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Exploration of poverty and social exclusion of Slovak population via contrast analysis associated with logit models

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Abstract
The aim of the paper is to assess the impact of socio-economic and socio-demographic factors on the risk of poverty or social exclusion. The paper focuses on the analysis of the probability of social exclusion of the Slovak population from 4 perspectives, from being at risk of poverty or social exclusion, at risk of poverty, severely materially deprived, and living in a (quasi-)jobless household. The least-square means analysis and contrast analysis linked to logit models were used to identify risk groups, and to estimate the social exclusion probabilities. Based on the EU-SILC 2020 database, unemployed persons with low education and persons from single-parent and multi-child households had the greatest risk of social exclusion in Slovakia. Under ceteris paribus conditions, the risk decreased with increasing age and improving health status. The riskiest marital status was divorced. Analyses revealed regional disparities from the point of view of all 4 perspectives, with people living in South-Center and Eastern Slovakia and people living in sparsely and moderately populated areas having the greatest risk. Since economic activity status, household type, and educational attainment level showed as the most relevant factors, the article pays special attention to the assessment of the mutual influence of these factors. Although the pattern of the risk of social exclusion of persons broken down by household type and education for the unemployed and employed is similar, the riskiness of the most vulnerable groups of people is more pronounced for employed persons.

Keywords At-risk-of-poverty or social exclusion · At-risk-of-poverty · Severe material deprivation · Very low work intensity · Contrast analysis · Logit model

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1 Introduction

Identifying groups of the population that are income poor or socially excluded is the key task for effectively setting the social policies of countries seeking social inclusion and ensuring well-being for the largest possible members of its population. The headline indicator to monitor the Europe 2030 target on poverty and social exclusion is the at-risk-of-poverty or social exclusion (AROPE) rate.

The AROPE indicator combines 3 dimensions: at-risk-of-poverty (AROP), severe material deprivation (SMD) and very low work intensity (VLWI), which is also referred to as (quasi-)joblessness (QJ). The paper is based on the EU-SILC 2020 database (with the reference year 2019) for Slovakia, in which the definition of AROPE persons used in the Europe 2020 strategy was still applied (Eurostat 2022).

According to the Europe 2020 strategy, at least 20 million EU citizens were to be brought out of the risk of poverty or social exclusion by 2020, whereas 107.5 million (20.9%) AROPE people were in the EU-28 in 2019, a decrease of only approximately 10 million in comparison with 2008 (European Commission, 2021b). This decline was mainly due to a sharp decline in the severely materially deprived population (decrease by 14.7 million) and, to a lesser extent, a reduction in the number of people living in (quasi-)jobless households (decrease by 3.9 million), but the number at risk of poverty increased (by 2.7 million). However, the AROPE indicator aggregated for the EU obscures significant differences between member states (from 12.5% in Czechia to 32.8% in Bulgaria) and, in addition, there are significant differences in sub-indicators between countries. The European Commission (2021a) states that in 2019 the share of AROPE people in Slovakia was one of the lowest (16.4%) within the EU (20.9%). This result was mainly caused by the relatively low share of the AROP population in Slovakia (11.9%; 16.5% in the EU) and the fact that this dimension is generally the most prevalent form of poverty and social exclusion. On the other hand, the share of the SMD population in Slovakia belonged to the upper first third (7.9%; 5.5% in the EU). The share of people living in QJ households (4.8%) was slightly lower than in the EU (6.1%).

Although Slovakia is one of the more successful countries in the fight against poverty and social exclusion, many challenges remain to improve social inclusion. In addition, the change in the methodology of AROPE may cause a relatively large increase in the AROPE population, especially in those countries where there is a high proportion of SMD persons, which is also the case in Slovakia. This phenomenon will be caused mainly by the replacement of the SMD rate by the severe material and social deprivation rate, which was according to Mysíková (2021) in 2018 in the V4 countries approximately 2 times higher than the SMD rate.

The paper analyses the risk of social exclusion, which we look at from 4 aspects, namely in terms of income poverty or social exclusion in at least one dimension (AROPE) and in terms of social exclusion in individual dimensions AROP, SMD, and VLWI. Following these 4 aspects, the aim of the paper is to assess the impact of relevant socio-economic and socio-demographic factors on the odds and probability of social exclusion. We focus on the following research tasks:

- for each relevant factor, to identify categories between which there are no significant differences and those categories or groups of categories between which there are demonstrable differences in social exclusion,

- to quantify the risk of social exclusion of individual groups of persons and identify risk groups of persons on whom social policy should focus,
- to compare the pattern of social exclusion risk for employed and unemployed persons.

In selecting the factors that entered the models as explanatory variables, we relied on the results of our previous research and the works of other researchers (see Literature review). The relevance of several considered regressors is also evident from the estimates of the subject measures provided by SO SR and Eurostat. Understandably, the biggest disparities are among persons with different economic activity statuses. Unemployed persons (AROPE: 66.8%) and employed persons (AROPE: 5.7%) were most at risk of poverty or social exclusion in the Slovak Republic in 2019. Large disparities in the risk of poverty and social exclusion in the Slovak Republic in 2019 were also caused by factors: educational attainment level (AROPE for ISCED 0–2: 35.8% vs. AROPE for ISCED 6–8: 4.7%), household type (AROP for households with 2 adults and at least 3 dependent children: 37.1% vs. AROP for two-person households (at least one aged 65^{+} without dependent children: 5.3%), region (AROPE for Central and Eastern Slovakia: over 19% vs. AROPE for Bratislava region: 6.8%) and degree of urbanization (AROPE for Rural areas: 17.2% vs. AROPE for Cities: 9.9%).

2 Literature review

The AROP rate is an indirect monetary measure that refers to outcomes and is a relative measure that is typically applied in rich and developed countries (Mysíková 2021). The preference for the relative measure in assessing income poverty is logical, as any absolute poverty line becomes less and less relevant as the income standard rises. However, Decerf (2021) states that if a country's growth is such that the income of its poorest citizens is sufficient to meet their subsistence needs, its poverty is likely to have decreased, even though these individuals are still socially excluded. This deficiency of the AROP rate is eliminated in the concept of AROPE, by combining the AROP dimension with the SMD and VLWI dimensions.

Material deprivation (MD) means a lack of certain items or non-participation in certain activities that are considered common or necessary in a given society. The dimension of material deprivation is measured by the SMD rate, which is a direct non-monetary measure (Boarini and d'Ercole 2006). Several studies have shown that Slovakia should focus specifically on SMD in the fight against poverty and social exclusion. Łuczak and Kalinowski (2020) assessed the level of MD in EU countries in 2016 using the TOPSIS approach and Slovakia was included in the third group with a medium level of deprivation. Ciacci and Traversa (2021) performed a non-compensatory time analysis of MD in Europe and found that in 2019 Slovakia had the 8th highest MD in the EU. On the other hand, in the period 2005–2019, Slovakia recorded one of the greatest achievements in the reduction of MD. Guio et al. (2021) based on a measure of LB ('left behind') found that in 2017, Slovakia had the lowest LB rate for the AROPE indicator among the EU-28 countries, but reached only the average level in the SMD dimension. It is clear that the SMD dimension is correlated with the AROP dimension. The correlation between them within the EU was also confirmed in 2015 by Salcedo and Izquierdo Llanes (2019). However, this correlation was only at a moderately strong level, which stems from the fact that there are no exceptional situations when a country with a high SMD rate has a lower AROP rate than countries with a lower SMD rate and vice versa.

The third dimension is exclusion from the labour market, which captures that part of the population that lives in (quasi-)jobless households. Dimension VLWI is closely related to the other 2 dimensions. De Graaf-Zijl and Nolan (2011) found that joblessness significantly affects the other two dimensions however household labour intensity does not show a consistent pattern in groups of countries categorized together in terms of welfare regime or geographically. The dependence development among poverty dimensions in the EU-28 countries between period 2008 and 2014 was examined by García-Gómez et al. (2021) who found that this dependence increased significantly in the countries most affected by the economic crisis. Verbunt and Guio (2019) confirmed that work intensity is very effective in explaining within-country differences in the risk of income poverty/material deprivation in some CEE countries (including Slovakia). Filandri et al. (2020) showed that having a job is not a sufficient condition to avoid poverty, either in terms of (monetary) objective or subjective poverty.

The paper also touches on the topic of in-work poverty, the prevention of which is very important for raising living standards and ensuring its convergence in all EU member states. As reported by Peña-Casas et al. (2019) the rise of non-standard employment patterns observed during the 2008 economic and financial crisis are among the important but non-exclusive factors which, together with the stagnation of growth in market income and social benefits, caused insufficient progress or even an increase in in-work poverty. The authors found that in the period 2012–2017 Slovakia recorded an increase in in-work poverty by 0.2 pp, although in the whole population there was a decrease of 0.8 pp. The large increase mainly concerns households of 1 parent with at least 1 child (13.2 pp), single-person households (7.3 pp) as well as households with VLWI (14.3 pp).

The paper analyses poverty and social exclusion through the logistic regression, which is popular in this area and has also been used by Abrar ul haq et al. (2018), Ćwiek and Ulman (2019), Dudek and Szczesny (2021), Filandri et al. (2020), González et al. (2021), Mysíková et al. (2019), Sánchez-Sellero and Garcia-Carro (2020), Verbunt and Guio (2019) and others. Unlike these works, this paper is based on a contrast analysis, which is linked to the logit model and has made it possible to analyse in more depth the differences between the various categories of relevant factors.

In selecting the factors that entered the models as explanatory variables, we relied on the results of our previous research and the works of other researchers. For instance, Sánchez-Sellero and Garcia-Carro (2020) identified the most vulnerable social groups in terms of poverty in Spain in 2015 using ordinal logistic regression. They found that unemployed people had the highest probability of serious and moderate poverty and that the probability of poverty decreased with increasing age and education. Verbunt and Guio (2019) concluded that higher education is rarer in less affluent countries and therefore more valuable in the labour market, with the result that education plays a much bigger role in explaining the risk of income poverty/material deprivation in Southern, Central, and Eastern European countries than in Western and Northern European countries. Verbunt and Guio (2019) also found that couples with more than two children, singles, and single parents are much more likely to be socially excluded, as compared to couples without children. According to Nieuwenhuis and Maldonado (2018), the risks of poverty among single-parent families are significantly higher than among complete families. Nieuwenhuis (2021) talks of the triple bind of single-parent families, namely a combination of three challenges: resources, employment, and policies that single-parent families face. Härkönen (2017) also states that the combination of low education and single parenthood often leads to very high poverty risks. Analyzing in-work poverty, Filandri and Struffolino (2019) found that risk factors include young age, low level of education, and households with a small number of earners and a high number of children.

In addition, studies focusing on poverty and social exclusion of children or elderly persons have supported us in choosing factors. González et al. (2021) found that in Spain AROPE children were more prevalent in unemployed, low educated, low social class and non-Spanish parents, with smoking habits, and in non -nuclear families (single-parent family, the larger extended family, or a family with more than two parents). Prattley et al. (2020) examined social exclusion in later life (50+) in England and found that the level of social exclusion was higher among never-married people, and those widowed, divorced, or separated than married people. Poor health and lower levels of education also increased the risk of social exclusion. Non-workers had, on average, higher exclusion scores than employed, however, pensioners had lower exclusion rates compared to employed people.

According to many studies (including those we have already mentioned), the risk of poverty and social exclusion of European population is associated with economic activity, education, the composition of the household, age, health, and marital status of the persons assessed. However, the degree of urbanization also has a fundamental impact, with rural areas being the most threatened. Although in Slovakia there is not such a big gap between rural and urban areas as in less developed regions of Asia (see, e.g., (Abrar ul haq et al. 2019)) and Africa (see, e.g., (Kassahun et al. 2022)), or as in some neighbouring countries (especially Poland and Hungary), the risk of poverty in rural areas is still significantly higher than in urban areas (Piwowar and Dzikuć 2020).

3 Methods

The logit model (Vojtková and Stankovičová 2019) models the logarithm of the odds for the category 1 of the binomial dependent variable Y depending on the explanatory variables of the continuous or categorical type. The odds are the probability ratio that the event will occur ($Y = 1$) to the probability $1 - \pi$, that the event will not occur ($Y = 0$). In the logit model, the log-odds are the linear combination of independent variables, i.e.

$$\mathrm{logit}\left(\pi_i\right) = \ln \frac{\pi_i}{1-\pi_i} = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} \tag{1}$$

where $\beta_0, \beta_1, \ldots, \beta_k$ are the parameters of the logit model and $x_{i1}, x_{i2}, \ldots, x_{ik}$ are the values of the explanatory variables $X_1, X_2, \ldots, X_k$ which are observed for the i-th statistical unit.

The significance of a logistic regression model is mostly verified by three different chi-square tests (Likelihood ratio, Score statistics, Wald statistics). In large samples, there is no reason to prefer any of these tests (Allison 2012). In order to validate the significance of the explanatory variable influence, a Wald test is used. It tests the null hypothesis that the respective explanatory variable does not affect the probability of occurrence of the explored event. To verify the hypothesis, the Wald statistic

$$Wald = \hat{\boldsymbol{\beta}}^T \cdot \mathbf{S}_{\mathbf{b}}^{-1} \cdot \hat{\boldsymbol{\beta}} \tag{2}$$

is used, where $\hat{\boldsymbol{\beta}}$ is the vector of regression coefficients estimates that stand as dummy variables for the respective factor (categorical explanatory variable) and $\mathbf{S}_{\mathbf{b}}$ is the variance–covariance matrix of $\hat{\boldsymbol{\beta}}$. The Wald statistic has asymptotically a χ^2 distribution with degrees of freedom equal to the number of parameters estimated for a given effect. A special case of the above test is the Wald test, which verifies the statistical significance of one regression coefficient (Allison 2005).

In logistic regression the effect of the explanatory variable X_j on the dependent variable Y is quantified by the odds ratio (OR—odds ratio) estimated by the formula

$$OR_j = e^{\hat{\beta}_j} \tag{3}$$

The odds ratio in binary logistic regression expresses a relative odds change due to a unit increase of the explanatory variable assuming ceteris paribus. If the explanatory variable is a dummy variable, the odds ratios are estimating the relative difference in the effect of each non-reference level compared to the reference level (in case of Reference coding) or compared to the average effect over all levels (in case of Effect coding). The coding type is essential for the interpretation of the results and the correct setting and interpretation of the contrast analysis. (Pasta 2005).

The logistic regression model is a special case of the generalized linear model, through which we want to estimate the typical response of a target variable to individual categories of a factor, and we want to compare its categories to find out which we can consider being equivalent and between which there is a significant difference (SAS Institute 2018). If the data are unbalanced, arithmetic means are not suitable for such a comparison because they do not take into account the fact that not all factors have the same chance of influencing the target variable (Cai 2014). In this case, it is appropriate to estimate the marginal means, also referred to as LS-means (Least Square Means; Lenth 2016; Goodnight and Harvey 1997).

Contrast analysis (Schad et al. 2020) is used for inductive reasoning about LS-means. It tests general combinations of model parameters using general linear hypotheses (Searle and Gruber 2017) $H_0 : \ \mathbf{L\beta} = \mathbf{0}$, where $\mathbf{L}$ is a contrast matrix and $\mathbf{L\beta}$ must be an estimable function (Littell et al. 2010). The Wald-type test statistic is used to verify the null hypothesis, which we obtain after rewriting the relation (2) using the general linear contrast matrix $\mathbf{L}$ as

$$\chi_W^2 = \left(\mathbf{L}\hat{\boldsymbol{\beta}}\right)^T \cdot \left(\mathbf{L}\mathbf{S}_\mathbf{b}\mathbf{L}^T\right)^{-1} \cdot \mathbf{L}\hat{\boldsymbol{\beta}} \tag{4}$$

χ_W^2 has an asymptotic chi-square distribution with r degrees of freedom l, where l is the rank of $\mathbf{L}$ (Paek 2009).

In our analysis, to estimate the logit models, we used the PROC GENMOD and the PROC LOGISTIC in SAS EG (SAS Institute 2018). We used the LSMEANS statement within PROC GENMOD to analyse the LS-means and the CONTRAST statement within PROC LOGISTIC to perform a contrast analysis. For the contrasts that were the subject of our interest, we calculated point and interval estimates of social exclusion probabilities for selected groups of people using the ESTIMATE option. We used a significance level of 0.05 for all inductive reasoning. Confidence intervals are usually given in parentheses after the point estimates.

4 Database

In the article the EU-SILC 2020 database provided by the Statistical Office of the Slovak Republic is used. This database contains cross-sectional data for 13,800 persons and covers the reference year 2019. The analyses are based on the logit models that have modelled the binomial target variables:

- AROPE, which equals 1 if the person is socially excluded in at least one dimension (AROP, SMD, VLWI) and equals 0 otherwise),
- AROP, which equals 1 if the person is at-risk-of-poverty and equals 0 otherwise,
- SMD, which equals 1 if the person is in severe material deprivation and equals 0 otherwise,
- VLWI, which equals 1 if the person lives in a (quasi-)joblessness household and equals 0 otherwise.

These models will be evenly referred to as target variables, i.e., AROPE, AROP, SMD and VLWI. These models will be evenly referred to as target variables, i.e., AROPE, AROP, SMD and VLWI. In the article, levels 1 are modelled by the AROP, SMD, and VLWI models. In other words, the probability that a person is income poor is modelled by the AROP model, which means that his equivalised disposable income (after social transfer) is below the at-risk-of-poverty threshold, which is set at 60% of the national median equivalised disposable income after social transfers (for more details see (Eurostat 2021a)). The SMD model models the probability that a person is severely materially deprived, which in terms of the definition used in the Europe 2020 strategy means that it is a person that cannot afford (rather than the choice not to do so) at least 4 out of 9 predefined material items considered by most people to be desirable or even necessary to lead an adequate life (for more details see (Eurostat 2021b)). The VLWI model models the probability that a person lives in a household with a very low work intensity ((quasi-)jobless household), which means that they are persons from 0–59 years living in households where the adults (those aged 18–59, but excluding students aged 18–24) worked a working time equal to or less than 20% of their total combined work-time potential during the previous year (for more details see (Eurostat, 2021c)). Similar to the case of the AROP, SMD, and VLWI models, also in the case of the AROPE model a statistical unit is a person, and this model models the probability that a person is socially excluded in at least one dimension (AROP, SMD, VLWI), which means that it is o person who is either at risk of poverty or severely materially deprived or living in a household with a very low work intensity (for more details see (Eurostat, 2022)). In the EU-SILC 2020 data set, there were 11.2% AROP persons, 6.7% SMD persons and 6.2% VLWI persons. Persons who were socially excluded in at least one dimension made up 15.5% of the entire set of 13,800 persons.

The explanatory variables stated in Table 1 will enter in the models.

5 An empirical application

5.1 Logit models for AROPE, AROP, SMD and VLWI

All the considered factors (Table 1) have a statistically significant effect (Table 2) on all four target variables. Economic activity status has the greatest impact on social exclusion in at least one dimension (AROPE), as well as on social exclusion in the AROP and VLWI dimensions, followed by the household type and education achieved. In the case of the SMD model, economic activity has a slightly lower impact than education. Except for the AROP model, the degree of urbanization has the smallest (but significant) impact on the target variables.

All 4 models are statistically significant (Table 3) and their success in predicting target variables is more than 80% (see AUC). Naturally, the riskiest status of economic activity is unemployed. The odds of social exclusion in at least one dimension (the odds are the ratio of the probability that a person from a given category will be socially excluded

Table 1 Description of input explanatory variables

Original variables (EU-SILC)—categories and description	New classification variables		
	Class level information		
	Titles of levels	Level	Frequency
RB210—Economic activity status	EAS		
Unemployed	Unemployed	1	4.27
Other inactive person	Inactive	2	13.57
Old-age pensioner, early retirement pensioner	Retired	3	33.26
Employed	At_work	4	48.90
HT—Household type	HT		
Single-person household	1A_0Ch	1	11.99
Single parent household with at least 1 dependent child	1A_1$^+$Ch	2	1.85
2 adults household, at least 1 aged 65+	2A(1$^+$R)	3	17.71
2 adults household without dependent children	2A_0Ch	4	13.38
2 adults household with 1 dependent child	2A_1Ch	5	7.87
2 adults household with 3+dependent children	2A_3$^+$Ch	6	2.33
Other households without dependent children	Other_0Ch	7	19.76
Other households with dependent children	Other_1$^+$Ch	8	16.38
2 adults household with 2 dependent children	2A_2Ch	9	8.73
PE040—The highest level of education achieved (ISCED)	Education		
Pre-primary (ISCED 0)	ISCED 0–2	1	14.97
Primary (ISCED 1)			
Lower secondary (ISCED 2)			
Upper secondary (ISCED 3)	ISCED 3–5	2	65.29
Post-secondary (not tertiary) (ISCED 4)			
Short cycle of tertiary education (ISCED 5)			
Bachelor or equivalent (ISCED 6)	ISCED 6–8	3	19.73
Master's or equivalent (ISCED 7)			
Doctorate or equivalent (ISCED 8)			
RX010—Age	Age		
Age at the end of income reference period	30–40	1	13.62
	40–50	2	15.56
	50–60	3	16.88
	60–70	4	20.78
	70$^+$	5	15.34
	30$^-$	6	17.82
PH010—General health	Health		
Very bad	Bad	1	15.87
Bad			
Fair	Fair	2	24.42
Good	Good	3	59.71
Very good			
PB190—Marital status	Marital status		
Widowed	Widowed	1	8.22
Single	Unmarried	2	28.34
Divorced			

Table 1 (continued)

Original variables (EU-SILC)—categories and description	New classification variables		
	Class level information		
	Titles of levels	Level	Frequency
Married	Married	3	63.44
Region	REGION		
Banská Bystrica	BB	1	13.49
Prešov	PO	2	14.70
Košice	KE	3	11.88
Žilina	ZA	4	12.72
Trenčín	TN	5	11.20
Trnava	TT	6	9.59
Nitra	NR	7	12.53
Bratislava	BA	8	13.90
DB100—Degree of urbanization	Urbanisation		
Thinly-populated area	Sparse	1	41.26
Intermediate area	Intermediate	2	35.23
Densely-populated area	Dense	3	23.51

Table 2 The statistical significance verification of the influence of factors on the probability of AROPE, AROP, SMD, and VLWI. *Source*: EU-SILC 2020 SO SR, own processing in SAS EG

Type 3 Analysis of effects					
Effect	DF	Wald Chi-Square			
		AROPE	AROP	SMD	VLWI
EAS	3	533.5246***	524.0462***	190.4367***	349.8305***
HT	8	315.2808***	429.9762***	102.8181***	125.6302***
Education	2	233.0579***	162.2047***	253.0275***	92.5044***
Age	5	111.3910***	50.2221***	22.3804***	38.2391***
Health	2	150.2963***	26.4629***	114.7562***	29.8396***
Marital status	3	103.9151***	76.6230***	48.0902***	10.0130**
Region	7	92.8163***	106.4189***	125.2013***	31.3275***
Urbanization	2	41.3604***	58.6534***	12.2357**	7.6645*

***$p<0.001$; **$0.001<p<0.01$; *$0.01<p<0.05$; • $0.05<p<0.1$, level of significance

and the probability that a person from this category will not be socially excluded) is 13.3 times higher for an unemployed person than for an employed person. In the individual dimensions (AROP, SMD, and VLWI), the odds of social exclusion of unemployed persons is 16.7, 6.5, and 199 times higher than for employed persons. The unemployed person directly contributes to the VLWI, and therefore the odds ratio in this dimension is many

Table 3 The statistical significance verification and quality evaluation of AROPE, AROP, SMD, and VLWI models. *Source*: EU-SILC 2020 SO SR, own processing in SAS EG

Test / Statistics	AROPE	AROP	SMD	VLWI
Likelihood Ratio	2377.44***	2064.04***	1420.44***	1795.82***
Score	2566.63***	2349.84***	1754.69***	2269.79***
Wald	1719.08***	1467.33***	1056.95***	669.00***
AIC	8044.11	6450.49	4546.91	1740.74
SC	8288.11	6694.49	4790.91	1955.13
−2 Log L	7978.11	6384.49	4480.91	1678.74
AUC	0.8126	0.8305	0.8422	0.9521

***$p<0.001$; **$0.001<p<0.01$; *$0.01<p<0.05$; • $0.05<p<0.1$, level of significance

times higher than in the other dimensions. This and also other interpretations are valid assuming ceteris paribus.

In terms of the household type, the riskiest are the persons from incomplete and multi-child households (1A_1$^+$Ch, 1A_0Ch, 2A_3$^+$Ch). These persons have the odds of social exclusion in at least one dimension (AROPE) of approximately 3, 2.5, and 2.3 times higher than persons from households 2A_2Ch. These three types of households are also the riskiest in terms of AROP. Incomplete households are the riskiest for the SMD dimension. In the VLWI dimension, the riskiest are childless households (2A(1$^+$R), 1A_0Ch, 2A_0Ch). The persons from households of 2A_2Ch are the least risky in terms of VLWI and SMD. In the case of AROPE and AROP, the least risky are persons living in households 2A(1$^+$R) and Other_0Ch.

The third most important factor is the education achieved. Persons with education ISCED 0–2 have the odds of AROPE as well as the odds of AROP and VLWI more than 4 times higher compared to the persons with tertiary education (ISCED 6–8). Education has the greatest impact on SMD, which has also been proven in terms of odds ratios. The odds of SMD for people with education ISCED 0–2 is up to 17.6 times higher than for people with education ISCED 6–8.

The estimated odds ratios also provide interesting information about the influence of other factors. However, we will pay more attention to the probabilities of social exclusion.

5.2 Analysis of LS-means and contrast analysis under logit models

Using the example of the HT factor (household type), let us illustrate the process of assessing the differences between individual categories and the process of quantifying the probability of social exclusion. Compared to the reference household type (2A_2Ch), some household types (2A_0Ch, 2A_1Ch, Other_1$^+$Ch) have a statistically insignificant different AROPE risk (Table 4). To verify the significance of the differences between the other pairs of HT, we performed an LS-means analysis using the LSMEANS statement in the SAS software (Fig. 1).

Persons from households 1A_1$^+$Ch, 1A_0Ch a 2A_3$^+$Ch have the highest risk of social exclusion in at least one dimension, while there is no demonstrable difference between the pairs of these types of households (p = 0.3036, p = 0.2315 and p = 0.6944). In order to reach a correct conclusion about the equality of AROPE probability for persons from these 3 types of households (according to Table 1 it is the 1st, 2nd, and 6th type of household) we verify the hypothesis

Table 4 Parameter estimates and odds ratios for AROPE, AROP, SMD, and VLWI models. *Source*: EU-SILC 2020 SO SR, own processing in SAS EG

Parameter		AROPE Estimate	AROPE OR	AROP Estimate	AROP OR	SMD Estimate	SMD OR	VLWI Estimate	VLWI OR
Intercept		−4.9339***	–	−4.8924***	–	−7.1070***	–	−9.6370***	–
Economic Activity	Unemployed	2.5883***	13.307	2.8175***	16.735	1.8738***	6.513	5.2937***	199.074
	Inactive	1.3301***	3.781	1.0781***	2.939	0.4271**	1.533	4.4251***	83.519
	Retired	1.0481***	2.852	1.1952***	3.304	0.3584	1.431	4.4792***	88.162
	at_Work	**0.0000**	**1.000**	**0.0000**	**1.000**	**0.0000**	**1.000**	**0.0000**	**1.000**
Household Type	1A_1$^+$Ch	1.1051***	3.019	1.0182***	2.768	1.2735***	3.573	1.7698***	5.870
	1A_0Ch	0.9151***	2.497	0.4412**	1.555	1.3650***	3.916	3.3333***	28.031
	2A_3$^+$Ch	0.8408***	2.318	0.8275***	2.288	1.0133***	2.755	0.8898*	2.435
	2A_1Ch	−0.0048	0.995	−0.2256	0.798	0.8433***	2.324	1.3754***	3.957
	2A_0Ch	0.0298	1.030	−0.6938***	0.500	1.0433***	2.839	2.4579***	11.681
	2A(1$^+$R)	−0.4214**	0.656	−1.4802***	0.228	0.4215	1.524	4.2168***	67.813
	Other_1$^+$Ch	−0.0891	0.915	−0.3964**	0.673	0.8606***	2.365	1.1619***	3.196
	Other_0Ch	−0.6140***	0.541	−1.3778***	0.252	0.1480	1.159	1.5059***	4.508
	2A_2Ch	**0.0000**	**1.000**	**0.0000**	**1.000**	**0.0000**	**1.000**	**0.0000**	**1.000**
Edu-cation	ISCED 0–2	1.5712***	4.812	1.4574***	4.295	2.8676***	17.595	1.3952***	4.036
	ISCED 3–5	0.6479***	1.912	0.5885***	1.801	1.5773***	4.842	−0.1187	0.888
	ISCED 6–8	**0.0000**	**1.000**	**0.0000**	**1.000**	**0.0000**	**1.000**	**0.0000**	**1.000**
Age	30–40	1.0086***	2.742	0.7730***	2.166	0.5472**	1.728	1.1335***	3.107
	40–50	0.9830***	2.672	0.7780***	2.177	0.5391**	1.714	1.3866***	4.001
	50–60	0.6719***	1.958	0.5546***	1.741	0.2429	1.275	1.0564***	2.876
	60–70	−0.2113	0.810	0.0797	1.083	-0.2188	0.803	–	–
	70$^+$	−0.4607•	0.631	−0.2081	0.812	−0.4310	0.650	–	–
	30$^-$	**0.0000**	**1.000**	**0.0000**	**1.000**	**0.0000**	**1.000**	**0.0000**	**1.000**

Table 4 (continued)

Parameter		AROPE		AROP		SMD		VLWI	
		Estimate	OR	Estimate	OR	Estimate	OR	Estimate	OR
Health	Bad	1.1356***	3.113	0.5134***	1.671	1.3648***	3.915	0.9476***	2.580
	Fair	0.6010***	1.824	0.3696***	1.447	0.7011***	2.016	0.8325***	2.299
	Good	0.0000	1.000	0.0000	1.000	0.0000	1.000	0.0000	1.000
MS	Divorced	0.8190***	2.268	0.5776***	1.782	0.7796***	2.181	0.6255*	1.869
	Single	0.4308***	1.538	0.1238	1.132	0.7041***	2.022	0.4983*	1.646
	Widowed	−0.3995**	0.671	−0.9986***	0.368	0.0009	1.001	−0.1509	0.860
	Married	**0.0000**	**1.000**	**0.0000**	**1.000**	**0.0000**	**1.000**	**0.0000**	**1.000**
Region	BB	0.6317***	1.881	0.6944***	2.003	0.8910***	2.438	0.2340	1.264
	PO	0.4987***	1.647	0.6782***	1.970	0.2708	1.311	−0.1125	0.894
	KE	0.3987**	1.490	0.5684***	1.766	0.4349*	1.545	0.3703	1.448
	ZA	0.3486**	1.417	0.5309***	1.700	−0.1969	0.821	−0.8412*	0.431
	TN	0.0371	1.038	−0.3729•	0.689	0.5458**	1.726	−0.5811•	0.559
	TT	−0.0078	0.992	0.1842	1.202	−0.6013*	0.548	−0.2376	0.788
	NR	−0.2497•	0.779	−0.0921***	0.912	−0.4220•	0.656	−0.4514	0.637
	BA	**0.0000**	**1.000**	**0.0000**	**1.000**	**0.0000**	**1.000**	**0.0000**	**1.000**
Urban	Sparse	0.6186***	1.856	0.8696***	2.386	0.4883***	1.630	0.3135	1.368
	Intermediate	0.5017***	1.652	0.6289***	1.876	0.4817***	1.619	0.5759*	1.779
	Dense	**0.0000**	**1.000**	**0.0000**	**1.000**	**0.0000**	**1.000**	**0.0000**	**1.000**

***$p<0.001$; ** $0.001<p<0.01$; * $0.01<p<0.05$; • $0.05<p<0.1$, level of significance

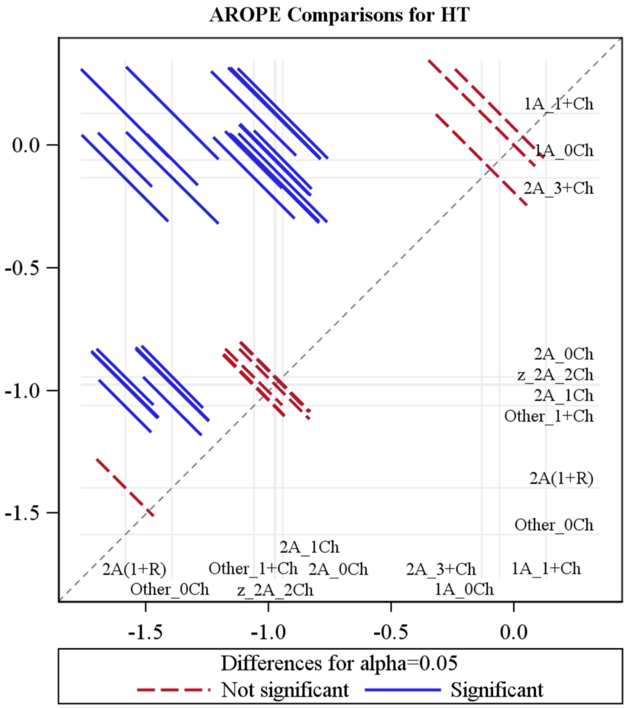

Fig. 1 Comparison of LS-means for the HT factor within the AROPE model. *Source*: EU-SILC 2020 SO SR, own processing in SAS EG

$$H_0 : \mu_1 = \mu_2 = \mu_6$$

through a simultaneous test of 2 null hypotheses. It could be, e.g., these 2 hypotheses

$$H_0 : \mu_1 = \mu_2 \quad \wedge \quad H_0 : \mu(\mu_1, \mu_2) = \mu_6$$

which need to be rewritten as linear combinations

$$H_0 : \mu_1 - \mu_2 = 0 \quad \wedge \quad H_0 : 0.5\mu_1 + 0.5\mu_2 - \mu_6 = 0$$

Their coefficients will be used in the contrast analysis. In the SAS programming language, the CONTRAST statement within PROC LOGISTIC

```
CONTRAST '1=2=6' HT 1 -1, HT 0.5 0.5 0 0 0 -1 /estimate=all;
```

generates Table 5.

Persons from households 1A_1$^+$Ch, 1A_0Ch a 2A_3$^+$Ch do not have a significantly different ($p = 0.4487$) probability of AROPE. Therefore, it makes sense to compute the probability of AROPE across these 3 household types:

$$\mu(\mu_1, \mu_2, \mu_6) = \frac{1}{3}(\mu_1 + \mu_2 + \mu_6)$$

Table 5 Verification of equality of household types 1A_1^{+}Ch, 1A_0Ch a 2A_3^{+}Ch in terms of AROPE. *Source*: EU– SILC 2020 SO SR, own processing in SAS EG

Contrast Test Results			
Contrast	DF	Wald Chi– Square	Pr > ChiSq
1 = 2 = 6	2	1.6026	0.4487

Table 6 Estimation of AROPE probability across household types 1A_1^{+}Ch, 1A_0Ch a 2A_3^{+}Ch

Contrast Estimation and Testing Results by Row								
Contrast	Type	Row	Estimate	Standard Error	Confidence Limits		Wald Chi– Square	Pr > ChiSq
1–2–6	PROB	1	0.4951	0.0222	0.4518	0.5386	0.0479	0.8267

We will use the coefficients of this linear combination in the CONTRAST statement. Syntax

```
CONTRAST '1-2-6' intercept 1 HT 0.3333 0.3333 0 0 0 0.3333 /
ESTIMATE=prob;
```

generates Table 6.

For persons from households 1A_1^{+}Ch, 1A_0Ch and 2A_3^{+}Ch, we estimate the probability of social exclusion in at least one dimension at 49.5% (45.2–53.9%).

The analysis of LS-means (Fig. 1) showed that a insignificantly different threat of social exclusion in at least one dimension also have persons from individual pairs of household types: 2A_0Ch, 2A_1Ch, 2A_2, Other_1^{+}Ch ($p = 0.8103$, $p = 0.8371$, $p = 0.3141$, $p = 0.9741$, $p = 0.5105$ and $p = 0.4775$). To verify the equality of these 4 categories

$$H_0 : \mu_4 = \mu_5 = \mu_8 = \mu_9$$

within the AROPE model, the null hypothesis was tested through a simultaneous test of 3 hypotheses:

$$H_0 : \mu_4 = \mu_5 \quad \wedge \quad H_0 : \mu\left(\mu_4, \mu_5\right) = \mu_8 \quad \wedge \quad H_0 : \mu\left(\mu_4, \mu_5, \mu_8\right) = \mu_9$$

Using the above procedure, we obtained Table 7.

Based on a simultaneous test of 3 hypotheses ($DF = 3$), there is no statistically significant difference ($p = 0.7381$) from the AROPE perspective between persons from the stated 4 types of households (2A_0Ch, 2A_1Ch, 2A_2Ch, and Other_1^{+}Ch) and for persons from these households we estimate the probability of AROPE at 28.1%

Table 7 Verification of equality of household types 2A_0Ch, 2A_1Ch, 2A_2Ch and Other_1^{+}Ch and estimation of AROPE probability across these households. *Source*: EU− SILC 2020 SO SR, own processing in SAS EG

Contrast Test Results									
Contrast	DF					Wald Chi− Square			Pr > ChiSq
4 = 5 = 8 = 9	3					1.2624			0.7381
Contrast Estimation and Testing Results by Row									
Contrast	Type	Row	Estimate	Standard Error	Alpha	Confidence Limits		Wald Chi− Square	Pr > ChiSq
4− 5− 8− 9	PROB	1	0.2809	0.0132	0.05	0.2557	0.3075	206.5072	< .0001

(25.6–30.8%). The findings presented in the following parts of the paper are based on LS-means analysis and contrast analysis.

5.3 Results of contrast analysis for individual factors

Figures 2 and 3 provide probability estimates of AROPE, AROP, SMD, and VLWI for individual factors based on logistics models.

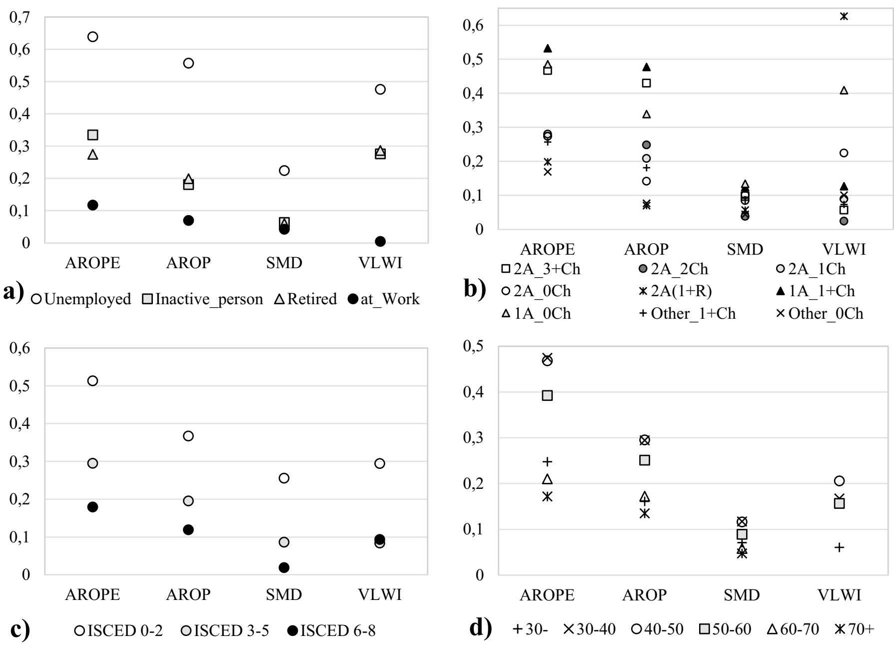

Fig. 2 AROPE, AROP, SMD, and VLWI probability estimates depending on economic activity status (top left), household type (top right), education (bottom left), and age (bottom right). *Source*: EU-SILC 2020 SO SR, own computations in SAS EG

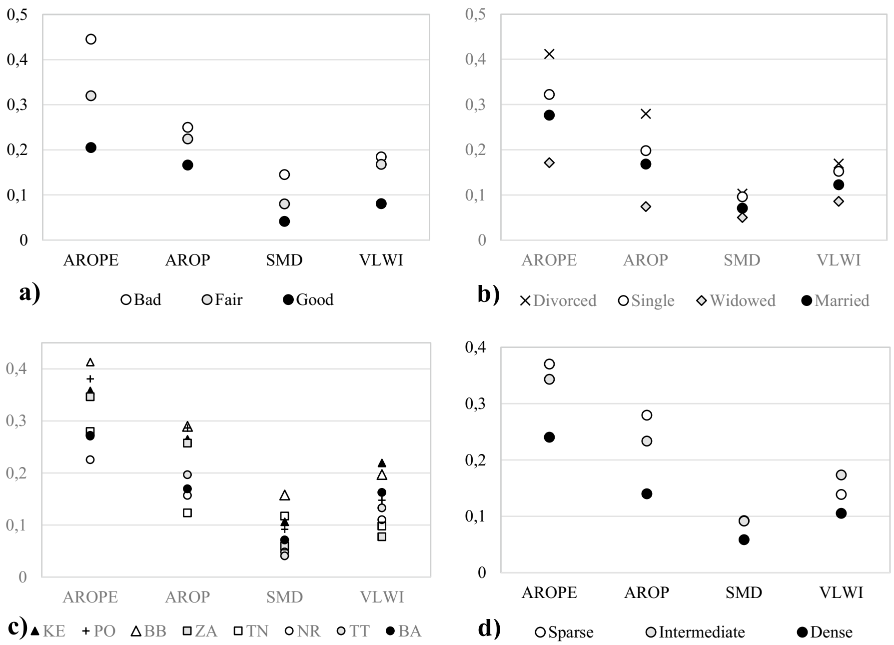

Fig. 3 AROPE, AROP, SMD, and VLWI probability estimates depending on health status (top left), marital status (top right), region (bottom left), and degree of urbanization (bottom right). *Source*: EU-SILC 2020 SO SR, own computations in SAS EG

5.3.1 Economic activity status

As expected, unemployed persons have the greatest threat of AROPE (63.9%; 57.7–69.6%) and employed persons have the lowest (11.7%; 9.9–13.8%). The probability that an unemployed person will be AROP, SMD, or will be living in QJ household is 55.7% (48.8–62.3%), 22.4% (17.0–28.9%), and 47.5% (39.0–56.2%), respectively. For the employed, these probabilities are significantly lower, and with a confidence of 0.975, they do not get above 10% (in the case of VLWI not even above 1%).

There is no significant difference between the pensioners and the otherwise inactive persons in terms of AROPE or in terms of partial dimensions ($p = 0.2283$, $p = 0.6402$, $p = 0.8220$, $p = 0.9247$). The probabilities for these two groups of persons are in all 4 cases significantly lower than for the unemployed and significantly higher than for the employed.

5.3.2 Household type

Persons from incomplete and multi-child households have the highest probability of AROPE and AROP, namely **1A_1$^+$Ch** (53.3%, 47.8%), **1A_0Ch** (48.6%, 33.9%)**,** **2A_3$^+$Ch** (46.7%, 43.0%). In the case of AROPE, there is no significant difference between them ($p = 0.4487$) and for persons from these 3 types of households, we estimate the probability as 49.5% (45.2–53.9%). In the case of AROP, there is no significant difference between **1A_1$^+$Ch, 2A_3$^+$Ch** ($p = 0.4053$) and the joint probability is 45.4%

(39.1–51.9%). Persons from single-person households have a significantly lower probability of AROP (33.9%; 29.9–38.2%), which is, however, demonstrably higher than for persons from other household types.

Also, in the case of SMD, persons from households 1A_1^{+}Ch (12.4%) and 1A_0Ch (13.5%) are the riskiest, however, there is no significant difference between them ($p = 0.7409$) and the joint probability is 12.9% (10.0–16.6%). This cluster has a demonstrably ($p = 0.0082$) higher probability of SMD than the second riskiest cluster. It consists of persons from households 2A_0Ch, 2A_1Ch, Other_1^{+}Ch and 2A_3^{+}Ch, among whom there is no significant difference ($p = 0.5986$). The joint SMD probability for this cluster is 9.2% (7.4–11.4%).

The riskiness of individual household types from the QJ perspective is significantly different compared to other dimensions of social exclusion. Persons from households who are childless, or have at most one adult of working age, have the highest probability of VLWI, i.e., households 2A(1^{+}R) (62.7%; 46.2–76.6%), 1A_0Ch (41.0%; 26.5–57.1%), 2A_0Ch (22.4%; 15.4–31.4%), 1A_1^{+}Ch (12.7%; 6.8–22.3%) and Other_0Ch (10.0%; 6.8–14.6%). Persons from households 2A_3^{+}Ch, who were among the riskiest in other dimensions, are less risky from the VLWI point of view (5.7%; 2.9–10.9%), while only persons from households 2A_2Ch (2.4%; 1.2–4.7%) have significantly lower probability of VLWI.

5.3.3 Education

All 4 models confirmed that with increasing education, the threat of income poverty or social exclusion decreases. The most at-risk educational group (ISCED 0–2) has a probability of AROPE of 51.4% (47.7–55.0%) and a probability of social exclusion in the partial dimensions (AROP, SMD and VLWI) of 36.8% (33.1–40.5%), 25.6% (22.3–29.3%) and 29.5% (21.6–38.7%), respectively. For persons with ISCED 6–8 education, the probability (AROPE, AROP, VLWI) is approximately 3 times lower. The exception is the SMD dimension, where it is only 1.9% (1.2–3.0%) for persons with ISCED 6–8 education. The probability of VLWI is not significantly different ($p = 0.6174$) for persons with ISCED 3–5 and ISCED 6–8 education. Significant differences were confirmed between the other pairs of education categories in all 4 models.

5.3.4 Age

The probability of AROPE generally decreases with increasing age. Exceptions are persons under the age of 30 years, for whom this probability (24.8%; 20.8–29.6%) is comparable ($p = 0.3825$) to the probability for 60–70-year-olds (21.1%; 16.2–27.0%). Thus, persons aged 30–40 (47.5%) and 40–50 years (46.8%) have the highest probability of AROPE. There is no significant difference between these age categories ($p = 0.8129$) and the joint AROPE probability is 42.1–52.4%. Other age categories have a demonstrably lower probability.

A similar pattern applies to the AROP and SMD dimensions, where, however, the probabilities are significantly lower. The probability of AROP and SMD for persons aged 30–50 years is 29.5% (24.8–34.5%) and 11.7% (8.8%-15.3%). In both dimensions, persons aged 70^{+} years are the least endangered, where the corresponding probabilities are 13.5% (9.3–19.2%) and 4.8% (2.9–7.8%).

According to the methodology of the Europe 2020 strategy, the work intensity for persons aged 60 + years is not assessed, therefore in Fig. 2, age categories 70^{+} and 60–70 are not captured for the VLWI dimension. The probability of VLWI is the lowest in the age category up to 30 years (6.1%; 3.7–9.8%). There is no significant difference ($p = 0.2475$) in terms of QJ among the other 3 age categories (30–40; 40–50 and 50–60) and we estimated a probability of 17.6% (13.0–23.3%) across these categories.

5.3.5 Health

A person's health condition also has a demonstrable impact on the risk of income poverty or social exclusion. Naturally, the most at risk are persons with a "bad" or "very bad" health condition. For these persons, the probability of AROPE is 44.5% (40.5–48.6%) and in the individual dimensions (AROP, SMD and VLWI) it is 25.0% (21.6–28.7%), 14.5% (11.6–17.9%) and 18.4% (12.3–26.7%), respectively. In the AROP and VLWI dimensions, there is no demonstrable difference between the "Bad" and "Fair" categories ($p = 0.1395$, $p = 0.5672$). In each dimension, the probability of social exclusion for persons with good health is about half that in the riskiest category "bad".

5.3.6 Marital status

The riskiest marital status is divorced, for which the probability of AROPE is 41.2% (36.6–45.9%) and the probabilities of AROP, SMD, and VLWI are 28.0% (23.8–32.6%), 10.3% (7.9–13.4%), and 17.0% (10.8–25.7%), respectively. However, in the case of SMD and VLWI, this probability is not significantly different from the probability for singles ($p = 0.6376$, $p = 0.6249$).

In all 3 dimensions, the widowed have the lowest risk followed by married, while in the case of SMD and VLWI there are no demonstrable differences ($p = 0.9958$, $p = 0.7654$) between them. The widowed have approximately half the probability of SMD and VLWI and only a quarter probability of AROP. All marital statuses have a significantly different probability of AROPE and the lowest is for the widowed (17.2%; 14.2–20.5%).

5.3.7 Region

The highest probability of AROPE have persons living in the regions of Banská Bystrica (41.3%; 37.2–45.5%), Prešov (38.1%; 34.1–42.2%), Košice (35.8%; 31.7–40.1%), and Žilina (34.6%; 30.6–38.9%). The Banská Bystrica region has a significantly higher probability of AROPE than the regions of Košice and Žilina ($p = 0.0150$, $p = 0.0033$) and in the case of the Prešov region, this is demonstrable for a significance level of 0.1 ($p = 0.0891$).

The 4 mentioned regions are also the riskiest in the case of AROP, in the same order (29.0%; 28.6%; 26.4%; 25.7%). However, there is no significant difference between them.

($p = 0.4055$) and across these 4 regions, the probability of AROP is 27.4% (24.8–30.2%).

In the SMD dimension, the Banská Bystrica region (15.8%; 12.8–19.3%) is the worst followed by the regions of Trenčín, Košice and Prešov. Between these 3 regions are no significant differences ($p = 0.1807$) and the joint SMD probability is 10.4% (8.6–12.7%). It is worth noting that the Žilina region, in which there was one of the highest probabilities of AROP, has a relatively low risk from the SMD perspective. The Žilina region has a comparable.

($p = 0.1697$) probability of SMD with the regions of Trnava and Nitra, with which it forms one cluster with a SMD probability of 4.9% (3.8–6.2%).

The Žilina region is even the least risky in terms of VLWI (7.7%). We estimated the highest probability of VLWI for the regions of Košice (21.9%; 15.2–30.6%) and Banská Bystrica (19.7%; 13.5–27.8%).

5.3.8 Urbanization

From the urbanization degree perspective, the areas with a sparse degree of settlement (AROPE: 37.0%, 33.9–40.2%; AROP: 27.9%, 25.1–31%; SMD: 9.2%, 7.5–11.3%) and areas with a medium degree of settlement (SMD: 9.2%, 7.5–11.2%; VLWI: 17.3%, 12.5%–23.6%) appear to be the riskiest. There is a significant difference between these 2 levels of settlement density only in the case of the AROP probability ($p = 0.0012$).

The significantly lowest risk of social exclusion according to AROPE (24.0%; 20.9–27.5%) as well as to the individual dimensions (AROP: 14.0%, 11.6–16.7%; SMD: 5.9%, 4.4–7.7%; and VLWI: 10.5%, 6.8–16.0%) is in the densely populated areas. However, for the VLWI dimension, this can be demonstrated only for the significance level up from 0.1 ($p = 0.0819$).

The factors such as economic activity status, household type, and education are the most fundamental, and therefore there are greater differences in probabilities among the individual categories of these factors than for other factors. Take AROPE, for example. While in the case of economic activity there is a difference of probabilities between the riskiest group (the unemployed) and the least risky group (the employed) of 52.2 pp (63.9% vs. 11.7%), in the case of the household type (1A_1 + Ch vs Other_0Ch) it is 36.3 pp (53.3% vs. 17.0%), and in the case of education (ISCED 6–8 vs. ISCED 0–2) 33.4 pp (51.4% vs. 18.0%). For the other 5 factors, this difference is below 30 pp (for Region and Urbanization even below 20 pp). In addition, the riskiest categories have a probability of AROPE above 50% for each of the 3 most fundamental factors, while for other factors it is below 50% (for Urbanization even below 40%).

5.4 Results of contrast analysis for mutual impact of economic activity, household type and education

In this section, we will look at the mutual impact of the three most relevant factors (economic activity, household type, education) on social exclusion, while in the case of economic activity we will focus only on employed and unemployed persons. Compared to unemployed persons, employed persons are significantly less likely to be socially excluded, therefore in Figs. 4 and 5, a different y-axis scale is used. This fact must be considered when optically comparing the graphs.

For employed persons, the probability of AROPE is approximately 50 pp lower than for the unemployed. This finding follows from Fig. 2 as well as from a comparison of Fig. 4 and Fig. 5. However, this is not a flat rate for all groups of people. The difference between the probability for employed and unemployed persons is smaller for higher education than for lower education. In other words, for people with low education, unemployment has a greater negative impact on social exclusion.

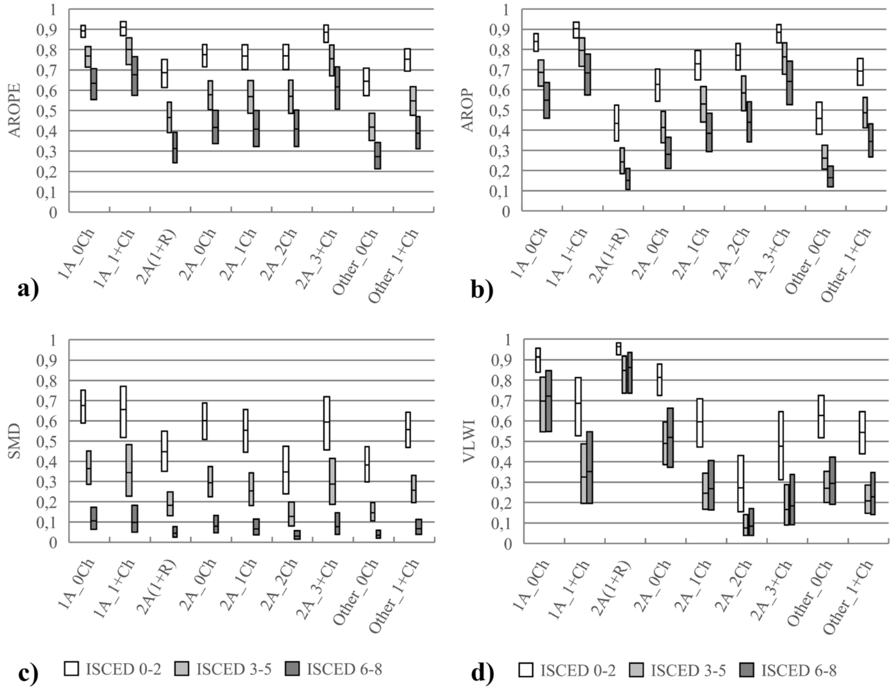

Fig. 4 Point and interval (95%) estimates of the probability of AROPE, AROP, SMD, and VLWI for **unemployed persons** depending on education and type of household. *Source*: EU-SILC 2020 SO SR, own computations in SAS EG

As regards the household type, unemployment has the greatest negative impact on persons from households 2A_3$^+$Ch, 1A_1$^+$Ch, 1A_0Ch. Persons from these households, if unemployed, have an AROPE probability of approximately 53 pp higher than employed persons. However, it should be noted that in the case of persons with ISCED 0–2 education, unemployment has the greatest negative impact on social exclusion in households 2A_0Ch, 2A_1Ch, 2A_2Ch, and Other_1$^+$Ch. On the contrary, the smallest difference in the probability of AROPE between the unemployed and the employed is observed in households Other_0Ch, 2A_0Ch, and 2A(1$^+$R), where it is about 40 pp, while it still varies depending on education and other factors.

For economic activity status “unemployed” (Fig. 4) and “employed” (Fig. 5), the probability of AROPE, AROP, SMD, and VLWI decreases significantly with increasing education, which applies to all types of households. The above pattern applies to the VLWI dimension only in part, because there is no significant difference between the ISCED 3–5 and ISCED 6–8 groups. The impact of education is the most pronounced for the SMD probability, and this is especially true for the unemployed. For unemployed persons, education determines greater differences in the probability of social exclusion in the SMD dimension than in the AROP and VLWI dimensions.

Unemployed persons, as well as employed persons, have the highest probability of AROPE if they live in households:

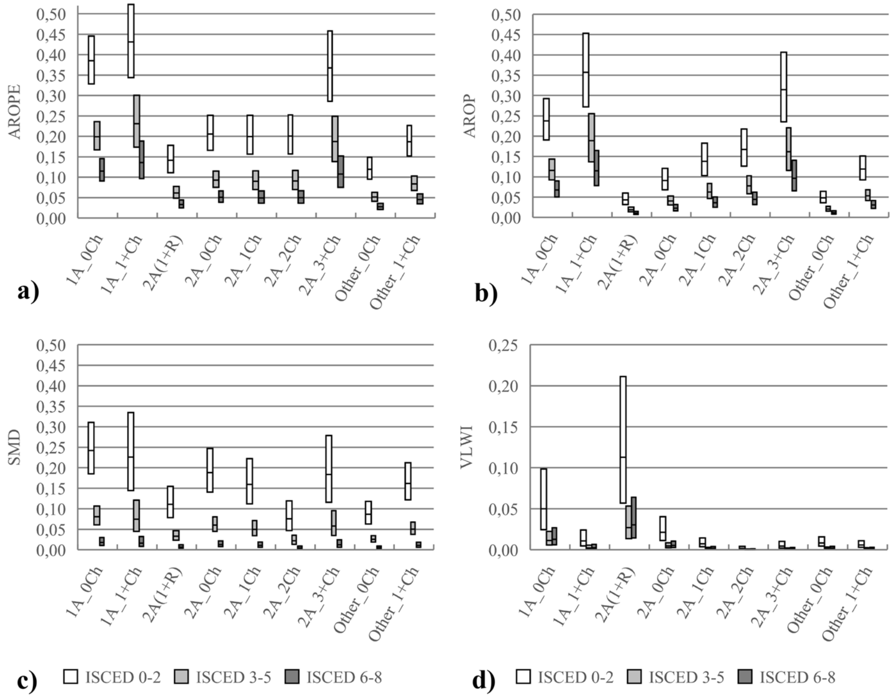

Fig. 5 Point and interval (95%) estimates of the probability of AROPE, AROP, SMD, and VLWI for **employed persons** depending on education and type of household. *Source*: EU-SILC 2020 SO SR, own computations in SAS EG

- 1A_1$^+$Ch; depending on education, it is 91.0%, 80.0%, and 67.7% for unemployed persons and 43.1%, 23.12%, and 13.6% for employed persons,
- 1A_0Ch; depending on education, it is 89.3%, 76.8%, and 63.4% for unemployed persons and 38.5%, 19.9%, and 11.5% for employed persons,
- 2A_3$^+$Ch; depending on education, it is 88.6%, 75.5%, and 61.7% for unemployed persons and 36.8%, 18.8%, and 10.8% for employed persons.

Unemployed persons from these 3 types of households with ISCED 0–2 education have a probability of AROPE higher than 83% with a confidence level of 0.975 and in the case of ISCED 6–8 education higher than 50%. For other types of households, it is demonstrably lower in both educational groups. Employed persons living in the above 3 types of households and having an ISCED 0–2 education have a probability with a high confidence of more than 30%, while in other types of households it is below 25%. Also, for other educational groups, these 3 types of households are the riskiest (this applies to both employed and unemployed persons).

We observe a similar pattern with the probability of AROP, which is in the case of a person from the above 3 types of households who is unemployed and has an ISCED 0–2 education, with a high confidence (approaching 1) of over 80%. If we compare individual types of households in terms of AROP, we see that with the increasing number of children, the probability of income poverty increases, and this is evident in households with 2 adults with different numbers of children (2A_0Ch, 2A_1Ch, 2A_2Ch, 2A_3$^+$Ch), with 1 adult (1A_0Ch, 1A_1$^+$Ch) as well as "other" households (Other_0Ch, Other_1$^+$Ch). We observe this pattern in the case of unemployed as well as employed persons.

In the SMD dimension, the above 3 types of households are also high risk, but this risk is not significantly higher than in households 2A_0Ch, 2A_1Ch, Other_1$^+$Ch, while this applies to both unemployed and employed persons. Significantly less threat of the SMD, in all educational categories, is in households 2A_2Ch, 2A(1$^+$R), and Other_0Ch. The differences in the probabilities of SMD between the unemployed and the employed are about half of the differences in the probabilities of AROP. While in the case of AROP, the maximum difference of the probability between employed and unemployed persons was 55 pp (for households 1A_1$^+$Ch, 1A_0Ch, 2A_3$^+$Ch), in the SMD dimension it is 27 pp (for households 1A_0Ch).

While the probability of AROP increases with the number of children, the number of children has the opposite effect on the probability of VLWI. In the case of households with 2 adults, this pattern is disrupted by households 2A_3$^+$Ch, which have a higher probability of VLWI than households 2A_2Ch, especially in the lowest educational group of persons.

The most endangered household type in terms of the VLWI dimension is 2A(1$^+$R). A person with ISCED 0–2 education from this household type, if unemployed, has a probability of VLWI of about 96% and with a reliability of 0.975 does not fall below 92%, and if employed, has a probability of 11% (5.7–21.1%). On the other hand, households 2A(1$^+$R) are among the least risky from the SMD and AROP perspective, thanks to which these households have the second lowest AROPE, while this applies to all 3 educational groups, both unemployed and employed persons. Only Other_0Ch households have a lower probability of AROPE.

Finally, let us focus on the least risky household type in terms of VLWI, which for both assessed statuses of economic activity is the type of household 2A_2Ch. If a person from such a household has an ISCED 0–2 education, then the probability of VLWI is 27.2% (15.6–43.1%) for an unemployed person and 0.2% (0.1–0.4%) for an employed person.

For persons with higher education, this probability is naturally even lower. For other household types, these probabilities are significantly higher. Households 2A_2Ch are also the least risky in terms of SMD (for both the unemployed and the employed). However, for the unemployed, they are among the riskiest in terms of AROP, and therefore this household type does not excel in the AROPE composite indicator (neither positively nor negatively).

6 Conclusion and discussion

The conclusions below are based on a contrast analysis applied within the logit models for poverty or social exclusion risk (AROPE), income poverty risk (AROP), severe material deprivation (SMD), and very low work intensity (VLWI). In Slovakia, these risks are most associated with the economic activity status, followed by the household type and education. However, in the case of SMD, education plays the most crucial role. Verbunt and Guio (2019) reached a similar conclusion for the EU-28. Age, health, marital status, region, and degree of urbanization also have a significant, but considerably smaller impact on these risks.

Not surprisingly, unemployed persons have the highest risk of social exclusion. The probability of AROPE for unemployed persons (63.9%) is approximately 5.5 times higher than for employed persons (11.7%). In absolute terms, this represents approximately 50 pp, which is however not a flat rate for all groups of persons in the breakdown of other factors.

In terms of household type, incomplete and multi-child households have the highest probability of AROPE, as found by Verbunt and Guio (2019). Our analyses have shown that imaginary scissors between these household types and other ones are even more open in Slovakia if we consider only employed persons. Such a finding also applies to the risk of income poverty, as confirmed by the research of Filandri and Struffolino (2019).

In terms of SMD, incomplete households are the riskiest. Nieuwenhuis (2021) states that the absence of a potential second earner makes it difficult for single-parent households to obtain an adequate income and at the same time makes a single-parent household more vulnerable to the consequences of (temporary) unemployment. However, in our analysis, in terms of the VLWI, the childless households or households that have at most one person of working age proved to be the riskiest. The threat of exclusion from the labour market in households with 1 adult depends on 1 person only and cannot be compensated by other persons as in households with a larger number of adults of working age. In addition, our results suggest that households with children are more motivated to work and therefore have a lower QJ risk than childless households. It is worth noting that although the households of 2 adults with at least 3 children are among the riskiest from the AROPE, AROP and SMD perspective, this is not the case from the VLWI point of view. As the number of children increases, the probability of AROP increases. The number of children has the opposite effect on QJ unless we talk about the households of 2 adults with at least 3 children. They have higher probability of VLWI than households of 2 adults with 2 children, which especially applies for people with ISCED 0-2 education.

With increase in education, the threat of social exclusion decreases significantly, and this is true in terms of AROPE, AROP, SMD, and VLWI, for the unemployed, the employed, and all household types. Low education was identified as a significant risk factor for social exclusion in other European countries also by Dudek and Szczesny (2021), Filandri and Struffolino (2019), González et al. (2021), Israel and Spannagel (2019), Sánchez-Sellero and Garcia-Carro (2020), and others. In Slovakia, persons with ISCED 0-2 education have a probability of AROPE of approximately 50% and a probability of social exclusion in the AROP dimension higher than 1/3 and in the SMD and VLWI dimensions higher than 1/5. The level of education determines large differences in the risk of social exclusion, especially for unemployed persons in the SMD dimension.

The probability of AROPE as well as in individual dimensions (AROP, SMD, and VLWI) decreases with increasing age. A similar finding was found for the AROP dimension in the Spanish population by Sánchez-Sellero and Garcia-Carro (2020). This pattern in Slovakia is disrupted by persons under 30 years old, for whom the probabilities are significantly lower than for persons aged 30–50 years. Social exclusion also increases with deteriorating health. For persons who rate their health as above average, this probability is twice as high as for persons with below-average health. The riskiest family status is divorced. Lee and Cagle (2018) also state that better health status and being partnered reduce social exclusion.

In Slovakia, we demonstrated regional disparities in social exclusion from all aspects assessed (AROPE, AROP, SMD, and VLWI), with people living in South-Center and Eastern Slovakia having the greatest risk, as confirmed by the European Commission (2021a). These are the regions of Banská Bystrica, Prešov, and Košice, and depending on the dimension of social exclusion, there is or is not a significant difference between these regions. Some regions do not have consistent results across the various dimensions of social exclusion. For example, in the Žilina region, one has the highest probability of AROP, but the lowest probability of VLWI.

In terms of degree of urbanization, sparsely and moderately densely populated areas are the riskiest. There is a demonstrable difference between them only in the case of the AROP dimension, to the detriment of sparsely populated areas. Our conclusions correspond to the finding of Weziak-Bialowolska (2016) that in the CEE countries considerably higher poverty was observed in thinly populated areas.

The above conclusions result from the contrast analysis, through which we evaluated the individual impact of the above-mentioned factors (fixing the impact of other factors) as well as the interaction of the most fundamental factors (economic activity, household type, and education) on social exclusion. To assess the interplay of the 3 most important factors on social exclusion, 216 interval estimates of AROPE, AROP, SMD, and VLWI were estimated, covering 54 groups of persons (depending on 9 household types, 3 levels of education, and 2 statuses of economic activity—the employed and the unemployed). These confirmed that unemployed persons have a significantly higher risk of social exclusion than employed persons in all types of households and all educational groups. Although the pattern of the risk of social exclusion of persons broken down by household type and education for the unemployed and employed is similar, the riskiness of the most vulnerable groups of people is more pronounced for employed persons.

Our conclusions for Slovakia support the statements of Peña-Casas et al. (2019), who state that although work should be the best route to avoid poverty, this is not always the case for a significant proportion of workers in the EU. One of the causes of in-work poverty can be weak social programs. Israel and Spannagel (2019) revealed that Slovakia has weak social support within the EU-28 and EFTA countries and at the same time point out that social programs that cover large segments of the population and a follow-up approach are linked to lower odds of being materially deprived.

In conclusion, we want to emphasize that the paper provides an empirical analysis for Slovakia and although we believe that many conclusions apply at least to the CEE countries, it needs to be verified by further research. The results of the analysis have their limitations, which are mainly related to the methodology of measuring poverty and social exclusion. According to Laparra et al. (2021), the AROPE rate fails to fully capture the multidimensionality of social exclusion, as this rate is limited to the economic dimensions only (income, material deprivation, and employment) and does not consider other dimensions. We agree with Ravallion (2011), who states that the goal of future efforts in poverty monitoring should be to create a set of more, reliable indices covering the poverty dimensions and not one multidimensional index. A weakness of the AROPE approach is also the fact that it does not consider the depth of the individual phenomena, which may distort the impact of dimensions on social exclusion, as pointed out in the case of young persons by Šoltés et al. (2020). The paper follows the original AROPE concept, which is also used in the EU-SILC 2020 database, although the methodology for measuring SMD is not entirely appropriate. According to Šoltés and Ulman (2015), there were less than 1% of households in Slovakia in 2012 that could not afford items such as washing machine, TV, and telephone. Guio et al. (2012) showed that the three mentioned items from the original concept do not have a significant impact on material deprivation in most EU member states and therefore proposed a new indicator, which proved to be optimal even after a five-year period (Guio et al., 2017). Another problem that we have not addressed is the overlap of the individual dimensions, as we are aware that it is precisely those who are socially excluded in several dimensions that should be given special attention. However, this remains a challenge for our further research. Special attention should also be paid to the social inclusion of marginalized Roma communities, which represents a significant challenge for Slovak social policy (Rusnáková and Rochovská 2016), information on ethnicity, however, is not collected as part of the EU-SILC survey.

Despite the mentioned limitations, the results obtained may be useful for national social policymaking for two reasons. First, the article reveals the most endangered population groups from the risk of poverty and social exclusion perspective, which should be the focus of social policy in Slovakia. Secondly, thanks to the quantification of the risk of individual population groups in terms of various forms of social exclusion, the article provides a good basis for setting the proportionality of social assistance for individual population groups at risk of poverty and social exclusion.

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Declarations

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References

Abrar ul haq, M., Jali, M.R.M., Islam, G.M.N.: Assessment of the role of household empowerment in alleviating participatory poverty among rural household of Pakistan. Qual. Quant. **52**(6), 2795–2814 (2018). https://doi.org/10.1007/s11135-018-0710-0

Abrar ul haq, M., Jali, M.R.M., Islam, G.M.N.: Household empowerment as the key to eradicate poverty incidence Asian. Soc. Work Policy Rev. **13**(1), 4–24 (2019). https://doi.org/10.1111/aswp.12152

Allison, P.D.: Fixed Effects Regression Methods for Longitudinal Data Using SAS. SAS Institute Inc, Cary, NC (2005)

Allison, P.D.: Logistic Regression using SAS. Theory and Application, 2nd edn. SAS Institute Inc., Cary, NC (2012)

Boarini, R., & d'Ercole, M.M: Measures of material deprivation in OECD countries. OECD Social, Employment and Migration Working Paper No. 37. (2006)

Cai, W.: Making comparisons fair: How LS-means unify the analysis of linear models. SAS Institute Inc. 2014. *Proceedings of the SAS® Global Forum 2014 Conference*. Cary, NC: SAS Institute Inc., Paper SAS060–2014 (2014)

Ciacci, A., & Traversa, S. (2021). A non-compensatory time analysis of material deprivation in the EU. *Rev. Estud. Andal.* 42, 118–137.

Commission, E.: Analysis of the recovery and resilience plan of Slovakia. Commission staff working document, Brussels (2021a)

Ćwiek, M.T., Ulman, P.: Income and poverty in households in selected European countries. Acta Univ. Lodz. Folia Oeconomica **6**(345), 9–34 (2019). https://doi.org/10.18778/0208-6018.345.01

de Graaf-Zijl, M., Nolan, B.: Household joblessness and its impact on poverty and deprivation in Europe. J. Eur. Soc. Policy **21**(5), 413–431 (2011). https://doi.org/10.1177/0958928711418854

Decerf, B.: Combining absolute and relative poverty: income poverty measurement with two poverty lines. Soc. Choice Welfare **56**(2), 325–362 (2021). https://doi.org/10.1007/s00355-020-01279-7

Dudek, H., Szczesny, W.: Multidimensional material deprivation in Poland: a focus on changes in 2015–2017. Qual. Quant. **55**(2), 741–763 (2021). https://doi.org/10.1007/s11135-020-01024-3

European Commission: Social protection committee annual report 2018. 2021b SPC annual review of the social protection performance monitor and developments in social protection policies. Publications Office of the EU, Luxembourg (2021b)

Eurostat: Glossary: at-risk-of-poverty rate [online]. [cit. 10.08.2022]. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:At-risk-of-poverty_rate(2021a)

Eurostat: Glossary: material deprivation [online]. [cit. 10.08.2022]. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Material_deprivation(2021b)

Eurostat: Glossary: persons living in households with low work intensity [online]. [cit. 10.08.2022]. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Persons_living_in_households_with_low_work_intensity(2021c)

Eurostat: Glossary: at risk of poverty or social exclusion (AROPE) [online]. [cit. 06.02.2022]. Available at: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:At_risk_of_poverty_or_social_exclusion_(AROPE) (2022)

Filandri, M., Struffolino, E.: Individual and household in-work poverty in Europe: understanding the role of labor market characteristics. Eur. Soc. **21**(1), 130–157 (2019). https://doi.org/10.1080/14616696.2018.1536800

Filandri, M., Pasqua, S., Struffolino, E.: Being working poor or feeling working poor? The role of work intensity and job stability for subjective poverty. Soc. Indic. Res. **147**(3), 781–803 (2020). https://doi.org/10.1007/s11205-019-02174-0

García-Gómez, C., Pérez, A., Prieto-Alaiz, M.: Copula-based analysis of multivariate dependence patterns between dimensions of poverty in Europe. Rev. Income Wealth **67**(1), 165–195 (2021). https://doi.org/10.1111/roiw.12461

González, L., Estarlich, M., Murcia, M., Larrañaga, I., Barreto, F.B., Santa-Marina, L., Arranz, E., Cirugeda, L., Simó, S., Rebagliato, M.: Risk of child poverty and social exclusion in two Spanish regions: social and family determinants. Gac. Sanit. **35**, 216–223 (2021). https://doi.org/10.1016/j.gaceta.2019.11.002

Goodnight, J.H., Harvey, W.R.: SAS Technical Report R-103 Least Squares Means in The Fixed Effects General Model. SAS Institute Inc, Cary, NC (1997)

Guio, A.-C., Gordon, D., Marlier, E.: Measuring Material Deprivation in the EU: Indicators for the Whole Population and Child-Specific Indicators. Eurostat methodologies and working papers Publications Office of the EU, Luxembourg (2012)

Guio, A.-C., Gordon, D., Najera, H., Pomati, M.: Revising the EU material deprivation variables. Publications Office of the EU, Luxembourg (2017)

Guio, A.-C., Marlier, E., Nolan, B. (eds.): Improving the understanding of poverty and social exclusion in Europe. Publications Office of the EU, Luxembourg (2021)

Härkönen, J.: Diverging Destinies in International Perspective: Education, Single Motherhood, and Child Poverty (No. 713). LIS Working Paper Series, (2017)

Israel, S., Spannagel, D.: Material deprivation in the EU: a multi-level analysis on the influence of decommodification and defamilisation policies. Acta Soc. **62**(2), 152–173 (2019). https://doi.org/10.1177/0001699318778735

Kassahun, T., Tessema, A., Adbib, K.: Analysis of rural household food and non-food poverty status in Ethiopia: the case study from Meskan district. Food Energy Secur. **11**, e363 (2022). https://doi.org/10.1002/fes3.363

Laparra, M., Mutilva, N.Z., Lautre, I.G.: The multidimensional conception of social exclusion and the aggregation dilemma: a solution proposal based on multiple correspondence analysis. Soc. Indic. Res. **158**, 1–30 (2021). https://doi.org/10.1007/s11205-021-02707-6

Lee, J., Cagle, J.G.: Social exclusion factors influencing life satisfaction among older adults. J. Poverty Soc. Justice **26**(1), 35–50 (2018). https://doi.org/10.1332/175982717X15127351091521

Lenth, R.V.: Least-squares means: the R package lsmeans. J. Stat. Softw. **69**(1), 1–33 (2016). https://doi.org/10.18637/jss.v069.i01

Littell, R.C., Stroup, W.W., Freund, R.J.: SAS for Linear Models, 4th edn. SAS Institute Inc., Cary, NC (2010)

Łuczak, A., Kalinowski, S.: Assessing the level of the material deprivation of European Union countries. PLoS ONE **15**(9), e0238376 (2020). https://doi.org/10.1371/journal.pone.0238376

Mysíková, M., Želinský, T., Garner, T.I., Večerník, J.: Subjective perceptions of poverty and objective economic conditions: Czechia and Slovakia a quarter century after the

dissolution of Czechoslovakia. Soc. Indic. Res. **145**(2), 523–550 (2019). https://doi.org/10.1007/s11205-019-02102-2
Mysíková, M.: Measuring Income Poverty in the EU: Visegrád Countries and European Empirical Data. Institute of Sociology of the Czech Academy of Sciences, Prague (2021)
Nieuwenhuis, R.: Directions of thought for single parents in the EU. Community Work Fam. **24**(5), 559–566 (2021). https://doi.org/10.1080/13668803.2020.1745756
Nieuwenhuis, R., Maldonado, L.: The triple bind of single-parent families: Resources, employment and policies to improve well-being. Policy Press (2018)
Paek, I.: Three statistical testing procedures in logistic regression: their performance in differential item functioning (DIF) investigation. ETS Res. Rep. Ser. **2009**(2), i–29 (2009)
Pasta, D. J.: Parameterizing models to test the hypotheses you want: Coding indicator variables and modified continuous variables. In: Proceedings of the Thirtieth Annual SAS Users Group International Conference (Paper 212–30) (2005).
Peña-Casas, R., Ghailani, D., Spasova, S., Vanhercke, B.: In-work poverty in Europe A study of national policies. European Social Policy Network. European Commission, Brussels (2019)
Piwowar, A., Dzikuć, M.: Poverty and social exclusion: is this a problem in rural areas in the visegrad group countries? Eur. Res. Stud. J. **23**(2), 45–54 (2020). https://doi.org/10.35808/ersj/1579
Prattley, J., Buffel, T., Marshall, A., Nazroo, J.: Area effects on the level and development of social exclusion in later life. Soc. Sci. Med. **246**, 112722 (2020). https://doi.org/10.1016/j.socscimed.2019.112722
Ravallion, M.: On multidimensional indices of poverty. J Econ. Inequal. **9**(2), 235–248 (2011). https://doi.org/10.1007/s10888-011-9173-4
Rusnáková, J., Rochovská, A.: Sociálne vylúčenie, segregácia a životné stratégie obyvateľov rómskych komunít z pohľadu teórie zdrojov. Geogr. Čas. **68**(3), 227–243 (2016)
Salcedo, A.M., Izquierdo Llanes, G.: Drawing the optimal monetary poverty lines based on empirical data: an application to Spain. Qual. Quant. **53**(1), 513–527 (2019). https://doi.org/10.1007/s11135-018-0766-x
Sánchez-Sellero, M.C., Garcia-Carro, B.: Which groups have a greater risk of poverty in Spain? Rev. Soc. Polit. **27**(1), 36–36 (2020). https://doi.org/10.3935/rsp.v27i1.1572
SAS Institute: SAS/STAT® 15.1 User's Guide. SAS Institute Inc., NC (2018)
Schad, D.J., Vasishth, S., Hohenstein, S., Kliegl, R.: How to capitalize on a priori contrasts in linear (mixed) models: a tutorial. J. Mem. Lang. **110**, 104038 (2020). https://doi.org/10.1016/j.jml.2019.104038
Searle, S.R., Gruber, M.H.J.: Linear Models, 2nd edn. John Wiley & Sons (2017)
Šoltés, E., Ulman, P.: Material deprivation in Poland and Slovakia–a comparative analysis. Crac. Rev. Econ. Manag. **11**(947), 19–36 (2015). https://doi.org/10.15678/ZNUEK.2015.0947.1102
Šoltés, E., Vojtková, M., Šoltésová, T.: Changes in the geographical distribution of youth poverty and social exclusion in EU member countries between 2008 and 2017. Morav. Geogr. Rep. **28**(1), 2–15 (2020). https://doi.org/10.2478/mgr-2020-0001
Verbunt, P., Guio, A.-C.: Explaining differences within and between countries in the risk of income poverty and severe material deprivation: Comparing single and multilevel analyses. Soc. Indic. Res. **144**(2), 827–868 (2019). https://doi.org/10.1007/s11205-018-2021-1
Vojtková, M., Stankovičová, I.: Viacrozmerné štatistické metódy s aplikáciami v softvéri SAS. Letra Edu, Bratislava (2019)
Weziak-Bialowolska, D.: Spatial variation in EU poverty with respect to health, education and living standards. Soc. Indic. Res. **125**(2), 451–479 (2016). https://doi.org/10.1007/s11205-014-0848-7