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Comparison of household work intensity in Slovakia and Czechia through least squares means analysis based on GLM

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Abstract

The work intensity (WI) of a household is primarily monitored in order to identify (quasi-)jobless (QJ) households. QJ households are those households whose members use less than 20% of their work potential. Individuals in such households, together with income-poor and severely materially and socially deprived persons are included in the Europe 2030 Strategy as socially excluded who need to be targeted by social policies.
The aim of the paper is to assess the impact of relevant factors and their interactions on the WI of households in Slovakia and Czechia. For this purpose, general linear models, contrast analysis and estimates of marginal means are employed. The presented analyses are based on the EU-SILC 2021 survey and carried out separately for Slovakia and Czechia. The paper reveals the common and different features of these countries in terms of the WI of households. Particular attention is devoted to the identification of the profiles of persons at high risk of living in QJ households.

Key words: work intensity, (quasi-)joblessness, general linear model, marginal means, contrast analysis.

1. Introduction

The work intensity (WI) of households is an indicator that is monitored within the Europe 2030 strategy. In addition to income poverty and material and social deprivation, special attention is directed towards the population residing in households

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with very low work intensity (VLWI). Such households are commonly referred to as (quasi-)jobless (QJ) households.

Not only unemployment but also (quasi-)joblessness (QJ) is associated with poverty and social exclusion. According to Eurostat (2023a), in 2021, the at-risk-of-poverty (AROP) rate in the EU for the segment of the population living in QJ households was 62.3%, whereas in the segment of the population residing in households with very high WI, it was 5.4%. For persons living in households with very low or very high WI, the AROP rates in Czechia were 59.0% and 3.0%, respectively, and in Slovakia, they were 74.7% and 5.5%, respectively. Within the EU, Slovakia recorded the 7th highest AROP rate among QJ households. Eurostat noted higher rates only in the Baltic countries, the Netherlands, Sweden, and Croatia.

The VLWI rate, along with the AROP rate and the rate of severe material and social deprivation (SMSD), constitute the composite indicator AROPE (at risk of poverty or social exclusion). This indicator and its component rates are significantly influenced by individuals' economic activity status, with the unemployed and disabled individuals being particularly vulnerable (Eurostat 2023b). While the VLWI rate among the population with a disability was 180% (11.9 p.p.) higher than among the population without limitations in the EU, in Slovakia, it was 320% (8.6 p.p.) higher, and in Czechia, it was as much as 570% (14.2 p.p.) higher for persons with disabilities.

The mentioned facts motivated us to analyze WI in Slovakia and Czechia from the perspective of different economic activity statuses. This paper is not limited only to the VLWI but focuses on the WI index. This index is a target continuous numerical variable, which we analyzed depending on various factors through the analysis of marginal means and contrast analysis, which are based on a general linear model. The aim of the paper is to assess the pure influence (by fixing the influence of other relevant factors) of the most fundamental socio-economic and socio-demographic factors on WI in Slovakia and Czechia and subsequently compare outcomes between these two countries. The following research objectives are also oriented on the most relevant factors:

- to assess whether the impact of factors on WI is different or the same for different statuses of economic activity,
- to identify categories with no significant differences and identify categories or clusters where demonstrable differences in WI exist,
- to estimate the marginal means of WI for individual groups of persons and identify risk groups of persons in terms of QJ.

2. Literature review

According to Treanor (2018), employment can be a pathway out of poverty if it involves stable and quality work. When adult household members have unstable employment, it is reflected in the household work intensity. Households with low WI struggle to earn an adequate annual income, which escalates their risk of poverty and material deprivation. In this paper, we do not deal only with VLWI, as other levels of WI can also be associated with poverty and social exclusion. E.g., Kis and Gábos (2016) showed that in the new member states of the EU not only low and very low household WI is positively associated with a higher risk of consistent poverty, but also medium WI. Fabrizi and Mussida (2020) showed that higher WI of Italian households with children significantly reduces the probabilities to fall into poverty and social exclusion. High utilization of the labour potential of households is therefore a key factor in combating poverty and social exclusion.

Low WI is correlated not only with income poverty but also with material deprivation. Duiella and Turrini (2014) and similarly García-Gómez et al. (2021) found relationship between poverty, material deprivation and WI which became stronger in countries most severely hit by the economic crisis in the period 2008–2014. Based on the above, we suppose that this relationship will intensify also due to the inflation, and war in Ukraine. Verbunt and Guio (2019) confirmed that WI is very effective in explaining within-country differences in the risk of income poverty/material deprivation in some CEE countries. In Slovakia, following the financial and economic crisis, unemployed persons living in households with a high and medium WI had markedly higher chances to move to employment, as compared to the unemployed in households with low WI (Gerbery and Miklošovic 2020). Fabrizi a Mussida (2020) found that living in a work-poor household is associated with living in consistent poverty (people at consistent poverty are those who are both at-risk-of-poverty and simultaneously experiencing enforced deprivation).

In addition, low WI of households has a negative impact on children and young people and on their social exclusion in the future. Analyses conducted by Treanor and Troncoso (2022) revealed that children in Scotland, whose parents consistently maintain high and medium WI, exhibit some of the lowest scores for both conduct and emotional problems. This suggests that stability in income and employment positively influences children's mental wellbeing. Guio and Vandenbroucke (2019) found out that QJ is an important driver of child deprivation in Belgium, even when income is controlled for. A similar conclusion was also reached by Regan and Maître (2020), when they demonstrated that during the period of 2008–2018, children in work-intensive households (households categorized as having high or very high WI) had a low AROP rate as well as a low deprivation rate. As noted by Hallaert et al. (2023), the proportion of children living in QJ households increased during the COVID-19 pandemic.

In selecting the explanatory factors, we relied on the results of our previous research and the works of other researchers. These factors include economic activity status, education, household type, age, marital status, health condition, region, and degree of urbanization. We focused especially on the impact of the first four factors on WI, whose significant influence on poverty and social exclusion has been confirmed, e.g. by the studies mentioned below. Verbunt and Guio (2019) concluded that education plays a much bigger role in explaining poverty and social exclusion in economically weaker countries. According to Nieuwenhuis and Maldonado (2018), the risks of poverty among single-parent families are significantly higher than among complete families. Watson et al. (2015) revealed that across different household types, living in a jobless household was associated with a reduced probability that a non-employed person would make a transition into employment. Hofmarcher (2021) found strong effects of an additional year of education in reducing the likelihood of living in poverty. Education reduced not only the likelihood of relative income poverty but also reduced the likelihood of lacking essential household necessities and living in a household with weak labor market attachment.

3. Research methods

In this paper, we proceed from two separated general linear models (GLMs), one for Slovakia and the other for Czechia, based on which the influence of categorical factors and their interactions on a continuous numerical response variable characterizing WI will be assessed. In terms of interpreting the results, it is important to note that in our research, we used factors with fixed effects (Searle and Gruber 2017), and for categorical factors, we used indicator (dummy) coding (Darlington and Hayes 2016). The interaction was based on the crossed classification structure (Littell et al. 2010).

The general linear model can be written in matrix form as follows:

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \tag{1}$$

The matrix $\boldsymbol{X}$ is of non-full-rank, and a generalized inverse method is used to estimate the vector of parameters $\boldsymbol{\beta}$, the result of which is an estimate:

$$\boldsymbol{b} = (\boldsymbol{X}^T\boldsymbol{X})^{-}\boldsymbol{X}^T\boldsymbol{y} \tag{2}$$

where the matrix $(\boldsymbol{X}^T\boldsymbol{X})^{-}$ is a generalized inverse matrix that must satisfy at least the first of the Penrose conditions (Searle and Gruber 2017). The estimation of the vector of parameters $\boldsymbol{\beta}$ obtained by the generalized inverse method is not unique, but there is a group of linear functions of the parameters, which we refer to as estimable functions $\boldsymbol{L\beta}$ (Elswick et al. 1991), for which there is a single solution (in more detail, e.g. Agresti 2015 and Littell et al. 2010).

As the aim of the paper is, among other things, to assess between which categories of relevant factors there is a significant difference, the subject of our interest will be the testing of general linear hypotheses. To verify the general linear hypothesis (see more detail in, e.g. McFarquhar 2016 or Searle and Gruber 2017)

$$H_0: \quad \boldsymbol{L\beta} = \mathbf{0} \tag{3}$$

the following test statistic is used:

$$F = \frac{\frac{(\boldsymbol{Lb})^T \cdot \left[\boldsymbol{L}\left(\boldsymbol{X}^T\boldsymbol{X}\right)^{-}\boldsymbol{L}^T\right]^{-1} \cdot (\boldsymbol{Lb})}{l}}{\frac{SSE}{n-p}} \tag{4}$$

where l *is* the number of independent rows of the matrix $\boldsymbol{L}$, the *SSE* is sum of squared residuals, n is the sample size, p is the number of parameters of the GLM. We reject the null hypothesis if the value of the test statistic satisfies the inequality:

$$F > F_{1-\alpha}(l;\ n-p) \tag{5}$$

The test mentioned above is used to verify simple hypotheses (if $l = 1$) and to simultaneously test multiple hypotheses (if $l \geq 2$). To verify simple hypotheses, of course, a t-test is also used, or alternatively, an interval estimate is constructed as well (see, e.g. Kuznetsova et al. 2017; Littell et al. 2010; and Westfall and Tobias 2007).

The analyses presented in the paper are based on unbalanced data, while we assess the impact of several effects. In such a situation, group arithmetic means do not provide an adequate picture of the response of the target variable for the particular factor because they do not take into account other effects, which may lead to the Simpson paradox (Wang et al. 2018). Cai (2014) states that if the data are unbalanced, arithmetic means are not appropriate because they do not consider that not all factors have the same chance of influencing the target variable. In such cases, it is appropriate to estimate the marginal means, which are based on the model (in our case on the GLM). The marginal mean is also referred to as the LS-mean (Least Squares mean; SAS Institute Inc. 1997) or the EM-mean (Estimated Marginal mean; Searle et al. 1980). LS-means are predicted means that are calculated from the fitted model and are adjusted appropriately for any other variable (Suzuki et al. 2019).

In this paper, we use marginal mean analysis using the LSMEANS statement. In addition, we employ contrast analysis (Dean et al. 2017; Schad et al. 2020) using the CONTRAST statement within PROC GLM (SAS Institute Inc. 2018) in the SAS programming language. Through contrast analysis we test the equality of marginal means of the target variable for individuals belonging to different groups determined by the interaction of two categorical factors.

For simplicity, let us consider the two-way classification model (see Little et al. 2010)

$$y_{ijk} = \underbrace{\mu + \alpha_i + \beta_j + (\alpha\beta)_{ij}}_{\mu_{ij}} + \varepsilon_{ijk} \tag{6}$$

where y_{ijk} is the k-th observed score for the (i, j)-th cell, α_i is the effect of the i-th $(i = 1,\ 2,\ \dots, a)$ level of factor A, β_j is the effect of the j-th $(j = 1,\ 2,\ \dots, b)$ level of factor B, $(\alpha\beta)_{ij}$ is the interaction effect for the i-th level of factor A and j-th level of factor B, μ is the overall mean, μ_{ij} is the marginal mean for the i-th level of factor A and j-th level of factor B, ε_{ijk} is the random error associated with individual observations.

Model (6) can be rewritten in the form of a regression model as follows:

$$y_{ij} = \mu + \sum_{i=1}^{a} \alpha_i X_{Ai} + \sum_{j=1}^{b} \beta_j X_{Bj} + \sum_{j=1}^{b} \sum_{i=1}^{a} (\alpha\beta)_{ij} X_{Ai} X_{Bj} + \varepsilon_{ij} \tag{7}$$

where μ is the intercept, X_{Ai} is the dummy variable for i-*th* level of factor A, X_{Bj} is the dummy variable for j-*th* level of factor B and α_i, β_j, $(\alpha\beta)_{ij}$ are regression coefficients.

Let us assume that our interest lies in verifying the equality of the following marginal means:

$$H_0 : \mu_{21} = \mu_{22} = \mu_{24} = \mu_{2b} \tag{8}$$

That is, we test the equality of the marginal means at the second level of factor A for the first, second, fourth, and last level of factor B. This hypothesis regarding the equality of 4 means needs to be reformulated into the form of 3 null hypotheses, each of which is a linear combination of the respective means. The mentioned null hypothesis can be expressed, for example, through these 3 null hypotheses:

$$H_0 : \mu_{21} = \mu_{22} \wedge H_0 : \mu\,(\mu_{21},\ \mu_{22}) = \mu_{24} \ \wedge\ H_0 : \mu\,(\mu_{21},\ \mu_{22},\ \mu_{24}) = \mu_{2b}$$

which we rewrite into linear combinations:

$$\mu_{21} - \mu_{22} = 0 \qquad \tfrac{1}{2}\mu_{21} + \tfrac{1}{2}\mu_{22} - \mu_{24} = 0 \qquad \tfrac{1}{3}\mu_{21} + \tfrac{1}{3}\mu_{22} + \tfrac{1}{3}\mu_{24} - \mu_{2b} = 0 \tag{9}$$

Based on these linear combinations, we then determine the elements of a contrast matrix **L**, which determines the general linear hypothesis (3). The elements of matrix **L** are obtained by rewriting each marginal mean μ_{ij} in hypotheses (9) according to equation (6). The coefficients associated with the effects α_i, β_j and $(\alpha\beta)_{ij}$ are the sought-after elements of the contrast matrix **L**. A simpler way to determine these elements is to utilize a contingency table in the form of Table 1.

Table 1: Coefficients of a contrast matrix **L** in the case of factor interaction

Factor α	**Factor β**						**Sum**
	1	**2**	**3**	**4**	$\cdots$	***b***	
1	l_{11}	l_{12}	l_{13}	l_{14}	$\cdots$	l_{1b}	$l_{1\bullet}$
2	l_{21}	l_{22}	l_{23}	l_{24}	$\cdots$	l_{2b}	$l_{2\bullet}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
a	l_{a1}	l_{a2}	l_{a3}	l_{a4}	$\cdots$	l_{ab}	$l_{a\bullet}$
Sum	$l_{\bullet 1}$	$l_{\bullet 2}$	$l_{\bullet 3}$	$l_{\bullet 4}$	$\cdots$	$l_{\bullet b}$	$l_{\bullet\bullet}$

Thus, to test the null hypothesis (8), we will simultaneously test hypotheses (9). Let us now show how we determine the coefficients for the last hypothesis in (9). We write the coefficients of the linear combination into the cells of Table 1 and do their summation in the sum row and sum column, as indicated in Table 2.

In the total row and total column in Table 2, there are coefficients for the factor A and factor B, respectively. The coefficients for interaction $A \cdot B$ are listed in the field of Table 2. Similarly, we could determine the coefficients for the other 2 partial hypotheses.

Table 2: Coefficients for the CONTRAST statement to test the null hypothesis $H_0: \frac{1}{3}\mu_{21} + \frac{1}{3}\mu_{22} + \frac{1}{3}\mu_{24} - \mu_{2b} = 0$

Factor α	Factor β						Sum
	1	**2**	**3**	**4**	…	***b***	
1	0	0	0	0	…	0	**0**
2	$\frac{1}{3}$	$\frac{1}{3}$	0	$\frac{1}{3}$	…	-1	**0**
3	0	0	0	0	…	0	**0**
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
a	0	0	0	0	0	0	**0**
Sum	$\mathbf{\frac{1}{3}}$	$\mathbf{\frac{1}{3}}$	**0**	$\mathbf{\frac{1}{3}}$	…	**-1**	**0**

The coefficients determined this way can be used in the CONTRAST statement, while the relevant variable and its associated coefficients for the individual partial hypotheses of simultaneous testing are separated by a comma. In our case the CONTRAST statement has the following syntax:

```
CONTRAST '21=22=24=2b'
          β 1 -1 α*β 0 … 0 1 -1,
          β 0.5 0.5 0 -1 α*β 0 … 0 0.5 0.5 0 -1,
          β 0.33333 0.33333 0 0.33333 … -1
          α*β 0 … 0 0.33333 0.33333 0 0.33333 … -1;
```

Let us note that:

- in all three partial hypotheses (9), the coefficients for factor A are equal to zero, so factor A is not given in the CONTRAST statement;
- for the interaction $A \cdot B$, the coefficients are initially 0 ... 0, representing the 0 coefficients given in the first row of the array of Table 2;
- the trailing zero coefficients for factor A, for factor B and for the interaction $A \cdot B$ need not be specified in the CONTRAST statement (we have not specified them);
- if factor A or factor B itself is not included in model (1), and only the interaction of these factors is included, then factor A and factor B, respectively, will not be listed in the CONTRAST statement.

To estimate the marginal means of the target variable, we employ ESTIMATE statements, whose construction is similar to that of CONTRAST statements. When estimating the marginal means, in addition to the effects, the overall mean is also included (see formula (6)), and its coefficient is the total sum $l_{\bullet\bullet}$ from Table 1. The procedures in SAS used in this paper are largely universal and are also used in other software and open-source systems (see Lenth 2016; Tabachnick and Fidell 2013).

4. Database

The paper analyses WI in Slovakia (SK) and Czechia (CZ) using a general linear model with explanatory variables listed in Table 3, while it should be emphasized that we focused only on persons whose economic activity status was employed, unemployed or disabled. The analyses are based on the EU-SILC 2021 database provided by the Statistical Office of the Slovak Republic (SO SR) and the Czech Statistical Office (CZSO). The presented analyzes are based on data on household members from Slovakia (6,277 persons) and Czechia (7,749 persons), while retired, students, housepersons, other inactive persons were not included.

Table 3: Description of input explanatory variables

Original variables (EU-SILC) – categories and description	Names of new dummy variables
HT – Household type	**HT**
Single-person household	1A_0Ch
Single parent household with at least 1 dependent child	1A_1^{+}Ch
2 adults' household, at least 1 aged 65+	2A(1^{+}R)
2 adults' household without dependent children	2A_0Ch
2 adults' household with 1 dependent child	2A_1Ch
2 adults' household with 3+ dependent children	2A_3^{+}Ch
Other households without dependent children	Other_0Ch
Other households with dependent children	Other_1^{+}Ch
2 adults' household with 2 dependent children	2A_2Ch
PE041 – The highest level of education achieved (ISCED)	**EDUCATION**
Pre-primary (ISCED 0)	ISCED 0-2
Primary (ISCED 1)	
Lower secondary (ISCED 2)	
Upper secondary (ISCED 3)	ISCED 3-5
Post-secondary (not tertiary) (ISCED 4)	
Short cycle of tertiary education (ISCED 5)	
Bachelor or equivalent (ISCED 6)	ISCED 6-8
Master's or equivalent (ISCED 7)	
Doctorate or equivalent (ISCED 8)	

Table 3: Description of input explanatory variables (cont.)

Original variables (EU-SILC) – categories and description	Names of new dummy variables
RX010 – Age	**AGE**
Age at the end of income reference period	-30
	30-40
	40-50
	50^{+}
PH010 – General health	**HEALTH**
Very bad	Bad
Bad	
Fair	Fair
Good	Good
Very good	
PB190 – Marital Status	**MARITAL STATUS**
Single	Single
Married	Married
Widowed	Widowed
Divorced	Divorced
RB090 – Gender	**GENDER**
Male	M
Female	F
DB100 – Degree of urbanisation	**URBANISATION**
Thinly populated area	Sparse
Intermediate area	Intermediate
Densely populated area	Dense

Source: own work based on EU-SILC data and European Commission (2021)

The definition of the target variable WI is given by the methodology used by Eurostat. Based on it, WI of a household is the ratio of the total number of months that working-age household members (aged less than 65 years) have worked during the income reference year and the total number of months the same household members theoretically could have worked in the same period.

We work with a continuous numerical variable WI according to the mentioned definition, but we also interpret the results of our analyses in relation to the level of WI: very low (VLWI – household working time was equal to or less than 20% of the full potential, QJ household), low (LWI), medium (MWI), high (HWI), which are defined for households' WI from intervals [20%; 45%), [45%; 55%], (55%; 85%] and very high (VHWI – household working time was more than 85% of the full potential).

5. General linear model for work intensity

5.1. Regressor selection and model estimation

Utilizing the stepwise regression method (Agresti 2015), we included the regressors listed in Table 4 into the model. Naturally, WI is fundamentally influenced by economic activity. The EA variable alone explains approximately 45% of the WI variability within each examined country. The impact of the other variables listed in Table 3 also proved to be significant. These variables affect WI differently for various statuses of economic activity, confirming the significance of individual interactions (Table 4). By incorporating these interactions, we were able to substantially increase the explained variability of WI to more than 50% (approximately 54% in Slovakia and around 53% in Czechia).

Table 4: Fundamental analysis of the models for WI in Slovakia and Czechia

R-Square		Coeff Var		Root MSE		WI Mean	
SK	CZ	SK	CZ	SK	CZ	SK	CZ
0.5395	0.5290	25.5575	18.9727	0.2020	0.1668	0.7904	0.8794

Source	DF	Partial R-Square		Type III SS		F Value		Pr > F	
		SK	CZ	SK	CZ	SK	CZ	SK	CZ
EA	2	0.4416	0.4515	19.6849	12.9115	241.21	231.90	<.0001	<.0001
EA×HT	24	0.0461	0.0463	15.5075	13.9110	15.84	20.82	<.0001	<.0001
EA×Education	6	0.0280	0.0037	14.1802	1.0287	57.92	6.16	<.0001	<.0001
EA×Age	9	0.0116	0.0123	6.5344	4.8655	17.79	19.42	<.0001	<.0001
EA×Gender	3	0.0024	0.0090	1.3544	4.3760	11.06	52.40	<.0001	<.0001
EA×Urbanisation	6	0.0048	0.0020	2.6302	0.8924	10.74	5.34	<.0001	<.0001
EA×Health	6	0.0027	0.0017	1.3963	0.8501	5.70	5.09	<.0001	<.0001
EA×Marital_status	9	0.0023	0.0026	1.0853	1.1868	2.96	4.74	0.0017	<.0001

Source: EU-SILC 2021, own processing in SAS EG.

Following the EA variable, WI is most strongly influenced by household type (HT). This factor, in interaction with EA, contributes to explaining approximately 4.6% of the variability of WI. These findings hold true for both countries. The contribution of further interactions is below 3% and varies between Slovakia and Czechia. The next most significant interaction is EA×Education in Slovakia and EA×Age in Czechia, yielding contributions of 2.8% and 1.2%, respectively. The contribution of each of the other interactions listed in Table 4 is less than 1%.

Table 5: Estimation of model parameters for WI in Slovakia and Czechia

Parameter		SK			CZ		
EA category		D	U	E	D	U	E
Intercept		0.896***	0.896***	0.896***	0.893***	0.893***	0.893***
EA intercept		-0.087	-0.139**	0.000	-0.405***	-0.347***	0.000
HT	1A_0Ch	-0.475***	-0.145**	0.091***	-0.353***	-0.140***	0.091***
	1A_1+Ch	-0.414***	-0.256***	0.032	-0.271***	-0.142***	0.053***
	2A(1+R)	-0.443***	-0.301***	0.104***	-0.319***	-0.265***	0.079***
	2A_0Ch	-0.151***	-0.138***	0.025**	-0.049	-0.036	0.057***
	2A_1Ch	-0.068	-0.082*	-0.002	-0.116*	0.061	0.010
	2A_3+Ch	-0.025	-0.169***	-0.064***	-0.153*	-0.127**	-0.052***
	Other_0Ch	-0.101*	-0.065*	0.004	-0.040	0.050	0.036***
	Other_1+Ch	-0.092	-0.114***	-0.059***	0.172**	-0.001	-0.017*
	2A_2Ch	0.000	0.000	0.000	0.000	0.000	0.000
EDU	ISCED 0-2	-0.084	-0.361***	-0.183***	0.069	-0.100**	-0.009*
	ISCED 3-5	-0.005	-0.090**	-0.006	0.041	0.049	0.001
	ISCED 6-8	0.000	0.000	0.000	0.000	0.000	0.000
Age	30-40	-0.251***	-0.095***	-0.012	-0.093**	-0.217***	0.007
	40-50	-0.207***	-0.163***	0.067***	-0.183***	-0.111***	0.056***
	50+	-0.176***	-0.102***	0.029***	-0.006	-0.151***	0.025***
	-30	0.000	0.000	0.000	0.000	0.000	0.000
Health	Bad	-0.077	0.000	-0.053***	-0.125***	-0.005	-0.035***
	Fair	-0.091	-0.033	-0.036***	-0.092**	-0.066**	-0.018***
	Good	0.000	0.000	0.000	0.000	0.000	0.000
Sex	M	0.005	-0.072***	-0.025***	0.089***	-0.011	-0.048***
	F	0.000	0.000	0.000	0.000	0.000	0.000
Urban.	Intermediate	-0.095***	0.050	-0.024***	-0.005	0.130***	0.000
	Sparse	-0.033	0.119***	-0.040***	0.025	0.118***	0.010*
	Dense	0.000	0.000	0.000	0.000	0.000	0.000
MS	Divorced	0.035	-0.127***	-0.006	0.058*	-0.086**	-0.005
	Never_married	-0.050*	-0.086***	0.003	-0.104***	-0.111***	0.006
	Widowed	0.030	0.064	0.012	0.111*	0.189	-0.015
	Married	0.000	0.000	0.000	0.000	0.000	0.000

***p < 0.01; **0.01< p < 0.05; *0.05< p < 0.1, level of significance

Source: EU-SILC 2021, own processing in SAS EG.

Table 5 illustrates the effects of individual factors (such as HT, Education, Age, and so on) on WI of households, wherein the person with the respective economic activity status (D - disabled, U - unemployed, E - employed) resides. Examining the HT factor, for disabled and unemployed persons, WI is lowest in single-person households

(1A_0Ch), households of 1 adult with at least 1 child (1A_1$^+$Ch), and households of 2 adults, at least 1 of whom is aged 65$^+$ (2A(1$^+$R)). If an adult with disabled status resides in these types of households, WI is generally more than 40 p.p. lower in Slovakia and about 30 p.p. lower in Czechia than in households of 2 adults with 2 children. In the case of unemployed persons, these differences are considerably smaller but still significant, even at a significance level of 0.01. Now turning our attention to the effect of education, the models reveal that low-educated individuals (ISCED 0–2) live in households with the lowest WI. This claim is statistically supportable for the unemployed and employed, but not for the disabled. This feature is also common to Slovakia and Czechia. If a disabled or unemployed person is under the age of 30, they live in a household with a significantly higher WI than older people. This phenomenon may be related to the fact that, for relatively young people, unemployment may be temporary, or the disability is such that the person is able to be employed. There are other intriguing findings arising from Table 5, but these will not be elaborated upon in this section, as the subsequent analyses in later sections of the paper will unveil them more comprehensively.

In the subsequent sections of the paper, in addition to examining the influence of economic activity itself, our focus will shift towards quantifying the effects of the other three most significant factors: household type, education, and age.

5.2. Analysis of LS Means and Contrast Analysis under GLM

In this section, we will employ an analysis of marginal means to identify significant differences in WI among pairs of categories within the household type (HT) factor, while controlling for the influence of other factors. Given the interaction of this factor with economic activity, this comparison will be conducted separately for each economic activity. Contrast analysis will be employed to form clusters of household types ensuring no significant difference between the household types within a cluster in terms of WI, while demonstrating a notable difference between the clusters. For these clusters, we will estimate the mean of WI, providing insight into the impact of the factor on WI, and enabling the identification of the most vulnerable individuals in terms of QJ.

5.2.1. Analysis of the impact of interaction *EA*×*HT*

The p-values matrix for LS-means equality tests (Table 6) indicates whether various types of households with a disabled person exhibit different WI. Let us narrow our focus to Slovakia, where the p-values are displayed above the main diagonal. We see that there are insignificant differences between the pairs of the first three types of households (1A_0Ch, 1A_1$^+$Ch, 2A(1$^+$R)) and between the pairs of the last 5 types of households (2A_1Ch, 2A_2Ch, 2A_3$^+$Ch, Other_0Ch, Oth_1$^+$Ch).

Table 6: Comparison of LS-means of WI for effect *EA×HT* for the disabled in Slovakia (above the diagonal) and in Czechia (below the diagonal)

Least Squares Means for effect EA×HT Pr > |t| for H0: LSMean(i)=LSMean(j)									
i/j	**1A 0Ch**	**1A 1^{+}Ch**	**2A (1^{+}R)**	**2A 0Ch**	**2A 1Ch**	**2A 3^{+}Ch**	**Other 0Ch**	**Other 1^{+}Ch**	**2A 2Ch**
1A_0Ch		0.4580	0.5143	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001
1A_1^{+}Ch	0.1027		0.7205	0.0007	<.0001	0.0020	<.0001	<.0001	<.0001
2A(1^{+}R)	0.4135	0.3766		<.0001	<.0001	0.0001	<.0001	<.0001	<.0001
2A_0Ch	<.0001	<.0001	<.0001		0.1025	0.0224	0.0726	0.0605	0.0086
2A_1Ch	<.0001	0.0057	<.0001	0.0846		0.6974	0.5302	0.6570	0.3288
2A_3^{+}Ch	0.0046	0.1281	0.0213	0.1142	0.5916		0.4636	0.5228	0.8303
O_0Ch	<.0001	<.0001	<.0001	0.7661	0.0611	0.0888		0.7813	0.0809
O_1^{+}Ch	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		0.1227
2A_2Ch	<.0001	0.0004	<.0001	0.4435	0.0936	0.0749	0.5367	0.0122	

Source: EU-SILC 2021, own processing in SAS EG.

The findings led us to assume that disabled persons living in the first three types of households have, on average, the same WI in their households ($H_0 : \mu_{11} = \mu_{12} = \mu_{13}$). This assumption was tested through a simultaneous test of two null hypotheses:

$$H_0 : \mu_{11} = \mu_{12} \wedge H_0 : \mu\,(\mu_{11},\ \mu_{12}) = \mu_{13}$$

To accomplish this, we employed the CONTRAST statement in the SAS programming language, as outlined in Section 3. The results are presented in the first row of Table 7, showing the test statistic value (4) and the corresponding p-value. Similarly, for disabled persons of the last 5 household types, we conducted tests for the equality of marginal means: $H_0 : \mu_{15} = \mu_{16} = \mu_{17} = \mu_{18} = \mu_{19}$.

Table 7: Equality tests for LS-Means of WI for the disabled from selected types of households in Slovakia

Contrast	DF	Contrast SS	MS	F Value	Pr > F
(EA=D)×HT 11=12=13	2	0.0297	0.0148	0.36	0.6953
(EA=D)×HT 15=16=17=18=19	4	0.1451	0.0363	0.89	0.4695
(EA=D)×HT 11=12=13 vs 15=16=17=18=19	1	3.4742	3.4742	85.14	<.0001
(EA=D)×HT 11=12=13 vs 14	1	2.3674	2.3674	58.02	<.0001
(EA=D)×HT 15=16=17=18=19 vs 14	1	0.3413	0.3413	8.36	0.0038

Source: EU-SILC 2021, own processing in SAS EG.

The contrast analysis (Table 7) did not reject the assumption that, in Slovakia, disabled persons living in household types 1A_0Ch, 1A_1^{+}Ch, and 2A(1^{+}R), have on average the same WI ($p = 0.6953$) under the condition of ceteris paribus. A similar conclusion was reached for household types 2A_1Ch, 2A_2Ch, 2A_3^{+}Ch, Other_0Ch, Oth_1⁺Ch ($p = 0.4695$). Moreover, these 2 clusters of household types have significantly different means of WI from each other ($p < 0.0001$) and are also significantly different from the fourth household type 2A_0Ch ($p < 0.0001$ and $p = 0.0038$). In this way, we have managed to create 3 distinct clusters of household types for disabled persons in Slovakia from the perspective of WI. To estimate the WI mean in the resulting household clusters, we used the ESTIMATE statement in the SAS programming language. The results are presented in Table 8.

Table 8: The estimate of $\mu(\mu_{11}, \mu_{12}, \mu_{13})$, μ_{14} and $\mu(\mu_{15}, \mu_{16}, \mu_{17}, \mu_{18}, \mu_{19})$ for the *EA×HT* interaction (disabled in Slovakia)

Parameter	Estimate	Standard Error	t Value	Pr > |t|
(EA=D)×HT 11=12=13	0.0854	0.0385	2.22	0.0268
(EA=D)×HT 14	0.3784	0.0359	10.55	<.0001
(EA=D)×HT 15=16=17=18=19	0.4722	0.0377	12.53	<.0001

Source: EU-SILC 2021, own processing in SAS EG.

We followed a similar procedure for the other two economic activity statuses (U – unemployed and E – employed), both for Slovakia and Czechia. For the analyzed three economic activity statuses (D, U, E), the resulting clusters are presented separately for Slovakia and Czechia in Table 9. For each cluster in the table, the estimated mean of WI is calculated along with its standard error (SE) and p-value for the test of equality of marginal means of WI across the household types included in the cluster.

Table 9: Estimates of the marginal means of work intensity in clusters of household types for disabled (D), unemployed (U), and employed (E) in Slovakia and Czechia.

EA	SK				CZ		
	Cluster	**Estimate (SE) [p-value]**	**HT**		**Cluster**	**Estimate (SE) [p-value]**	**HT**
D	**1**	0.085 (0.038) [0.6953]	1A_0Ch 1A_1⁺Ch 2A(1⁺R)		**1**	0.120 (0.035) [0.2494]	1A_0Ch 1A_1⁺Ch 2A(1⁺R)
	2	0.378 (0.036) [-]	2A_0Ch		**2**	0.300 (0.045) [0.5916]	2A_1Ch 2A_3⁺Ch
	3	0.472 (0.038) [0.4695]	2A_1Ch 2A_3⁺Ch Other_0Ch Other_1⁺Ch 2A_2Ch		**3**	0.404 (0.036) [0.7360]	2A_0Ch Other_0Ch 2A_2Ch
	-	-	-		**4**	0.606 (0.041) [-]	Other_1⁺Ch

Table 9: Estimates of the marginal means of work intensity in clusters of household types for disabled (D), unemployed (U), and employed (E) in Slovakia and Czechia (cont.)

EA	SK			CZ		
	Cluster	**Estimate (SE) [p-value]**	**HT**	**Cluster**	**Estimate (SE) [p-value]**	**HT**
U	**1**	0.210 (0.043) [0.5453]	1A_1$^+$Ch 2A(1$^+$R)	**1**	0.196 (0.078) [-]	2A(1$^+$R)
	2	0.348 (0.025) [0.4293]	1A_0Ch 2A_0Ch 2A_3$^+$Ch Other_1$^+$Ch	**2**	0.325 (0.053) [0.9713]	1A_0Ch 1A_1$^+$Ch 2A_3$^+$Ch
	3	0.440 (0.028) [0.1637]	2A_1Ch Other_0Ch 2A_2Ch	**3**	0.476 (0.048) [0.2734]	2A_0Ch 2A_1Ch Other_0Ch Other_1$^+$Ch 2A_2Ch
E	**1**	0.731 (0.012) [0.7826]	2A_3$^+$Ch Other_1$^+$Ch	**1**	0.818 (0.012) [-]	2A_3$^+$Ch
				2	0.853 (0.010) [-]	Other_1$^+$Ch
	2	0.793 (0.010) [0.8761]	2A_1Ch Other_0Ch 2A_2Ch	**3**	0.875 (0.007) [0.1499]	2A_1Ch 2A_2Ch
				4	0.906 (0.009) [-]	Other_0Ch
	3	0.821 (0.012) [0.7325]	1A_1$^+$Ch 2A_0Ch	**5**	0.925 (0.008) [0.6878]	1A_1$^+$Ch 2A_0Ch
	4	0.890 (0.013) [0.4478]	1A_0Ch 2A(1$^+$R)	**6**	0.955 (0.009) [0.3364]	1A_0Ch 2A(1$^+$R)

Source: EU-SILC 2021, own processing in SAS EG.

For the disabled, we revealed the lowest WI in the cluster of household types 1A_0Ch, 1A_1$^+$Ch, and 2A(1$^+$R), which corresponds to households with at most 1 adult in the productive age. The identical cluster emerged for both countries. In Czechia (11.96%), we estimated the respective marginal mean to be almost 3.5 p.p. higher than in Slovakia. However, in both countries, it was at a very low level (below the 20%), which identifies QJ. If a disabled person lives in a household with a higher number of adults, the risk of QJ naturally decreases, as confirmed by our analyses. While in Czechia, households with 2 adults and a disabled person typically have low WI, in Slovakia, this is slightly higher. The 3rd cluster for disabled persons in Slovakia, which includes households with 2 adults with children, has the mean of WI at the middle level (see also Figure 1). For the disabled, the mean of WI is convincingly high only for households of type "other" with at least 1 child (Other_1$^+$Ch), and only in Czechia. Our analysis indicated that the disabled in Czechia generally live in households with lower WI. This finding aligns with official statistics, which state that in 2021, the QJ rate for the disabled was 16.7% in Czechia and 11.3% in Slovakia, despite the fact that the overall QJ rate in the population was lower in Czechia (2.5%) than in Slovakia (2.7%).

Figure 1: Interval estimates (95%) of LS-Means of WI for *EA×HT* interaction (for the disabled at the top, unemployed in the middle, employed at the bottom)

Source: EU-SILC 2021, own processing in SAS EG.

The better situation in the entire population in Czechia compared to Slovakia is confirmed by a significantly higher mean of WI for employed persons. Employed individuals live in households with the highest WI when it comes to childless households with at most one adult in the productive age (1A_0Ch and 2A(1^{+}R)), for which we estimated a very high WI. While in Slovakia it was almost 89%, in Czechia it was 6.5 p.p. higher. For employed persons, the mean of WI in all corresponding clusters in Slovakia was significantly lower than in Czechia. However, even in households with the lowest WI (2A_3^{+}Ch and Other_1^{+}Ch), the mean WI for employed persons was at least at a high level (HWI). The composition of clusters of household types for employed persons was very similar in Slovakia and Czechia (see Table 9).

For unemployed persons, the similarity between Slovakia and Czechia in the composition of clusters was lower. Also for this reason, we provide point and interval estimates of the mean of WI in graphical form for individual household types rather than for their clusters (Figure 1). Unemployed persons faced the highest risk of QJ when they lived in households with 2 adults, at least 1 of whom was 65^{+}. We estimated the mean of their WI to be on the borderline between VLWI and LWI. Among the other household types, those with a single adult were the most at risk in both countries, similar to the case with the disabled (1A_0Ch and 1A_1^{+}Ch). For these households, LWI was typical. However, this degree of WI was characteristic for most household types for unemployed individuals both in Slovakia and in Czechia. An unemployed person from a household with 2 adults and 2 children mostly lived in a household MWI. For unemployed persons, the MWI was also typical for Czech households of 2 adults and 1 child, 2 adults without children and other types of households without or with children (Other_0Ch, Other_1^{+}Ch).

5.2.2. Analysis of the impact of interaction *EA*×*Education*

Not surprisingly, higher WI is associated with higher education, but this does not apply to all statuses of economic activity (Figure 2).

In 2021, in both countries, the education of a disabled individual did not have a significant impact on WI of households, as confirmed by Figure 2 and the non-significant parameters (Table 5). However, this does not hold true for the impact of education on unemployed person. This influence is significant in both countries, but it is greater in Slovakia. For Slovakia, we found that while low-educated unemployed persons mostly live in QJ households, for unemployed persons with tertiary education, households with a medium WI are characteristic. In Czechia, even low-educated unemployed persons mostly do not live in QJ households because their households achieve a low (and not very low) level of WI. For unemployed persons with higher education (ISCED 3-5 or ISCED 6-8), households in Czechia are characterized by WI at the border between a low (LWI) and a medium level (MWI).

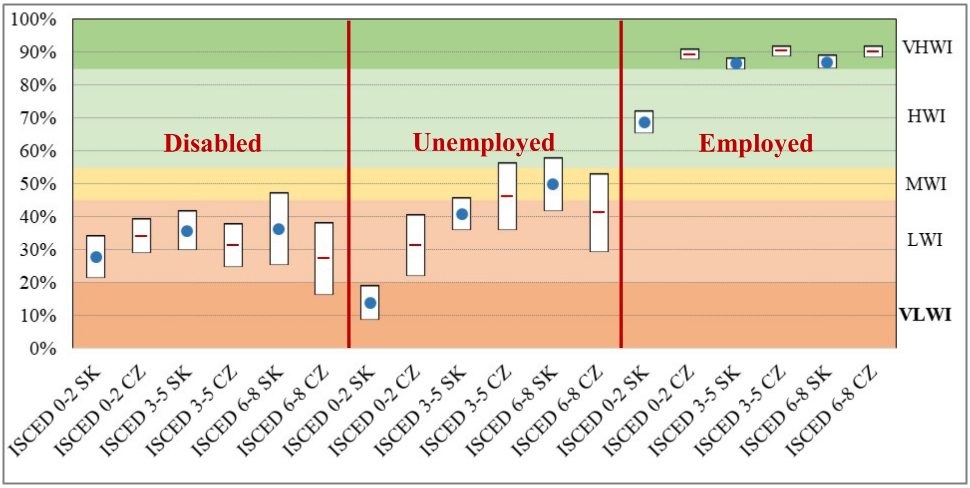

Figure 2: Interval estimates (95%) of LS-Means of WI for *EA× Education* interaction

Source: EU-SILC 2021, own processing in SAS EG.

As unemployed individuals with higher education (at least ISCED 3) have a mean WI at a low to medium level, they appear to experience shorter periods of unemployment and/or have another adult in the household (spouse or partner) who is employed. However, the status of economic activity "unemployed" have such a significant effect on WI that education cannot sufficiently compensate for this and therefore persons who are unemployed and whose education is tertiary generally live in households with significantly lower WI as employed persons. This applies even to the employed persons in Slovakia with ISCED 0-2 education, for whom the average WI is "only" at a high level (HWI).

5.2.3. Analysis of the impact of interaction *EA×Age*

In 2021, disabled and unemployed persons aged under 30 lived in households with higher WI compared to older people (Figure 3). In this context, we are referring to WI levels bordering between low and medium, and in the case of disabled individuals in Slovakia and the unemployed in Czechia, reaching up to the high level. For disabled persons and the unemployed in age categories above 30 years (age categories 30–40, 40–50, 50^{+}), households with a low level of WI were typical, and there were no significant differences among these age categories.

When specifically examining disabled and unemployed persons, there were no significant differences in WI between Slovakia and Czechia within individual age categories. However, this is not the case for the employed. For this economic activity status, we found demonstrably higher WI in Czechia than in Slovakia in all age categories.

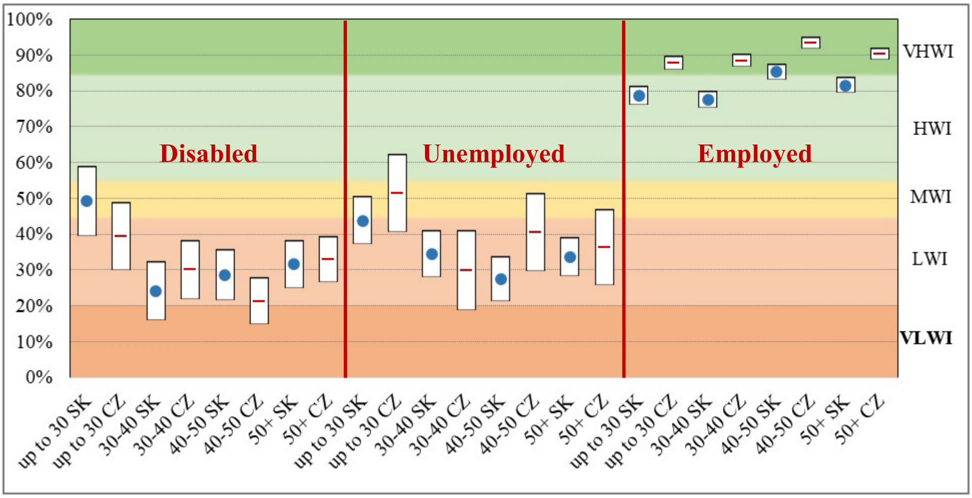

Figure 3: Interval estimates (95%) of LS-Means of WI for *EA×Age* interaction

Source: EU-SILC 2021, own processing in SAS EG.

6. Conclusion and discussion

The type of household a person lives in, their education, age, gender, health conditions, marital status, as well as the degree of urbanization in their residential area are factors that significantly influenced WI in Slovakia and Czechia in 2021, but this impact varied across different economic activity statuses. These factors are considered very important by other researchers (Watson et al. 2015; Horemans et al. 2018; Verbunt and Guio 2019) when assessing employment/unemployment and atypical employment in relation to social exclusion.

The general linear models, in which we considered the interactions of these factors with the status of economic activity, explained the variability of WI to about 53%. The status of economic activity, household type, education, and age participated the most in this explained variability. In this paper, we focused on assessing the net impact (i.e. by fixing the influence of other relevant factors) of household type, education and age of the person on WI of the household, considering only employed, unemployed and disabled persons and abstracting from other statuses. The last two mentioned groups of persons belong among the most vulnerable groups in terms of WI, as well as in terms of social exclusion. In addition to economic activity, van der Zwan and de Beer (2021) also used the above factors (age, education, and household type) as control variables, applying them to the assessment of employment for disability and non-disability persons.

The paper provides estimates of the marginal means of WI households for employed, unemployed and disabled persons with different education, age and from different types of households in Slovakia and in Czechia. Given the large number of household types, we identified, for each economic activity status, between which types of households there are no significant differences from the perspective of WI. On the basis of simultaneous testing of WI marginal means, clusters of household types were created that were largely similar, but not identical, in Slovakia and Czechia.

Our analyses confirmed that in 2021, in Czechia and Slovakia, disabled and unemployed persons lived in households with significantly lower WI compared to the employed, which is natural based on their main economic activity status. According to Calegari et al. (2022) households with disabled members experience a greater risk of social exclusion compared to households without disabled members. Our research even showed that in 2021 in Czechia and Slovakia households with one adult person (with or without children) had demonstrably lower WI if it concerned person with a disability (very low WI) compared to an unemployed person (low WI). The WI mean for disabled persons can be assumed to be around 50% (medium WI) only exceptionally and applies to persons under the age of 30 years or to persons living in complete households, while these findings concern only Slovakia and not Czechia.

Following the above finding, let us focus on the effect of age. For the disabled in Czechia, the age category "under the age of 30 years" is also the least risky, although the WI mean was approximately 10 p.p. lower compared to Slovakia, corresponding to low WI. This age category is also the least risky for unemployed persons. Conversely, for persons with an employed status, the age category under the age of 30 years along with the 30–40 category exhibited the lowest WI. However, in the case of employed persons, we are discussing high (Slovakia) or very high (Czechia) WI.

While WI increases with higher education levels, this trend does not hold for persons with disabilities. In 2021, in Slovakia, both unemployed and employed persons with low education lived in households that had WI lower by one level compared to individuals with higher education. In Slovakia, low-educated unemployed persons generally showed QJ. In the case of Czechia, the impact of education on WI was significantly lower, where low-educated unemployed persons lived in households with low WI. In Czechia, employed individuals at every educational level generally lived in households with very high WI. In Slovakia, this WI level was achieved by employed persons with education at the ISCED 3–5 and ISCED 6–8 level. However, those employed with low education (ISCED 0-2) lived in households that utilized their work potential at around 70% (high WI). Education has been identified as a risk factor for poverty and social exclusion in other EU countries as well, as demonstrated in studies by authors such as Dudek and Szczesny (2021), Filandri and Struffolino (2019), and Hofmarcher (2021). Our findings indicate that, in terms of WI, education plays a crucial role for unemployed persons, but not for disabled persons. This finding supports the conclusion of Mussida and Sciulli (2024), who state that higher education is a protective factor against poverty, in addition to being positively associated with work intensity/labor market participation, while it exerts a less clear role on disability.

In terms of household type, disabled and unemployed persons in both countries faced the highest risk of QJ in households of 2 adults, at least 1 aged 65^+ and in incomplete households such as single-person households and households of 1 adult with at least 1 child. However, this conclusion does not hold for employed individuals, because if they lived in the above 3 household types [1A_0Ch, 2A(1^+R), 1A_1^+Ch], then on average, their households achieved the highest WI (very high WI). The only exception was the household type of 1 adult with at least 1 child in Slovakia, for which high WI was typical. For employed persons in Slovakia, the average WI of other household types was also at a high level, with the lowest (73%) observed for households of 2 adults with at least 3 children. This type of household also recorded the lowest average WI in Czechia (82% for employed persons). For other household types with employed persons in Czechia, we estimated very high WI.

If we exclude the most risky household types [1A_0Ch, 2A(1^+R), 1A_1^+Ch] for the unemployed and disabled statuses, the remaining household types have either low or medium WI, which is valid for both countries. If unemployed persons lived in complete households, they had the lowest WI (32% in Slovakia, 33% in Czechia), if it was a household of 2 adults with at least 3 children. This type of household was also the riskiest of the complete households for disabled in Czechia (WI of 28%). Disabled persons living in complete households with children had a significantly higher WI mean in Slovakia compared to Czechia, reaching a medium level.

To summarize the previous findings for the economic activity status "employed", it can be concluded that individuals with education at the ISCED 0-2 level, within the age categories of up to 30 years and 30–40 years, and those living in households with 2 adults and at least 3 children are the most at-risk based on the WI perspective. This is consistent with the conclusions of Filandri and Struffolino (2019), who found that risk factors in terms of in-work poverty include young age, a low level of education, and households with a high number of children. Their findings about the riskiness of households with a small number of earners can be confirmed in our study only for disabled and unemployed persons.

Our analyses also confirmed that households in Slovakia have, on average, lower WI than in Czechia. This phenomenon was confirmed for employed persons in all household types, as well as across all educational groups and age categories. There are a few exceptions in the case of unemployed persons, such as for education at the ISCED 6–8 level, where our analyses did not confirm this phenomenon. In the case of disabled persons, we cannot confirm the mentioned phenomenon at all, as in many compared categories, we observed comparable results for both countries and in certain categories, such as complete households with children, we identified a significantly higher WI in Slovakia than in Czechia. However, our conclusions align with the findings of Eurostat (2023b), which indicate that people in Czechia with a disability have a relatively low probability of living in QJ households but a difference between people with a disability and people with no disability is large since in 2021 Czechia had the largest relative gap.

We are convinced that the paper fills a gap in research on poverty and social exclusion that mostly focuses on income poverty and material deprivation but rarely on QJ and even rarer on WI as continuous variable or on all levels of WI. Our research provides only a partial answer to the question of which population groups to target with social measures. This is because WI is only one of several aspects that determine social exclusion and although it is correlated with other dimensions (income poverty, material deprivation), it does not have a complete overlap with them. The form and intensity of social support are also a question, as demonstrated by Lehwess-Litzmann and Nicaise (2020), who found that the generosity of social benefits is negatively connected to the speed at which households increase their WI. A topic for further research is whether this relationship holds equally for households with unemployed members as well as for households with disabled members.

Between Slovakia and Czechia, we have uncovered some differences in WI but there were numerous similarities that could stem from the shared historical development and geopolitical and cultural similarities of these countries. While we hold the belief that many of these conclusions may be applicable to CEE countries, further research is necessary to verify this assertion.

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