0.17	0.18	0.18	0.19	0.21	0.20	0.18	0.12
BG	0.18	0.20	0.19	0.19	0.18	0.19	0.33	0.18	0.19	0.18	0.19	0.18	0.18	0.28
CZ	0.20	0.22	0.24	0.24	0.20	0.20	0.52	0.20	0.20	0.22	0.21	0.19	0.20	0.36
EE	0.27	0.26	0.27	0.29	0.27	0.26	0.20	0.17	0.18	0.18	0.21	0.18	0.18	0.21
FI	0.28	0.28	0.29	0.26	0.29	0.29	0.17	0.18	0.19	0.18	0.21	0.17	0.19	0.19
FR	0.26	0.25	0.25	0.19	0.25	0.25	0.17	0.16	0.17	0.18	0.15	0.17	0.16	0.17
GR	0.27	0.26	0.27	0.23	0.26	0.27	0.24	0.21	0.20	0.22	0.21	0.21	0.20	0.15
HR	0.31	0.31	0.33	0.24	0.31	0.30	0.40	0.20	0.19	0.19	0.19	0.19	0.19	0.35
HU	0.24	0.24	0.24	0.21	0.24	0.25	0.32	0.20	0.21	0.21	0.21	0.20	0.20	0.23
IE	0.35	0.35	0.36	0.30	0.34	0.32	0.30	0.25	0.25	0.26	0.27	0.25	0.26	0.28
IT	0.24	0.25	0.25	0.22	0.24	0.25	0.23	0.19	0.19	0.20	0.18	0.18	0.19	0.25
LT	0.25	0.24	0.24	0.15	0.24	0.25	0.26	0.16	0.15	0.16	0.10	0.16	0.16	0.24
NL	0.36	0.35	0.35	0.29	0.35	0.36	0.22	0.20	0.20	0.19	0.15	0.21	0.20	0.09
PT	0.39	0.40	0.42	0.35	0.40	0.41	0.14	0.22	0.22	0.21	0.18	0.23	0.21	0.20
SI	0.18	0.17	0.19	0.20	0.18	0.18	0.15	0.14	0.12	0.14	0.11	0.14	0.13	0.16
SK	0.20	0.21	0.21	0.29	0.21	0.21	0.35	0.18	0.16	0.17	0.19	0.17	0.18	0.31

Table 52: Means of the Overlap coefficient between the observed and imputed distributions of the target variables "Immigration rejection" and "Perceived benefits of immigration" for the 10 replications across countries.

	Immigration rejection							Perceived benefits of immigration						
	FCSsl	*FCSri*	*FCSrs*	*JMsep*	*JMri*	*JMrs*	*Jmint*	*FCSsl*	*FCSri*	*FCSrs*	*JMsep*	*JMri*	*JMrs*	*Jmint*
All countries	**0.813**	**0.818**	**0.817**	**0.923**	**0.817**	**0.820**	**0.896**	**0.905**	**0.905**	**0.909**	**0.920**	**0.902**	**0.905**	**0.914**
BE	0.65	0.66	0.66	0.66	0.65	0.67	0.86	0.81	0.81	0.80	0.80	0.80	0.82	0.89
BG	0.82	0.80	0.80	0.78	0.81	0.80	0.76	0.81	0.80	0.81	0.80	0.80	0.81	0.81
CZ	0.80	0.78	0.77	0.79	0.81	0.81	0.49	0.80	0.80	0.80	0.79	0.80	0.80	0.66
EE	0.71	0.70	0.71	0.67	0.70	0.71	0.83	0.80	0.79	0.79	0.76	0.79	0.80	0.81
FI	0.68	0.69	0.68	0.69	0.68	0.67	0.83	0.84	0.82	0.83	0.80	0.84	0.82	0.80
FR	0.69	0.70	0.70	0.77	0.70	0.70	0.86	0.83	0.84	0.82	0.82	0.83	0.83	0.84
GR	0.73	0.74	0.71	0.78	0.72	0.71	0.79	0.77	0.78	0.75	0.76	0.77	0.77	0.84
HR	0.63	0.65	0.61	0.75	0.65	0.65	0.62	0.79	0.80	0.80	0.80	0.81	0.80	0.67
HU	0.73	0.72	0.73	0.77	0.74	0.72	0.65	0.78	0.77	0.76	0.76	0.77	0.78	0.75
IE	0.59	0.59	0.59	0.68	0.61	0.64	0.71	0.75	0.75	0.74	0.73	0.76	0.75	0.71
IT	0.72	0.72	0.72	0.75	0.73	0.72	0.79	0.80	0.80	0.80	0.80	0.81	0.79	0.76
LT	0.73	0.74	0.74	0.85	0.74	0.72	0.77	0.83	0.83	0.84	0.90	0.84	0.83	0.76
NL	0.58	0.59	0.59	0.67	0.59	0.58	0.81	0.78	0.78	0.80	0.83	0.77	0.78	0.90
PT	0.53	0.52	0.50	0.61	0.53	0.52	0.85	0.76	0.78	0.78	0.80	0.76	0.77	0.80
SI	0.79	0.81	0.78	0.76	0.80	0.80	0.89	0.85	0.87	0.86	0.88	0.86	0.86	0.86
SK	0.80	0.79	0.79	0.70	0.79	0.78	0.66	0.84	0.86	0.84	0.81	0.84	0.84	0.73

At the global level, `Jmint` and `JMsep` yield the lowest average Hellinger distances (0.134 and 0.072, respectively) for *Immigration rejection*, and `Jmint` achieves a high average overlap for both traits (0.896 and 0.914) second only to the country wise model. These results indicate that joint modeling approaches, particularly when integrated across imputations, offer superior distributional recovery. In contrast, single-level methods such as `FCSsl` perform worse in most countries, with particularly high distances observed in Ireland (IE), the Netherlands (NL), and Portugal (PT). Country-specific values confirm these trends: for example, `Jmint` achieves high overlap in Belgium (0.86), France (0.86), Slovenia (0.89), and the Netherlands (0.90) for *Perceived benefits of immigration*, suggesting robust recovery of latent trait distributions. Furthermore, the overall accuracy is generally higher for *Perceived benefits of immigration* than for *Immigration rejection*, as shown by consistently lower Hellinger distances and higher overlaps. This may reflect a more stable relationship between the observed covariates and the latent construct. Altogether, these findings support the use of multilevel, parametric imputation methods—particularly joint modelling with integrated pooling—for statistically matching latent traits across surveys in a cross-national context.

Distributional Fit conditional on common variables When conditioning on covariate levels (Tables 53 and 54), the results indicate that the imputation models generally maintain strong alignment with the ESS for socio-demographic groups such as women, unemployed individuals, and those living in small middle towns. However, it appears to face some challenges in capturing distributional nuances for students, rural residents, and those with high life and economic satisfaction.

Table 53: Means of the Hellinger distance between the observed and imputed distributions of the target variables "Immigration rejection" and "Perceived benefits of immigration" for the 10 replications conditional on common variable levels.

		Immigration rejection							Perceived benefits of immigration						
		FCSsl	*FCSri*	*FCSrs*	*JMsep*	*JMri*	*JMrs*	*Jmint*	*FCSsl*	*FCSri*	*FCSrs*	*JMsep*	*JMri*	*JMrs*	*Jmint*
Gender	Woman	0.07	0.15	0.15	0.15	0.15	0.15	0.16	0.06	0.10	0.09	0.09	0.09	0.09	0.12
	Man	0.08	0.15	0.15	0.16	0.15	0.15	0.11	0.07	0.09	0.09	0.08	0.09	0.08	0.09
Occupation	Employed	0.08	0.16	0.16	0.16	0.16	0.16	0.16	0.07	0.10	0.09	0.10	0.09	0.10	0.14
	Unemployed	0.09	0.16	0.15	0.15	0.15	0.15	0.14	0.09	0.10	0.09	0.09	0.10	0.09	0.09
	Retired	0.12	0.14	0.14	0.14	0.14	0.14	0.16	0.10	0.08	0.08	0.08	0.08	0.08	0.13
	Education	0.16	0.17	0.17	0.17	0.17	0.17	0.20	0.12	0.11	0.11	0.11	0.11	0.11	0.14
Domicile	A big city or large town	0.09	0.15	0.15	0.16	0.15	0.15	0.15	0.08	0.09	0.09	0.09	0.09	0.10	0.10
	Small middle town	0.09	0.16	0.16	0.16	0.16	0.16	0.14	0.06	0.09	0.09	0.09	0.09	0.09	0.10
	Rural Area or village	0.08	0.15	0.14	0.14	0.14	0.14	0.15	0.08	0.09	0.09	0.08	0.08	0.09	0.11
Economic difficulties	No	0.08	0.16	0.16	0.16	0.16	0.16	0.14	0.06	0.09	0.08	0.08	0.09	0.09	0.10
	Yes	0.10	0.15	0.15	0.15	0.15	0.15	0.18	0.12	0.11	0.11	0.10	0.11	0.11	0.14
Political Orientation	Left	0.12	0.19	0.19	0.19	0.19	0.19	0.14	0.12	0.11	0.11	0.11	0.11	0.11	0.09
	Centre	0.08	0.16	0.16	0.16	0.16	0.16	0.23	0.08	0.09	0.09	0.09	0.09	0.09	0.15
	Right	0.09	0.12	0.12	0.13	0.12	0.12	0.18	0.11	0.10	0.10	0.10	0.10	0.09	0.17
Attachment country	Not at all attached	0.11	0.19	0.19	0.18	0.17	0.19	0.18	0.15	0.16	0.18	0.18	0.17	0.16	0.14
	Not very attached	0.07	0.15	0.15	0.14	0.14	0.14	0.14	0.07	0.09	0.09	0.10	0.10	0.09	0.10
	Fairly attached	0.08	0.17	0.17	0.17	0.16	0.16	0.15	0.07	0.10	0.10	0.10	0.10	0.10	0.12
	Very attached	0.08	0.15	0.15	0.16	0.15	0.15	0.27	0.09	0.10	0.10	0.10	0.10	0.10	0.24
Life Satisfaction	Not at all satisfied	0.20	0.18	0.18	0.17	0.18	0.17	0.15	0.24	0.15	0.15	0.14	0.16	0.16	0.10
	Not very satisfied	0.08	0.16	0.16	0.16	0.15	0.15	0.15	0.07	0.09	0.09	0.09	0.09	0.09	0.12
	Fairly satisfied	0.08	0.16	0.16	0.16	0.17	0.16	0.16	0.10	0.11	0.11	0.10	0.11	0.10	0.13
	Very satisfied	0.09	0.14	0.14	0.14	0.14	0.14	0.30	0.10	0.09	0.09	0.09	0.09	0.09	0.29
Economy Satisfaction	Very bad	0.12	0.15	0.15	0.15	0.16	0.15	0.15	0.16	0.13	0.13	0.13	0.13	0.13	0.11
	Rather bad	0.07	0.16	0.16	0.16	0.16	0.16	0.13	0.07	0.09	0.09	0.09	0.09	0.09	0.09
	Rather good	0.10	0.16	0.16	0.16	0.16	0.16	0.19	0.09	0.09	0.09	0.08	0.09	0.09	0.21
	Very good	0.12	0.17	0.17	0.17	0.17	0.17	0.26	0.15	0.14	0.14	0.14	0.15	0.14	0.23

Table 54: Means of the Overlap coefficient between the observed and imputed distributions of the target variables "Immigration rejection" and "Perceived benefits of immigration" for the 10 replications conditional on common variable levels.

		Immigration rejection							Perceived benefits of immigration						
		FCSsl	*FCSri*	*FCSrs*	*JMsep*	*JMri*	*JMrs*	*Jmint*	*FCSsl*	*FCSri*	*FCSrs*	*JMsep*	*JMri*	*JMrs*	*Jmint*
Gender	Woman	0.82	0.82	0.82	0.92	0.82	0.82	0.86	0.90	0.90	0.90	0.93	0.90	0.90	0.89
	Man	0.82	0.82	0.81	0.91	0.82	0.82	0.92	0.91	0.91	0.92	0.94	0.91	0.91	0.93
Occupation	Employed	0.81	0.81	0.81	0.91	0.81	0.81	0.87	0.90	0.90	0.90	0.92	0.90	0.90	0.87
	Unemployed	0.81	0.82	0.82	0.92	0.83	0.83	0.88	0.91	0.91	0.91	0.90	0.90	0.91	0.91
	Retired	0.85	0.85	0.84	0.88	0.85	0.84	0.88	0.92	0.92	0.92	0.90	0.92	0.92	0.90
	Education	0.79	0.80	0.80	0.83	0.80	0.80	0.83	0.88	0.89	0.90	0.87	0.89	0.89	0.86
Domicile	A big city or large town	0.82	0.81	0.81	0.90	0.82	0.82	0.88	0.90	0.90	0.91	0.90	0.90	0.90	0.92
	Small middle town	0.83	0.84	0.83	0.91	0.83	0.83	0.89	0.91	0.91	0.91	0.92	0.91	0.91	0.92
	Rural Area or village	0.81	0.81	0.81	0.91	0.81	0.81	0.88	0.90	0.90	0.91	0.93	0.90	0.91	0.89
Economic difficulties	No	0.81	0.81	0.81	0.91	0.81	0.81	0.88	0.91	0.91	0.92	0.93	0.91	0.91	0.91
	Yes	0.82	0.82	0.82	0.90	0.82	0.82	0.83	0.90	0.89	0.90	0.88	0.89	0.90	0.88
Political Orientation	Left	0.78	0.78	0.77	0.86	0.77	0.78	0.88	0.89	0.90	0.90	0.87	0.90	0.89	0.92
	Centre	0.81	0.81	0.81	0.91	0.81	0.81	0.78	0.90	0.91	0.91	0.91	0.91	0.91	0.85
	Right	0.86	0.87	0.86	0.91	0.86	0.86	0.84	0.90	0.90	0.90	0.90	0.90	0.90	0.83
Attachment country	Not at all attached	0.81	0.81	0.81	0.89	0.82	0.81	0.88	0.84	0.82	0.83	0.84	0.85	0.83	0.87
	Not very attached	0.84	0.83	0.84	0.93	0.84	0.84	0.89	0.91	0.91	0.91	0.94	0.90	0.91	0.91
	Fairly attached	0.80	0.80	0.80	0.90	0.81	0.81	0.87	0.90	0.90	0.90	0.91	0.90	0.90	0.90
	Very attached	0.83	0.82	0.82	0.91	0.82	0.82	0.79	0.89	0.89	0.90	0.92	0.89	0.90	0.80
Life Satisfaction	Not at all satisfied	0.81	0.81	0.81	0.79	0.80	0.81	0.88	0.86	0.86	0.87	0.73	0.86	0.85	0.91
	Not very satisfied	0.83	0.85	0.85	0.91	0.84	0.84	0.84	0.91	0.91	0.91	0.90	0.91	0.91	0.90
	Fairly satisfied	0.82	0.81	0.81	0.91	0.82	0.82	0.88	0.90	0.90	0.90	0.93	0.90	0.90	0.89
	Very satisfied	0.81	0.81	0.81	0.91	0.81	0.81	0.73	0.90	0.91	0.90	0.89	0.90	0.90	0.72
Economy Satisfaction	Very bad	0.83	0.82	0.82	0.88	0.81	0.83	0.88	0.87	0.87	0.87	0.83	0.87	0.87	0.91
	Rather bad	0.81	0.82	0.81	0.92	0.82	0.81	0.87	0.90	0.90	0.90	0.93	0.90	0.90	0.92
	Rather good	0.80	0.81	0.80	0.89	0.81	0.81	0.86	0.91	0.90	0.91	0.90	0.90	0.91	0.80
	Very good	0.83	0.82	0.82	0.86	0.82	0.83	0.77	0.87	0.86	0.87	0.84	0.86	0.87	0.83

Correlation between the imputed data and the control variable "Aversion to immigrants" As detailed in Section 3.5, we derived a latent trait—*Aversion to immigrants*—from the Eurobarometer survey, based on four questionnaire items conceptually related to the target variables *Immigration rejection* and *Perceived benefits of immigration*. Although these items reflect a combination of perceived benefits and rejection, they are theoretically consistent with the underlying construct of attitudinal aversion toward immigration. This control variable serves as an external criterion, allowing us to assess the convergent validity of the imputations produced by different methods. By comparing how well the imputed values correlate with this latent trait, we gain insight into the substantive plausibility and fidelity of the imputation models.

Tables 55 reports the bivariate association between the control latent trait *Aversion to Immigrants* and the two target latent traits: *Immigration Rejection* (left panel) and *Perceived Benefits of Immigration* (right panel). Correlations are computed for each imputation method across countries, and significance is indicated with an asterisk. The first row reports overall correlations, while the subsequent rows display country-specific values.

Table 55: Estimated pooled correlation coefficients between the target variables Immigration rejection and Perceived benefits of immigration and the control variable Aversion to immigrants.

	Immigration rejection ~~ Aversion to immigrants							Perceived benefits of immigration ~~ Aversion to immigrants						
	FCSsl	*FCSri*	*FCSrs*	*JMsep*	*JMri*	*JMrs*	*JMint*	*FCSsl*	*FCSri*	*FCSrs*	*JMsep*	*JMri*	*JMrs*	*JMint*
All	**0.12 ***	**0.12 ***	**0.13 ***	**0.01**	**0.12 ***	**0.14 ***	**0.48 ***	**-0.14 ***	**-0.14 ***	**-0.15 ***	**0.00**	**-0.14 ***	**-0.15 ***	**-0.54 ***
BE	0.04	0.05	0.05 *	0.01	0.04	0.04	0.08	-0.06	-0.05	-0.07 *	0.00	-0.07	-0.07 *	-0.16 *
BG	0.03	0.07	0.06	0.00	0.04	0.09	0.17 *	-0.04	-0.06	-0.05 *	0.01	-0.04	-0.07	-0.15 *
CZ	0.07	0.07 *	0.06	0.02	0.07 *	0.06	0.18 *	-0.09	-0.10 *	-0.05 *	-0.01	-0.09 *	-0.10 *	-0.23 *
EE	0.11 *	0.10 *	0.10 *	-0.02	0.11 *	0.12 *	0.22 *	-0.12 *	-0.12 *	-0.12 *	0.04	-0.13 *	-0.13 *	-0.25 *
FI	0.10 *	0.10 *	0.14 *	-0.02	0.11 *	0.14 *	0.22 *	-0.12 *	-0.13 *	-0.20 *	0.02	-0.14 *	-0.19 *	-0.37 *
FR	0.12 *	0.10 *	0.12 *	0.01	0.07	0.12 *	0.25 *	-0.14 *	-0.13 *	-0.13 *	-0.03	-0.08	-0.14 *	-0.28 *
GR	0.06 *	0.05	0.03	-0.03	0.07	0.00	0.01	-0.08 *	-0.05	-0.06	0.01	-0.08 *	-0.05	-0.11 *
HR	0.06 *	0.08 *	0.00	-0.01	0.04	0.02	-0.02	-0.11 *	-0.10 *	-0.04	0.01	-0.07 *	-0.05	-0.13 *
HU	0.02	0.02	0.04	0.02	0.04	0.01	0.10 *	-0.02	0.00	-0.06	-0.03	-0.03	-0.03	-0.12 *
IE	0.04	0.05	0.07	0.03 *	0.05	0.07 *	0.12 *	-0.06 *	-0.06	-0.07 *	-0.04 *	-0.06 *	-0.07 *	-0.15 *
IT	0.10 *	0.08 *	0.07	0.04 *	0.08	0.09 *	0.23 *	-0.12 *	-0.11 *	-0.08	-0.03	-0.10 *	-0.12 *	-0.23 *
LT	0.05	0.06	0.07	-0.05	0.03	0.04	0.11 *	-0.05	-0.07	-0.06	0.08 *	-0.03	-0.04	-0.09 *
NL	0.06	0.07	0.09 *	0.00	0.08 *	0.08 *	0.14 *	-0.08 *	-0.09 *	-0.09 *	0.01	-0.08 *	-0.11 *	-0.19 *
PT	0.07 *	0.09	0.09	0.01	0.11 *	0.10 *	0.25 *	-0.08 *	-0.09	-0.07	0.00	-0.10 *	-0.09 *	-0.26 *
SI	0.02	0.01	0.03	0.07 *	0.03	0.04	0.02	-0.05	-0.03	-0.06	-0.04	-0.04	-0.06	-0.16 *
SK	0.08 *	0.06	0.07 *	0.03	0.09 *	0.09	0.21 *	-0.10 *	-0.07 *	-0.10 *	-0.01	-0.11 *	-0.10 *	-0.21 *

The overall results show that *Aversion to Immigrants* is positively and significantly correlated with *Immigration Rejection* across all imputation methods, with the strongest correlation observed under the `JMint` approach (0.48). In contrast, its relationship with *Perceived Benefits of Immigration* is negative, again most strongly so under `JMint` (-0.54). These patterns suggest that the imputed latent constructs preserve their expected directional relationship with the control variable more clearly under joint modelling with integrated pooling.

At the country level, variation in correlation strength and significance is evident. For example, Estonia (EE), Finland (FI), and France (FR) show consistently significant positive correlations between aversion and rejection, particularly under FCS and JM multilevel strategies. Similarly, the negative association with perceived benefits is most robust and pronounced under `JMint` in countries like Finland, Estonia, and Portugal, where the estimates reach significance and higher magnitude.

Methods that neglect multilevel structure or do not integrate across imputations (e.g., JMsep, FCSsl) tend to produce weaker or nonsignificant associations, especially for more complex traits like perceived benefits. Overall, these findings confirm the external validity of the imputed latent constructs and highlight the superior performance of multilevel and integrated imputation approaches in preserving meaningful trait associations.

Correlation between the imputed data and the variable "Euroskepticism on Common Migration Policy" Table 56 shows the estimated correlations coefficients between the target variables Immigration rejection and Perceived benefits of immigration and the variable Euroskepticism on Common Migration Policy.

Table 56: Estimated pooled correlation coefficients between the target variables Immigration rejection and Perceived benefits of immigration and the variable Euroskepticism on Common Migration Policy.

	Immigration rejection ~~ Euroskepticism							Perceived benefits of immigration ~~ Euroskepticism						
	FCSsl	*FCSri*	*FCSrs*	*JMsep*	*JMri*	*JMrs*	*JMint*	*FCSsl*	*FCSri*	*FCSrs*	*JMsep*	*JMri*	*JMrs*	*JMint*
All	**0.07 ***	**0.07 ***	**0.07 ***	**0.01**	**0.07 ***	**0.07 ***	**0.14 ***	**-0.08 ***	**-0.08 ***	**-0.09 ***	**0.00**	**-0.08 ***	**-0.09 ***	**-0.09 ***
BE	0.12 *	0.14 *	0.15 *	-0.01	0.14 *	0.16 *	0.38 *	-0.14 *	-0.08 *	-0.17 *	-0.01	-0.16 *	-0.17 *	-0.40 *
BG	0.11 *	0.11 *	0.17 *	0.00	0.08	0.15 *	0.36 *	-0.15 *	-0.09 *	-0.17 *	0.01	-0.12	-0.18 *	-0.41 *
CZ	0.09 *	0.10 *	0.07	0.04 *	0.09 *	0.07	0.27 *	-0.11 *	-0.06 *	-0.09 *	-0.01	-0.10 *	-0.10 *	-0.33 *
EE	0.18 *	0.17 *	0.18 *	0.00	0.17 *	0.19 *	0.40 *	-0.17 *	-0.10 *	-0.19 *	0.03	-0.17 *	-0.18 *	-0.42 *
FI	0.18 *	0.17 *	0.21 *	-0.04	0.17 *	0.20 *	0.42 *	-0.21 *	-0.15 *	-0.27 *	0.02	-0.21 *	-0.25 *	-0.52 *
FR	0.18 *	0.16 *	0.18 *	0.02	0.18 *	0.21 *	0.44 *	-0.19 *	-0.11 *	-0.19 *	-0.02	-0.19 *	-0.23 *	-0.45 *
GR	0.09 *	0.10 *	0.07 *	0.03	0.10 *	0.06	0.13 *	-0.11 *	-0.08 *	-0.12 *	-0.01	-0.12 *	-0.11 *	-0.27 *
HR	0.05	0.10 *	0.02	-0.02	0.04	0.03	0.08	-0.07	-0.04 *	-0.04	0.06 *	-0.06	-0.06	-0.18 *
HU	0.07	0.06	0.04	0.03	0.09 *	0.03	0.12 *	-0.09 *	-0.01 *	-0.06	-0.01	-0.10 *	-0.05	-0.18 *
IE	0.11 *	0.12 *	0.15 *	0.02	0.10 *	0.14 *	0.32 *	-0.12 *	-0.06 *	-0.15 *	-0.01	-0.11 *	-0.13 *	-0.32 *
IT	0.16 *	0.13 *	0.15 *	0.02	0.13 *	0.16 *	0.39 *	-0.20 *	-0.10 *	-0.16 *	-0.01	-0.17 *	-0.20 *	-0.44 *
LT	0.02	0.03	0.09	-0.03	0.03	0.09	0.20 *	-0.03	0.04	-0.10	0.02	-0.04	-0.10 *	-0.18 *
NL	0.14 *	0.13 *	0.13 *	-0.02	0.14 *	0.16 *	0.38 *	-0.16 *	-0.10 *	-0.16 *	0.00	-0.15 *	-0.18 *	-0.41 *
PT	0.08 *	0.12 *	0.13 *	-0.04	0.11 *	0.13 *	0.32 *	-0.09 *	-0.06 *	-0.14 *	0.02	-0.12 *	-0.12 *	-0.35 *
SI	0.09 *	0.08 *	0.12 *	0.07 *	0.10	0.12 *	0.29 *	-0.08 *	-0.01 *	-0.13 *	-0.06 *	-0.09 *	-0.11 *	-0.35 *
SK	0.16 *	0.15 *	0.18 *	0.02	0.15 *	0.20 *	0.47 *	-0.20 *	-0.11 *	-0.23 *	-0.01	-0.19 *	-0.22 *	-0.52 *

At the aggregate level, a weak but consistently positive correlation is observed between *Euroskepticism* and *Immigration Rejection* across all methods except JMsep. This relationship becomes notably stronger under JMint, where the correlation reaches 0.14. In contrast, the correlation with *Perceived Benefits of Immigration* is negative across all methods (except JMsep), with a marked increase in magnitude under JMint (-0.09), suggesting greater construct coherence under fully integrated joint modelling.

At the country level, results confirm the theoretical expectations of a positive association between Euroskepticism and immigration rejection and a negative association with perceived benefits. Countries such as Finland (FI), France (FR), and Slovakia (SK) exhibit strong and statistically significant relationships under most methods, with JMint yielding the highest and most consistent correlations. In several countries, the associations are weak or nonsignificant under simpler imputation models (e.g., FCSsl or JMsep), suggesting reduced validity in those configurations.

Overall, these findings support the external consistency of the target constructs and further emphasize the advantage of joint multilevel imputation with integrated pooling (JMint) in recovering theoretically plausible and statistically robust associations.

Modeling Rejection of Common Migration Policy Through Latent Attitudes Toward Immigration In line with the research hypothesis, Euroskepticism—operationalized as rejection of a common EU migration policy—is modeled as a function of the two latent traits derived through multiple imputation: one capturing perceived benefits of immigration and the other reflecting immigration rejection. These latent constructs allow us to test the hypothesized relationship between deeper attitudinal dimensions and policy-specific Euroskepticism. The models are estimated across multiple imputation methods to assess both the consistency of the findings and the impact of different imputation strategies on the robustness of the results.

The regression analysis results across the different MI strategies are provided in Table 57. The analysis was conducted using the `lme4::lmer` function (Bates et al., 2015) for model fitting and `mitml::testEstimates` for pooling the estimates across imputations.

Table 57: Regression results of Euroskepticism on migration policy, based on the imputed datasets using different methods.

	JMsep	*FCSsl*	*FCSri*	*FCSrs*	*JMri*	*JMrs*	*JMint*
(Intercept)	0.06	0.06	0.06	0.06	0.06	0.06	-0.60 **
Age	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Woman	-0.03 *	-0.03 *	-0.03 *	-0.03 *	-0.03 *	-0.03 *	-0.04
Unemployed	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.06
Retired	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.03
Education	-0.08 *	-0.08 *	-0.08 *	-0.08 *	-0.08 *	-0.08 *	-0.16 *
Small middle town	0.04 *	0.04 *	0.04 *	0.04 *	0.04 *	0.04 *	0.05
Rural Area or village	0.04 *	0.04 *	0.04 *	0.04 *	0.04 *	0.04 *	0.03
Economic difficulties	0.06 **	0.06 **	0.06 **	0.06 **	0.06 **	0.06 **	0.16 **
Centre	0.08 **	0.08 **	0.08 **	0.07 **	0.08 **	0.07 **	0.04
Right	0.22 **	0.22 **	0.22 **	0.21 **	0.22 **	0.21 **	0.22 **
Attachment_country.L	-0.20 **	-0.20 **	-0.20 **	-0.20 **	-0.20 **	-0.19 **	-0.46 **
Attachment_country.Q	0.09 *	0.09 *	0.09 *	0.09 *	0.09 *	0.09 *	0.18 *
Attachment_country.C	0.02	0.02	0.02	0.02	0.02	0.02	0.01
Life_Satisfaction.L	-0.12 **	-0.12 **	-0.12 **	-0.12 **	-0.12 **	-0.12 **	-0.19 *
Life_Satisfaction.Q	0.05 *	0.05 *	0.05 *	0.05 *	0.05 *	0.05 *	0.14 **
Life_Satisfaction.C	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.05
Economy_Satisfaction.L	-0.02	-0.02	-0.03	-0.02	-0.02	-0.02	0.03
Economy_Satisfaction.Q	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Economy_Satisfaction.C	0.00	0.00	0.00	0.00	0.00	0.00	-0.02
Trust in institution	-0.21 **	-0.21 **	-0.21 **	-0.21 **	-0.21 **	-0.21 **	-0.21 **
Immigration rejection	0.01	0.00	0.01	0.00	0.00	0.00	0.20
Perceived benefits of immigration	0.00	0.00	0.01	0.00	0.00	-0.01	-0.34 *

Results are largely consistent across methods, especially for standard covariates, but notable differences emerge when comparing the integrated joint modeling approach (`JMint`) with simpler imputation alternatives.

Across all strategies, sociodemographic variables such as *being female*, *higher education*, and *greater trust in institutions* are significantly associated with lower levels of Euroskepticism. Conversely, individuals identifying politically with the *Right*, reporting *economic difficulties*, or expressing *strong affective attachment to their country* exhibit higher levels of Euroskepticism. These patterns remain stable across all imputation configurations, highlighting the robustness of key associations.

Under `JMint`, however, we observe stronger standardized effects for several variables, including *Education* ($\beta = -0.16$), *Attachment to country (L)* ($\beta = -0.46$), and *Life Satisfaction (L)* ($\beta = -0.19$), suggesting an amplification of meaningful signals through integrated modeling. Notably, only under `JMint` do the target traits — *Immigration Rejection* and *Perceived Benefits of Immigration* — emerge as significant predictors. *Immigration Rejection* shows a positive effect ($\beta = 0.20$), while *Perceived Benefits* displays a negative association ($\beta = -0.34$), both aligning with theoretical expectations regarding their relationship with Euroskeptic attitudes.

These results underscore the superior external validity and discriminative capacity of the

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`JMint` approach, especially in recovering nuanced relationships between latent attitudes and socio-political dispositions.

4.5 Deep learning approaches for Statistical Matching

Recent advancements in deep generative models (DGMs)—a subclass of deep learning models—have shown strong potential in synthetic data generation and data imputation. Trained on real data, DGMs can reproduce the complex structure and variability of original datasets without copying real individual records (Jacobs et al., 2023; Nazábal et al., 2020). This makes them valuable tools for data integration and privacy-preserving data sharing.

Compared to traditional statistical imputation methods, deep learning (DL) models offer key advantages: they do not require distributional assumptions, can handle multiple missing features with a single model, and effectively capture latent structures in high-dimensional data (Boursalie et al., 2022). Notable DL-based imputation techniques include generative adversarial nets (GANs) (Yoon et al., 2018), variational autoencoders (VAEs) (Nazábal et al., 2020), and denoising autoencoders (Lall & Robinson, 2022).

In the following section, we present the results obtained using denoising autoencoders, as implemented in the rMIDAS package for R (Lall & Robinson, 2022; Lall & Robinson, 2023).

4.5.1 Data integration through the rMIDAS package in R

Multiple Imputation with Denoising Autoencoders (MIDAS) (Lall & Robinson, 2022; Lall & Robinson, 2023) employs unsupervised neural networks—specifically denoising autoencoders (DAs)—to impute missing data by combining dimensionality reduction with data reconstruction. MIDAS treats missing values as inherently corrupted inputs and trains the model to reconstruct them by minimizing the reconstruction error on the observed data. To enhance generalization and avoid overfitting, the method introduces stochastic noise into the input and applies dropout regularization within the network's deeper layers, allowing the model to effectively learn the underlying data structure.

The core foundation of MIDAS is *multiple imputation (MI)*, which consists of three main steps:

- Each missing value is replaced with m independently drawn imputed values that preserve the relationships found in the observed data;
- The m completed datasets are analyzed separately to estimate the parameters of interest;
- The resulting parameter estimates are then pooled using standard rules that account for the uncertainty inherent in the imputation process. Specifically, the final estimate is obtained by applying "Rubin's Rules" to produce a single, combined estimate of the regression parameters and uncertainty.

MIDAS performs this multiple imputation process using artificial neural networks (ANNs) as its modeling engine.

This integration procedure can be implementd using the package rMIDAS (Robinson et al., 2023). The core code base is written in Python using the efficient and flexible architecture of the TensorFlow library. Therefore, a Python environment needs to be installed. Currently, Python versions from 3.6 to 3.10 are supported.

In addition to leveraging Python for executing the core algorithm, the package includes tools for preprocessing and postprocessing data, performing diagnostics on imputation models, creating multiple imputed datasets, and conducting regression analyses on these datasets. Below, the results obtained by applying MIDAS model are reported following the same structure utilised for the other models by setting the default parameters utilised in (Robinson et al., 2023). While when considering the ovarall imputation, country was used as supporting variable, when comparing the performance in each country, different models were trained for each country separately.

Comparison of observed and imputed data Figure 61 displays density plots of the original (black) and imputed (red) values for the two main target variables. Figures 62, 63 show the same comparison disaggregated by country. The alignment between the observed and imputed distributions suggests that the imputations are sufficiently consistent with the empirical data structure at the overall level and for each country.

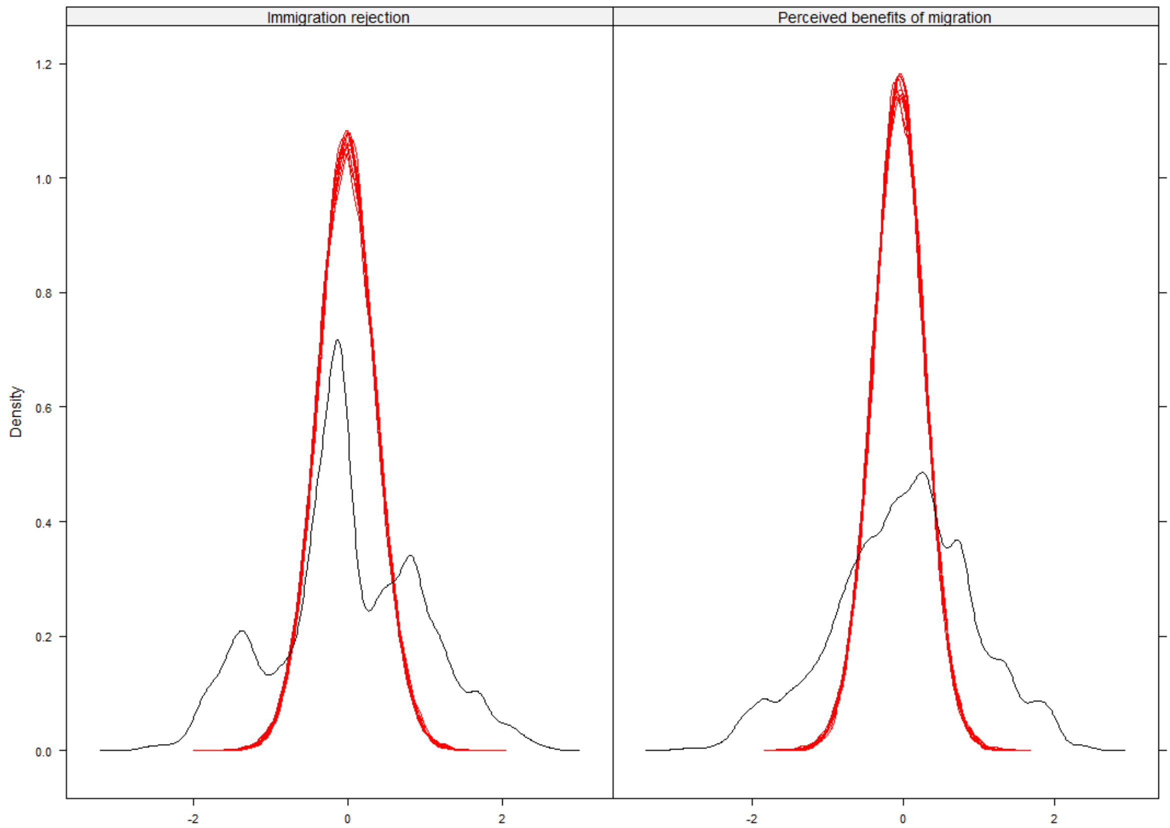

Figure 61: *MIDAS*: Density plots for the observed (black) and imputed (red) distribution of the target variables

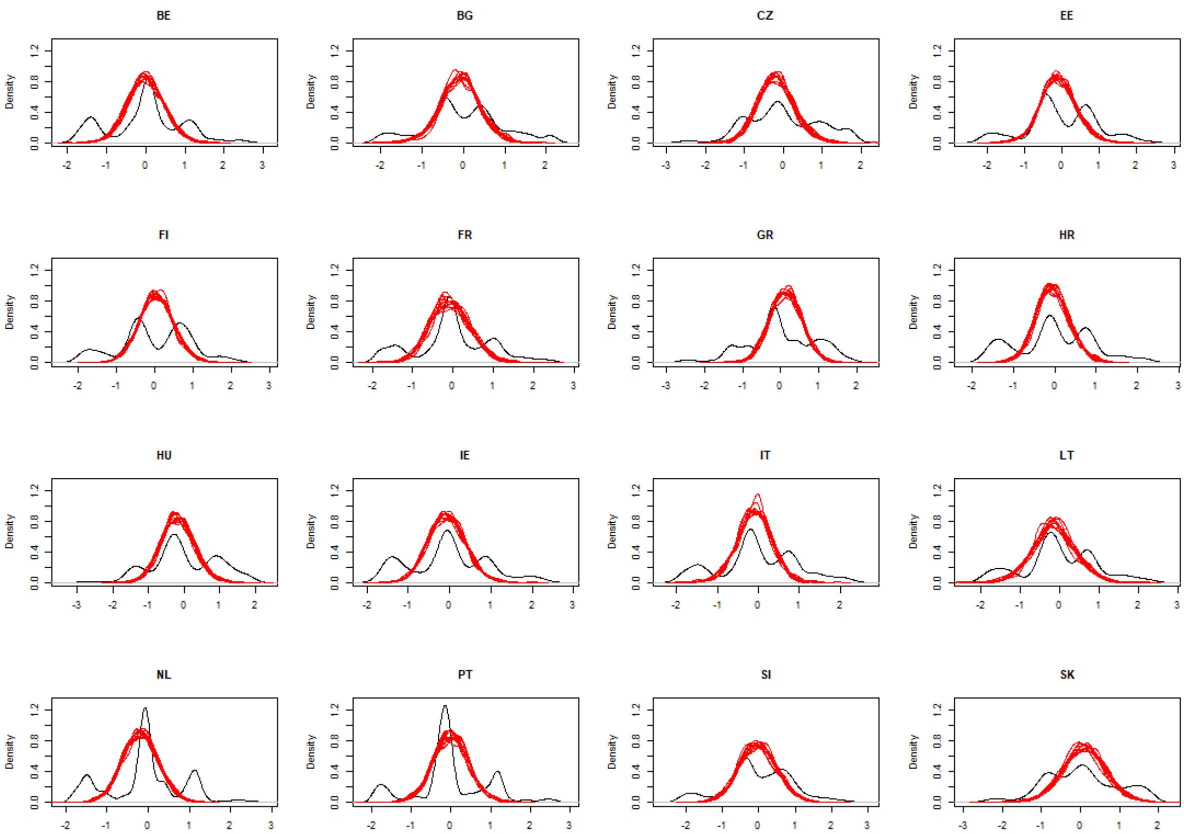

Figure 62: *MIDAS*: Density plots for the observed (black) and imputed (red) distribution of the target variable “Immigration rejection” across the EU countries

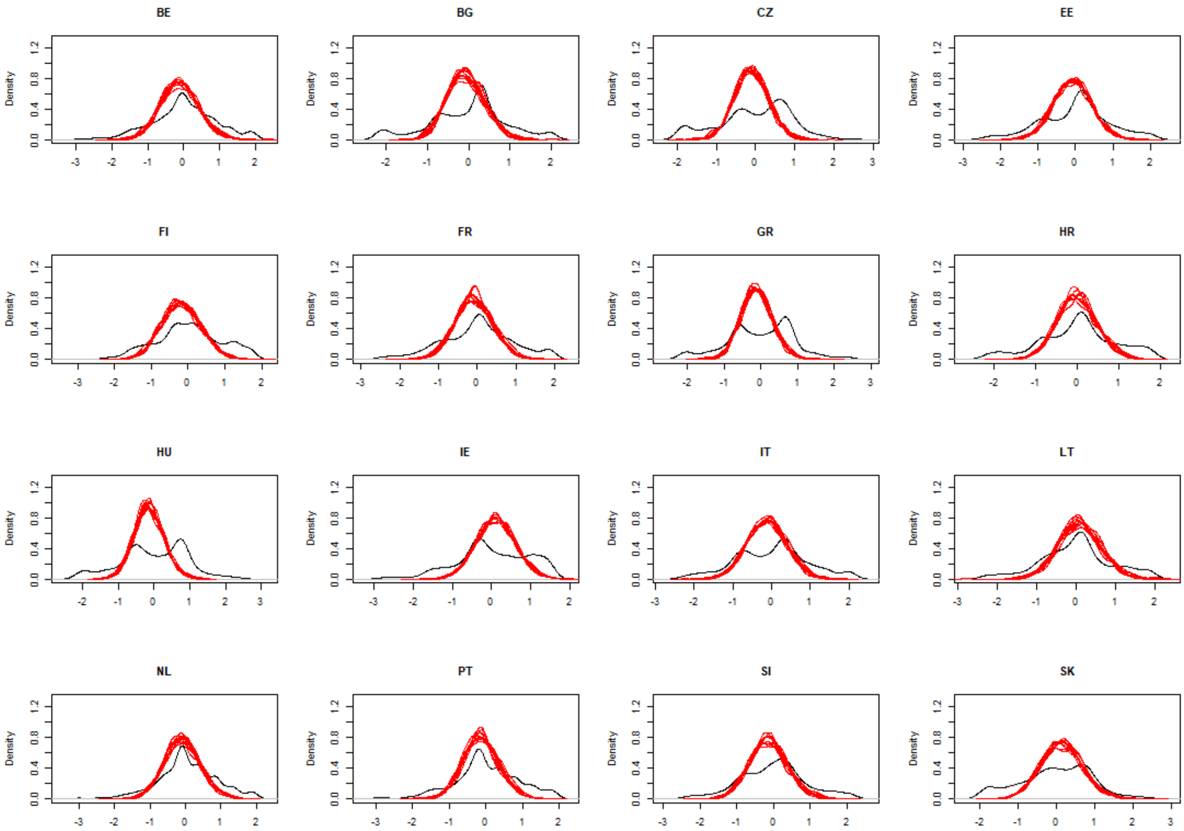

Figure 63: *MIDAS*: Density plots for the observed (black) and imputed (red) distribution of the target variable "Perceived benefits of immigration" across the EU countries

Distributional Fit From figure 64, 65, it is possible to notice that the distribution of the imputed data through the MIDAS model, trained with default parameters, are not perfectly aligned with the original values.

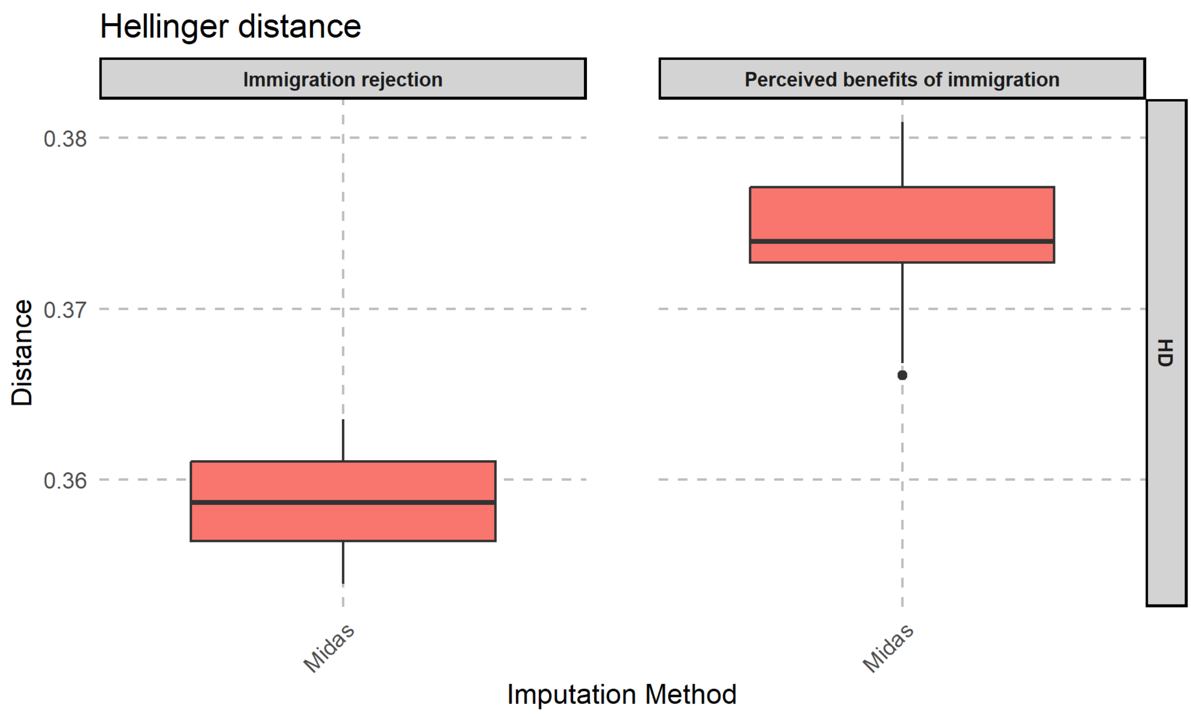

Figure 64: Hellinger distance (HD) divergences between the observed and imputed distributions of the target variables across the m replications

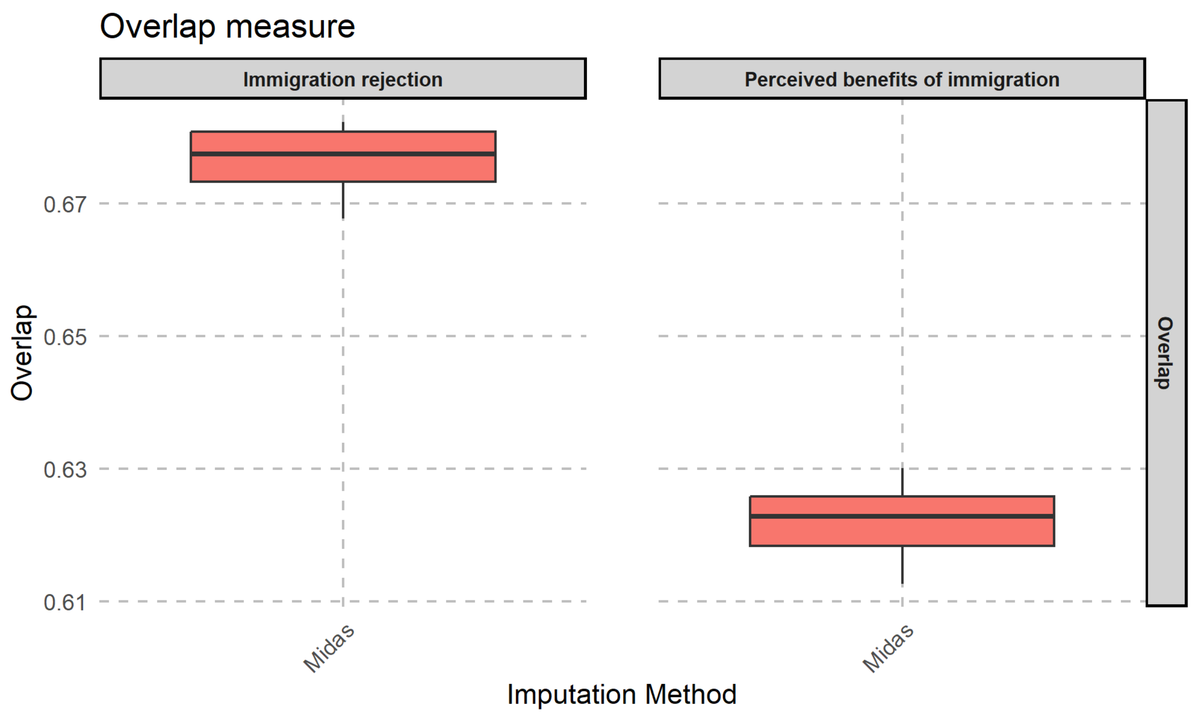

Figure 65: Overlap statistic between the observed and imputed distributions of the target variables across the m replications

Distributional Fit Across Countries When comparing the distributional distances between observed and imputed data across countries (Table58) it is possible to appreciate that, for the immigration rejection, the distances range between 0.26 and 0.46 and the overlap between 0.50 and 0.73, while for the perceived benefits of immigration, the same values range between 0.23 and 0.41 and between 0.55 and 0.78, indicating a variable degree of concordance between the imputed and original values across countries.

Table 58: Means of the Hellinger distance (HD) and the Overlap coefficient between the observed and imputed distributions of the target variables "Immigration rejection" and "Perceived benefits of immigration" for the m replications across countries.

	Immigration rejection		**Perceived benefits**	
country	***Overlap***	***Hellinger***	***Overlap***	***Hellinger***
BE	0.584	0.395	0.696	0.269
BG	0.718	0.320	0.674	0.329
CZ	0.640	0.353	0.581	0.390
EE	0.609	0.356	0.690	0.267
FI	0.556	0.429	0.731	0.304
FR	0.626	0.334	0.682	0.300
GR	0.559	0.404	0.553	0.397
HR	0.543	0.429	0.703	0.288
HU	0.603	0.398	0.565	0.409
IE	0.499	0.459	0.639	0.334
IT	0.607	0.379	0.649	0.313
LT	0.688	0.331	0.780	0.234
NL	0.511	0.463	0.687	0.294
PT	0.528	0.464	0.640	0.340
SI	0.728	0.257	0.749	0.240
SK	0.692	0.299	0.721	0.300

Distributional Fit conditional on common variables When conditioning on covariate levels, although moderate, some differences in model performance for "Immigration rejection" and "Perceived benefits of immigration" (Table 59) can be spotted. For instance, the overlap is higher for the "Immigration rejection" for all the levels of the variables "Gender" and "Political orientation".

Table 59: Means of the Hellinger distance (HD) and the Overlap coefficient between the observed and imputed distributions of the target variables "Immigration rejection" and "Perceived benefits of immigration" for the m replications conditional on common variable levels.

		Immigration rejection		Perceived benefits	
		Overlap	*Hellinger*	*Overlap*	*Hellinger*
Gender	Man	0.660	0.368	0.631	0.370
	Woman	0.689	0.354	0.609	0.382
Occupation	Employed	0.618	0.415	0.598	0.398
	Unemployed	0.670	0.368	0.604	0.385
	Retired	0.586	0.402	0.604	0.389
	In Education	0.586	0.431	0.600	0.404
Domicile	A big city or large town	0.664	0.367	0.629	0.367
	Small middle town	0.669	0.367	0.593	0.399
	Rural Area or village	0.688	0.347	0.623	0.375
Economic difficulties	No	0.667	0.364	0.610	0.389
	Yes	0.634	0.388	0.600	0.374
Political Orientation	Left	0.679	0.351	0.633	0.359
	Centre	0.600	0.435	0.533	0.453
	Right	0.652	0.380	0.585	0.422
Attachment country	Not at all attached	0.606	0.414	0.609	0.396
	Not very attached	0.681	0.355	0.630	0.363
	Fairly attached	0.665	0.365	0.600	0.388
	Very attached	0.526	0.499	0.511	0.502
Life Satisfaction	Not at all satisfied	0.698	0.336	0.641	0.353
	Not very satisfied	0.650	0.385	0.554	0.449
	Fairly satisfied	0.627	0.395	0.605	0.390
	Very satisfied	0.576	0.461	0.536	0.471
Economy Satisfaction	Very bad	0.672	0.352	0.615	0.370
	Rather bad	0.677	0.353	0.631	0.376
	Rather good	0.603	0.423	0.545	0.452
	Very good	0.656	0.383	0.510	0.492

Correlation between the imputed data and the Eurobaromenter latent traits "Euroskepticism on Common Migration Policy" and "Aversion to immigrants"
Tables 60 show how the data imputed using the MIDAS method correlate meaningfully with the variables "Aversion to immigrants". In particular, the correlations obtained are consistently statistically significant across most countries for both outcome variables. This pattern supports the idea that also the MIDAS model recovers plausible and interpretable relationships between the control and target variables, which supports the reliability of the imputed data .

Table 60: Correlation between "Aversion to immigrants" and "Immigration rejection" and "Perceived benefits of immigration" across countries.

	Immigration rejection			Perceived benefits		
	correlation coefficient	2.5%	97.5%	correlation coefficient	2.5%	97.5%
Overall	0.104	0.088	0.120	-0.139	-0.156	-0.121
BE	0.169	0.133	0.204	-0.155	-0.215	-0.094
BG	0.168	0.065	0.267	-0.247	-0.380	-0.105
CZ	0.091	0.000	0.181	-0.142	-0.199	-0.085
EE	0.197	0.147	0.247	-0.204	-0.258	-0.149
FI	0.164	0.117	0.210	-0.264	-0.299	-0.228
FR	0.221	0.138	0.300	-0.167	-0.256	-0.075
GR	0.033	-0.035	0.101	-0.160	-0.269	-0.048
HR	0.019	-0.045	0.082	-0.089	-0.144	-0.033
HU	0.023	-0.061	0.106	-0.042	-0.096	0.011
IE	0.140	0.101	0.179	-0.079	-0.139	-0.017
IT	0.111	0.023	0.196	-0.259	-0.315	-0.201
LT	0.125	0.063	0.187	-0.100	-0.191	-0.007
NL	0.186	0.111	0.259	-0.156	-0.231	-0.080
PT	0.177	0.089	0.262	-0.140	-0.191	-0.088
SI	0.106	0.018	0.193	-0.121	-0.196	-0.046
SK	0.184	0.123	0.244	-0.340	-0.377	-0.301

The correlation analysis presented in Table 61 provides insights into the relationship between Euroskepticism on Common Migration Policy and the two latent imputed traits: Immigration Rejection and Perceived Benefits of Immigration, again in the Eruobarometer dataset . Compared to the stronger correlations observed with Aversion to Immigrants, the associations here are slightly weaker, reflecting a more nuanced or indirect link between Euroskeptic attitudes and perceptions of immigration.

Table 61: Correlation between "Euroskepticism on Common Migration Policy" and "Immigration rejection" and "Perceived benefits of immigration" across countries.

	Immigration rejection			Perceived benefits		
	correlation coefficient	2.5%	97.5%	correlation coefficient	2.5%	97.5%
Overall	0.035	0.027	0.044	-0.063	-0.075	-0.051
BE	0.019	-0.053	0.091	-0.059	-0.099	-0.018
BG	0.119	0.048	0.188	-0.056	-0.119	0.008
CZ	0.049	-0.010	0.108	-0.106	-0.195	-0.016
EE	0.101	0.045	0.156	-0.120	-0.176	-0.063
FI	0.094	0.048	0.140	-0.193	-0.262	-0.122
FR	0.137	0.068	0.204	-0.110	-0.165	-0.054
GR	-0.016	-0.075	0.042	-0.058	-0.104	-0.012
HR	-0.025	-0.111	0.061	-0.107	-0.148	-0.065
HU	0.023	-0.061	0.107	-0.013	-0.072	0.046
IE	0.021	-0.027	0.069	-0.054	-0.113	0.005
IT	0.033	-0.020	0.086	-0.145	-0.218	-0.070
LT	0.069	-0.007	0.144	-0.023	-0.099	0.054
NL	0.079	0.025	0.132	-0.080	-0.171	0.013
PT	0.114	0.037	0.190	-0.078	-0.151	-0.005
SI	-0.033	-0.091	0.026	-0.058	-0.119	0.004
SK	0.103	0.040	0.165	-0.165	-0.234	-0.095

5 Conclusion

This report investigated European citizens' attitudes toward immigration and their influence on support for a unified EU migration agenda by integrating two major cross-national surveys: the European Social Survey (ESS10) and Eurobarometer 93.1.

A structured data harmonization process allowed to derive variables common to both surveys. Multilevel Item Response Theory (IRT) modeling enabled the estimation of key latent traits such as "Immigration rejection" and "Perceived benefits of immigration" in the donor dataset (ESS).

To impute these latent constructs into the recipient dataset (Eurobarometer), we implemented a wide array of statistical matching procedures. These included both non-parametric and parametric approaches. The parametric methods were explored in the multiple imputation settings for multivariate missing data via two main frameworks: Fully Conditional Specification (FCS) using the `mice` package, and Joint Modeling (JM) using the `mitml` package. These approaches were evaluated under different multilevel assumptions – single-level, random intercept, and random slope structures – to assess how model complexity influences imputation quality.

In addition to conventional MI strategies, we proposed and applied a fully integrated Bayesian approach to statistical matching, that jointly models the latent structures and the imputation process in a coherent probabilistic framework. This method provides both flexibility and inferential transparency, especially when dealing with latent constructs in hierarchical data.

To explore scalability and modeling flexibility, we further experimented with a deep learning-based integration approach using the `rMIDAS` package. This neural network-based method offers a data-driven alternative that is particularly useful when traditional assumptions (e.g., linearity or Gaussianity) may be violated.

Our results confirm that the imputed latent traits display external and predictive validity, particularly in their association with an independently derived latent measure of aversion to immigrants and with public support for a common EU migration policy. Importantly, while all imputation strategies broadly agree on the direction and significance of key effects, differences in distributional fit and predictive power emphasize the importance of model selection in applied statistical matching.

In sum, this case study demonstrates how data integration – when carefully aligned with multilevel modeling and supported by robust imputation procedures – can enhance the analytic value of existing cross-national surveys. It also illustrates the potential of combining classical, Bayesian, and machine learning techniques to address complex challenges in comparative public opinion research.

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6 Appendix

ENCLOSE: Parametric imputation methods

Workflow: Harmonization, Imputation, and Analysis

1. Data Preparation & Latent Trait Estimation

Input files:
- `EES10.sav`
- `ZA7649_v2-1-0.sav`

Code: `ENCLOSE_data_harmonization_clean.Rmd`
Output: `ENCLOSE_harmonized_data.RData`

Description:
Harmonizes datasets, aligns variable coding, estimates latent traits.

---

2. Common Variable Distribution Comparison

Input: `ENCLOSE_harmonized_data.RData`
Code: `ENCLOSE_common_variable_comparison_distances_clean.Rmd`
Output: `covariate_distance.xlsx`

Description:
Computes distances between distributions of common variables across datasets.

---

3. Effect of Common Variables on Target Variables

Input: `ENCLOSE_harmonized_data.RData`
Code: `ENCLOSE_regression_on_common_variables_clean.Rmd`
Output: Regression plots and graphs.

---

4. Matching (Multilevel & Single-Level Imputation)

Input: `ENCLOSE_harmonized_data.RData`
Code: `ENCLOSE_mice_mitml_imputation_multilevel_clean.Rmd`
Output: `ENCLOSE_mice_mitml_imputation.RData`

Description:
Performs imputations using `mice` and `mitml` for single and multilevel parametric approaches.

---

5. Imputation Result Analysis – Regression & Correlation

Input: `ENCLOSE_mice_mitml_imputation.RData`
Code: `ENCLOSE_analysis_mice_mitml_imputation_clean.Rmd`
Output:
- Density plots (original vs imputed data)
- `mice_mitml_results.xlsx` (regression and correlation coefficients)

---

6. Imputation Result Analysis – Distance Metrics

Input: `ENCLOSE_mice_mitml_imputation.RData`
Code: `ENCLOSE_analysis_mice_mitml_imputation_clean.Rmd`
Output:
- Plots of Hellinger distance and Overlap index
- `mice_mitml_distance.xlsx` (metrics by method and country)

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7. Summary Workflow Diagram