Entrepreneurial Business and Economics Review

OPEN ACCESS

2018, Vol. 6, No. 1 DOI: 10.15678/EBER.2018.060107

Work Intensity in Slovakia in Relationship with Socio-Economic Characteristics of Households

Erik Šoltés, Mária Vojtková

ABSTRACT

Objective: The aim of this article is to evaluate the relationship between work intensity and educational attainment of the household head and household type in Slovakia.

Research Design & Methods: Statistical analyses were carried out in analytics software SAS Base and SAS Enterprise Guide by means of contingency, correspondence analysis and multinomial logistic regression. Empirical analyses are based on data from the survey EU-SILC 2015.

Findings: The article provides estimates of the probabilities of individual degrees of households' work intensity depending on the household type and educational attainment level of the household head, while simultaneously in both cases households are broken down by economic activity of the household head. The presented analysis revealed categories of households which are the most and the least threatened by labour market exclusion from the point of view of the considered factors.

Implications & Recommendations: While the social inclusion monitor in Europe says that in 2012 (quasi-) joblessness was typical for households with three or more children, our analysis for 2014 did not confirm this. The exclusion from the labour market in 2014 was the most typical in Slovakia for households without dependent children, where there is no more than one person in productive age.

Contribution & Value Added: The article is not limited only to the very low work intensity which is used to assess the progress in the reduction of (quasi-) joblessness, but focuses on all the levels of work intensity (very low, low, medium, high and very high).

Article type: research paper

Keywords: poverty and social exclusion; work intensity; (quasi-) joblessness; EU SILC – European Union Statistics on Income and Living Conditions; correspondence analysis; multinomial logistic regression

JEL codes: I31, J21, C31

Received: 28 November 2017 Revised: 12 February 2018 Accepted: 26 February 2018

Suggested citation:

Šoltés, E., & Vojtková, M. (2018). Work Intensity in Slovakia in Relationship with Socioeconomic Characteristics of Households. *Entrepreneurial Business and Economics Review,* 6(1), 115-134. https://doi.org/10.15678/EBER.2018.060107

INTRODUCTION

The key objective of the Europe 2020 strategy is to combat income poverty and social exclusion, with people at risk of poverty or social exclusion, namely those at risk of income poverty and/or being materially deprived and/or living in households with very low work intensity. Therefore, the methodology for measuring poverty and social exclusion used in the Europe 2020 strategy is based on a three-dimensional concept with the following dimensions: income poverty, material deprivation and exclusion from the labour market. Exclusion from the labour market is monitored by very low work intensity. Households with very low work intensity are also referred to as (quasi-) jobless households.

Quasi-jobless households were a centre of interest, especially during the economic crisis, when the living conditions of individuals living in such households, were more severe and affecting most of the population. At present, when economists do not anticipate a new global crisis or recession, politicians working with experts should seek ways to effectively eliminate unemployment and exclusion from the labour market.

Based on the methodology used by Eurostat to monitor exclusion from the labour market, household work intensity is defined as the proportion of the total number of months during which in the course of the income reference year all members of the productive-age household worked and the total number of months that the same household members could theoretically work, under state legislation, during the same period. A person of productive age means a person aged 18-59 with the exclusion of students in the 18-24 age group. Households consisting only of children, students under 25 and/or persons aged 60 and above are totally excluded from the calculation of the indicator (Eurostat).

Contrary to most scientific papers, this article focuses not only on households with very low work intensity (quasi-jobless households), but also to households whose work intensity is at a different level (low, medium, high or very high; Table 1).

The first aim of this article is to evaluate the relationship between work intensity and educational attainment of the household head and household type. However, the main objective is to estimate the probability of the individual degrees of work intensity of households depending on the type of household and education of the person at the head of the household, and in both cases apart from the breakdown by economic activity of the person at the head of the household. Based on the EU-SILC 2015, the article analyses the impact of the household type and the education of the person at the head of the household on the level of work intensity in determining the economic activity of the person at the head of the household and it focuses on the estimation of individual degrees of work intensity in the population of Slovak households in 2014 (reference period for EU-SILC 2015 surveys), for individual households in classification by breaking down by the factors mentioned above. The survey itself is conducted on a sample of 5.637 households, using the cross-sectional weights in the analysis. Statistical analysis is realised through correspondence analysis, contingency analysis and multinomial logistic regression models.

LITERATURE REVIEW

Employment is a source of regular income for both persons in productive-age as well as households and it is also prevention of the risk of poverty. On the other hand, 100%

employment does not guarantee that the household will be out of poverty risk. Finally, in-work poverty is an up-to-date subject in the fight against poverty, and many of the scientific papers are considered with this issue (e.g., Halleröd, Ekbrand, & Bengtsson, 2015; Horemans, Marx, & Nolan, 2016; Hick & Lanau, 2017). However, poverty and social exclusion are mainly linked to unemployment. As stated (Atkinson, Guio, & Marlier, 2017), unemployment affects not only the unemployed person, but the whole household, which has to face greater economic uncertainty. The most important is long-term unemployment, as the long-term loss of contact with the world of work can lead to social exclusion, health deterioration and negatively affect the well-being of children.

According to Corluy and Vandenbroucke (2017), in 2012, in terms of household type, the highest incidence of very low work intensity was in Slovakian households with at least three children. Households with very low work intensity use their work potential at less than 20% (see definition in the next section above Table 1) and in 2012 households with three or more children in Slovakia accounted for approximately 41% of such (quasi-) jobless households. Within EU countries, the representation of such multi-child households among (quasi-) jobless households was only in Bulgaria (49.7%) and in Greece (47.5%). On the contrary, in Scandinavia and Germany, households with 3 or more children were less than 10% (only 1.3% in Denmark) among households with very low work intensity. In these countries, the exclusion from the labour market was mainly referred to single-parent households.

In 2012 in the EU-27, 87% of households which were recorded with very low work intensity had total unemployment (Corluy & Vandenbroucke, 2017). In Slovakia, this share was even higher, at 90%, where Slovakia joined together with Malta, the Czech Republic, the Netherlands, Slovenia and Romania among the countries with the largest share of total unemployment among (quasi-) jobless households. However, in 2012, but also in the following period (by 2015, when the most up-to-date data is available), Slovakia was counted among the countries with the lowest level of very low work intensity. In the whole period (2011-2015), Slovakia, as well as Sweden, Luxembourg, the Czech Republic, Poland and Romania (and from non-EU countries also Switzerland, Iceland and Norway) did not record the share of people living in households with very low work intensity above 8% (Eurostat).

As we have already indicated, the work intensity of household affects the risk of poverty and the threat of material deprivation. The impact of work intensity on income poverty in Slovakia and the Czech Republic in the period 2006-2013 was demonstrated by Mysíková, Ramon and Želinský (2015). Kis and Gábos (2016) through logistic regression showed that labour intensity has a significant impact on consistent poverty in the EU. Ayllón and Gábos (2015) confirmed the relationship between severe material deprivation and low work intensity in Central and Eastern Europe. The strong positive relationship between low work intensity and poverty was quantified by the authors in all analysed countries (not only in Central and Eastern Europe). Guagnano, Santarelli and Santini (2013) revealed that work intensity is one of the major socio-economic factors influencing the perception of subjective poverty in Europe.

The close relationship between the different dimensions of the AROPE (at-risk-of-poverty or social exclusion) also indicates that in the EU-27 in 2012 there were households with very low work intensity, of which up to 65% were at the risk of monetary poverty or were severely materially deprived. In Slovakia we register about 10 pp greater value of that share (Corluy & Vandenbroucke, 2017).

From the perspective of the methods used in this article, there is logistic regression, which is a popular statistical tool in poverty and social exclusion analysis. Řezanková and Želinský (2014) used logistic analysis for one of the partial indicators of poverty, namely material deprivation in relation to selected household characteristics. We can come across the estimation of the chance to become an unemployed person, which is relatively closely related to work intensity, in the work by Lučkaničová, Ondrušeková and Rešovsky (2012). Through logistic regression, Hick and Lanau (2017) quantified the impact of selected factors on in-work poverty and examined the impact of risk factors on very low work intensity in Ireland.

Most scientific articles analysing poverty and social exclusion use logistic regression with a binary dependent variable. The ambition of this article is the use of a multinomial dependent variable in modelling the probability of the occurrence of a certain degree of work intensity in relation to the selected socio-economic characteristics of the household.

MATERIAL AND METHODS

The work intensity of households is divided into five categories (Table 1). For the purpose of analysing the work intensity of Slovak households, we created a categorical variable WI (Work Intensity) with variations from 0 to 4. The target variable WI – degree of work intensity expresses the use of households' work potential from their theoretical work potential. So, households which use their work potential at less than 20% are characterised as household with very low work intensity (VLWI), then households which use their work potential to at least 20% but at less than 45% are household with low work intensity, etc.

Table 1. Levels of households work intensity

Level of work intensity	Value ranges of work intensity index	Category designation (degree of severity)	Abbreviation
Very low	$\langle 0; 0.2)$	4	VLWI
Low	$\langle 0.2; 0.45)$	3	LWI
Medium	$\langle 0.45; 0.55\rangle$	2	MWI
High	$(0.55;\ 0.85\rangle$	1	HWI
Very high	$(0.85;\ 1\rangle$	0	VHWI

Source: own study on the basis of Eurostat.

On the basis of a number of scientific papers showing the impact of selected predictors on one of the dimensions of poverty and social exclusion (Gerbery, 2013; Rastrigina, Leventi, & Sutherland, 2015; Watson, Maitre, & Whelan, 2012; Whelan & Maître, 2014) and on the basis of our own experience (e.g., Šoltés & Šoltésová, 2016), we assume that the degree of work intensity of households is affected primarily by the status of economic activity, the highest level of education and the type of household. For the sake of clarity in analyses, we used custom labels of variables and their variations (categories). As counts of households were low in some categories of education, we combined them with similar categories of a relevant factor. The description of the input variables and the above changes in the titles and in the definition of the categories of these variables are captured in Table 2.

Table 2. Description of input explanatory variables

Variable in EU SILC	Variable name	Category of variables	Value	Label
RB210	Economic activity status *EAS*	at work	1	–
		unemployed	2	
		retired	3	
		inactive_person	4	
HT	Household type *HT*	1adult	5	Single person
		2adult_0ch	6	Two adults younger than 65 years
		2a_1r	7	Two adults, at least one aged 65 years or above
		other_0ch	8	Households without dependent children
		1a_at_least_1c	9	Single person with dependent children
		2a_1ch	10	Two adults with one dependent child
		2a_2ch	11	Two adults with two dependent children
		2a_at_least_3c	12	Two adults with 3 or more dependent chil-
		other_with_ch	13	Households with dependent children
PE040	*EDUCATION* by ISCED	less_than_ secondary	0	Less than primary
			1	Primary education
			2	Lower secondary education
		upper_second-	3	Upper secondary education
		post_secondary	4	Post-secondary non-tertiary education
		tertiary_1	5	Short cycle tertiary education
			6	Bachelor´s or equivalent level of education
		tertiary_2_3	7	Master´s or equivalent level of education
			8	Doctoral or equivalent level of education

Source: own study on the basis of Eurostat.

Correspondence Analysis

Correspondence analysis is a method which is based on the analysis of the structure of mutual dependencies of two or more variables. Because it focuses on examining the dependence of predominantly nominal or ordinal variables, in the case of a continuous variable it is necessary to categorise its values. It solves this problem in a similar way as factor analysis or the principal component method, while hidden or latent variables can be represented as axes of the reduced coordinate system (correspondence maps), in which the individual categories of variables will eventually be displayed. This is a method that in its essence belongs to exploration methods, and can be a good instruction for deciding which categories of variable should be merged and which can be kept separate. It is mainly used in marketing, but its interesting applications are also found in other areas.

In the case of a simple correspondence analysis (Greenacre, 2016), we deal with a two-dimensional contingency table. From the values of this table (n_{ij}) we can deduce the correspondence matrix **P** with the elements p_{ij}.

$$p_{ij} = \frac{n_{ij}}{n} \tag{1}$$

where:

$i = 1, 2, \ldots, r;$

$j = 1, 2, \ldots, s.$

Row marginal relative frequencies p_{i+} are called row loads (r_i), with their line percentages being referred to as row profiles. Similarly, column marginal relative frequencies p_{+j} are called column loads (c_j), with their column percentages being referred to as column profiles. The whole correspondence matrix can be schematically expressed as follows:

$$\begin{bmatrix} \mathbf{P} & \mathbf{r} \\ \mathbf{c}^{\mathrm{T}} & 1 \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1s} & r_1 \\ p_{21} & p_{22} & \cdots & p_{2s} & r_2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ p_{r1} & p_{r2} & \cdots & p_{rs} & r_r \\ c_1 & c_2 & \cdots & c_s & 1 \end{bmatrix} \tag{2}$$

where:

c - is the *s*-elements vector of the column loads;
r - is the *r*-elements vector of the row loads.

Each row (column) of the correspondence matrix can be represented as a point in a *s*-dimensional (*r*-dimensional) space with coordinates corresponding to the values of the respective profiles. We can then calculate the distances between individual points, while the most commonly used is the chi-squared distance between the *i*-th and the i'-th line produced by the relation:

$$\chi^2 = \sqrt{\sum_{j=1}^{s} \frac{\left(r_{ij} - r_{i'j}\right)^2}{c_j}} \tag{3}$$

where:

r_{ij} - are the elements of the row profiles matrix **R**;
c_j - weights correspond to the elements of the column load vector $\mathbf{c}^{\mathrm{T}}$.

Similarly, we proceed in computing the differences (dissimilarities) between column categories.

The goal of the method is to reduce the multidimensional space of vectors of row and column profiles, while maximally preserving the information contained in the original data. Usually, a two-dimensional space is used, i.e. plane. The point which lies directly in the plane and is closest to the corresponding point in space is called projection. The solution comes from a matrix **Z** of standardised residuals with elements:

$$z_{ij} = \frac{p_{ij} - p_{i+}p_{+j}}{\sqrt{p_{i+}p_{+j}}} \tag{4}$$

and its singular decomposition according to relationship

$$\mathbf{Z} = \mathbf{U} \cdot \mathbf{\Gamma} \cdot \mathbf{V}^{\mathrm{T}} \tag{5}$$

where $\mathbf{\Gamma}$ is the diagonal matrix and where the relationship $\mathbf{U}^{\mathrm{T}} \cdot \mathbf{U} = \mathbf{V}^{\mathrm{T}} \cdot \mathbf{V} = \mathbf{I}$ applies.

Prior to the estimation of the co-ordinates of each category, the choice of the normalisation method should be made, i.e. the way to show points in the correspondence map. The so-called symmetric normalisation is most commonly used, in which we are interested in the mutual comparison of both row and column categories. In interpreting the results, the points are considered closer when there is a higher similarity between the corresponding categories.

Multinomial Logit Analysis

The logistic regresson model is a special case of the general linear model (Ramon *et al.* 2010) and serves to model the categorical dependent variable depending on the explanatory variables of the continuous or categorical type. In the case of binary logistic regression, the logarithmic transformation of the odds of probability p for the desired event to occur ($y_i = 1$; the event that is being examined) to the probability $1 - p$ of occurrence of the undesired event ($y_i = 0$), is used. The natural logarithm of the odds is called logit and, unlike probability p, acquires any real values and can be modelled by a linear regression model (Hair, Black, Babin, & Anderson, 2010).

$$\text{logit}(p_i) = ln\frac{p_i}{1 - p_i} = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_k x_{ik} \tag{6}$$

where:

p_i - is the probability;

so that $y_i = 1$ ($i = 1, 2, \dots, n$), then $\beta_0, \beta_1, \dots, \beta_k$ are the parameters of the logit model and $x_{i1}, x_{i2}, \dots, x_{ik}$ are the values of the explanatory variables $X_1, X_2, \dots, X_k$ which are observed for the *i*-th statistical unit. To obtain maximum likelihood estimators of parameters of the logistic regression model the Newton-Raphson algorithm is generally used (see Allison, 2012).

After estimating the logistic model, it is important to verify its statistical significance and also verify whether the influence of the individual explanatory variables on probability p is significant. The significance of a logistic regression model is revealed by a zero hypothesis test $\boldsymbol{\beta}^{\mathrm{T}} = (\beta_1 \quad \beta_2 \quad \dots \quad \beta_k) = \mathbf{0}^{\mathrm{T}}$ against an alternative hypothesis – at least one regression coefficient should be not zero, while three different chi-square statistics are mostly used (Likelihood ratio, Score statistics, Wald statistics). Allison (2012) discusses the differences between these statistical methods and at the same time notes that in large samples there is no reason to prefer any of these statistics and they will generally be quite close in value.

In order to validate the significance of the explanatory variable influence, a Wald test is used. It tests the zero hypothesis showing that the respective explanatory variable does not affect the probability of the occurrence of the explored event. To verify the hypothesis, Wald statistic:

$$Wald = \widehat{\boldsymbol{\beta}}^{\mathrm{T}} \boldsymbol{S}_{\mathbf{b}}^{-1} \widehat{\boldsymbol{\beta}} \tag{7}$$

is used, where $\widehat{\boldsymbol{\beta}}$ is the vector of regression coefficients estimates which stand at dummy variables for the respective factor (categorical explanatory variable) and $\mathbf{S_b}$ is the variance-covariance matrix of $\widehat{\boldsymbol{\beta}}$. Wald statistic has asymptotically 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.

The quality of the logistic model can be evaluated by different measures. Among criteria which measure a relative quality of statistical models there are AIC – Akaike Information Criterion and SC – Schwarz-Criterion, which are based on the logarithmic transformation of the likelihood function, i.e. $-2lnL$.

Binary logistic regression is used if the explanatory variable is binomial. If the dependent variable has more than two categories (generally these are *s* categories), we can use a multinomial logit model which is created by $(s - 1)$ logit functions:

$$\ln\left[\frac{P(y_i=1|\mathbf{x})}{P(y_i=0|\mathbf{x})}\right] = \beta_{10} + \beta_{11}x_{i1} + \beta_{12}x_{i2} + \cdots + \beta_{1k}x_{ik}$$
$$\ln\left[\frac{P(y_i=2|\mathbf{x})}{P(y_i=0|\mathbf{x})}\right] = \beta_{20} + \beta_{21}x_{i1} + \beta_{22}x_{i2} + \cdots + \beta_{2k}x_{ik} \tag{8}$$
$$\ln\left[\frac{P(y_i=(s-1)|\mathbf{x})}{P(y_i=0|\mathbf{x})}\right] = \beta_{(s-1)0} + \beta_{(s-1)1}x_{i1} + \beta_{(s-1)2}x_{i2} + \cdots + \beta_{(s-1)k}x_{ik}$$

The probability that a dependent variable will take the values 0, 1, 2, ..., $(s-1)$ for the variable explanatory vector $\mathbf{x}_i$ is estimated by equations

$$\hat{P}(y_i=1) = \frac{e^{\hat{\boldsymbol{\beta}}_1^{\mathrm{T}}\mathbf{x}_i}}{1+\sum_{l=1}^{s-1} e^{\hat{\boldsymbol{\beta}}_l^{\mathrm{T}}\mathbf{x}_i}}, \dots,$$
$$\hat{P}(y_i=s-1) = \frac{e^{\hat{\boldsymbol{\beta}}_{s-1}^{\mathrm{T}}\mathbf{x}_i}}{1+\sum_{l=1}^{s-1} e^{\hat{\boldsymbol{\beta}}_l^{\mathrm{T}}\mathbf{x}_i}},\ \hat{P}(y_i=0) = \frac{1}{1+\sum_{l=1}^{s-1} e^{\hat{\boldsymbol{\beta}}_l^{\mathrm{T}}\mathbf{x}_i}} \tag{9}$$

where:

$\hat{\boldsymbol{\beta}}_l^{\mathrm{T}} = (\hat{\beta}_{l0} \quad \hat{\beta}_{l1} \quad \dots \quad \hat{\beta}_{lk})$, while $l = 1, 2, \dots, (s-1)$.

RESULTS AND DISCUSSION

Based on the EU-SILC 2015 survey, we estimated that Slovak households used their work potential on average at 77% in 2014, with almost 7% of households experiencing total exclusion from the labour market and 52% of households with 100% work intensity. In the households headed by an unemployed person, the situation was, of course, worse. Such households used their work potential on average only at 27% and total exclusion from the labour market is estimated in almost half of households with the unemployed person at the head of the household. In the case of households with an employed person at the head of the household, we estimate an average work intensity of up to 86%, with 61% of these households we have identified 100% use of work potential. Approximately 85% of Slovak households in 2014 had an employed person at the head of the household and 7% of Slovak households had an unemployed person at the head of the household. At the head of the other households there was an inactive person or an old-age pensioner, or a person in early retirement, respectively.

Table 3. Assessment of the contingency between the analysed factors and the degree of work intensity of Slovak households

Statistic	EAS			HT			Education		
	DF	Value	Prob	DF	Value	Prob	DF	Value	Prob
Chi-Square	12	1608.74	<0.0001	32	849.21	<0.0001	16	409.45	<0.0001
Likelihood Ratio Chi-Square	12	1325.38	<0.0001	32	861.98	<0.0001	16	265.47	<0.0001
Cramer's V		0.4097			0.2578			0.1790	

Source: own processing in SAS Enterprise Guide (EU-SILC 2015).

By analysing the contingency, by using the Chi-square of the tests listed in Table 3, we confirmed that the work intensity of Slovak households in 2014, was significantly affected by the status of economic activity and the education of the person at the head of the household, as well as the type of household. In order to assess the intensity of this dependence, we used Cramer's V, which is based on the average square contingency and it is a suitable measure when comparing the degree of association for pivot tables of different dimensions. This association rate has shown that the work intensity of households is clearly most affected by the economic activity of the person at the head of the household. If we have quantified a moderate relationship between the work intensity of the household and the economic activity of the person at the head of the household, both the work intensity of the household and the household type the education of the person of the household head, respectively, we see weak (significant) dependence (AcaStat Software, 2015).

Although the contingency analysis showed that the work intensity of a household is closer to the type of a household than the education of the person at the head of the household, in accordance to Figure 1 and Figure 2 which are the results of the correspondence analysis, it was the opposite. Correspondent analysis, which is based on the analysis of the interdependence structure of two or more variables (Greenacre, 2016) did not identify any type of household, for which very low work intensity was typical (Figure 2).

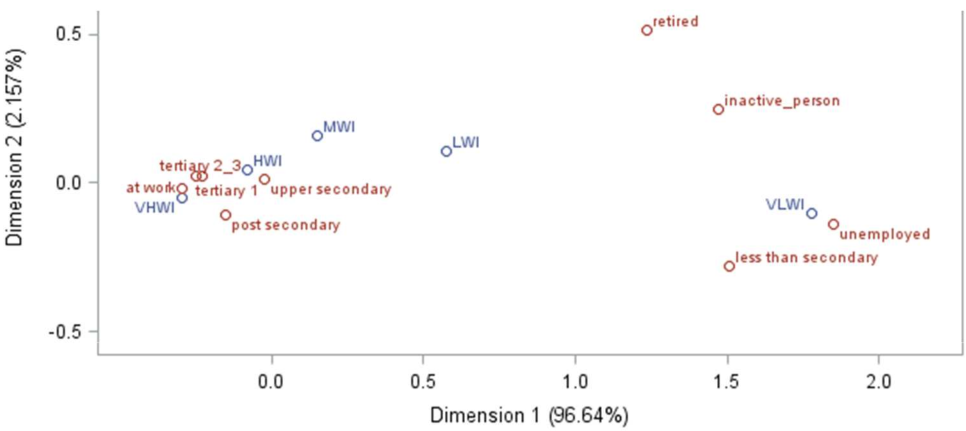

Figure 1. Correspondence analysis of work intensity of Slovak households for factors, such as economic activity and education of the person at the head of the household

Source: own processing in SAS Enterprise Guide (EU-SILC 2015).

From Figure 1 we find, which we naturally assumed, that very low work intensity (VLWI) is characteristic for households headed by an unemployed person or a person with lower secondary education. On the other hand, very high work intensity (VHWI) is typical for households headed by an employed person and for households headed by a college student of the 2nd or 3rd grade but also with completed bachelor studies.

As we have already mentioned, for any type of household very low level of work intensity (VLWI) is not characteristic. This most serious work intensity when a household uses less than 20% of its work potential is most typical for households with a maximum of one person in productive age, specifically for households of two adults, of whom at least one is aged 65+ and for single-member households. In general, their work potential is best used by two adult households with two dependent children or one dependent child. These types of households are most associated with very high work intensity (VHWI) and together with 'other' households are at least associated with very low work intensity. For 'other' households, (whether childless or with dependent children) high level of work intensity (HWI) is much more typical when compared to other types of households (Figure 2).

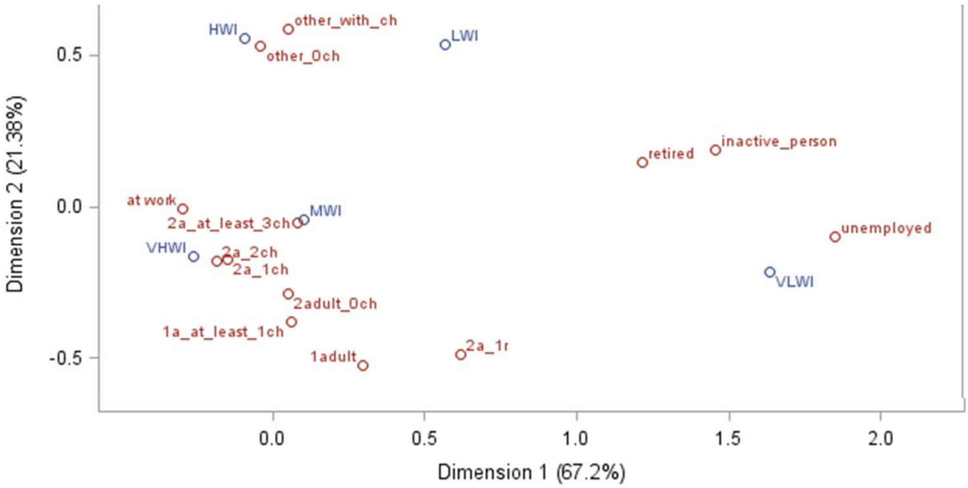

Figure 2. Correspondent analysis of work intensity of Slovak households for the factors the economic activity of the person at the head of the household and the type of household
Source: own processing in SAS Enterprise Guide (EU-SILC 2015).

Analysis of the Mutual Influence of Economic Activity and Type of Household on the Work Intensity of Slovak Households

In the previous part of the article we found that the use of household's work potential is significantly affected by the status of the economic activity of the person at the head of the household, the type of household and the education of the person at the head of the household. In this section, we will fix the impact of the economic activity of the person at the head of the household and we will estimate the share of households at the individual levels of work intensity for each type of household.

For this purpose, we will use a multinomial logistic model containing two explanatory categorical variables, namely the status of the economic activity of the person at the head of the household and the type of household. The presented results are based on the estimates, made in SAS analytical software, in its application Enterprise Guide using the LOGISTIC procedure with LINK = GLOGIT (generalised logit), respectively. The Newton-Raphson algorithm (Allison, 2012) was used to obtain the most reliable estimates of model parameters.

The analysis of the multinomial logistic regression model (Table 4) confirmed that the economic activity of the person at the head of the household and the type of household in 2014 significantly influenced the degree of work intensity of Slovak households. The two explanatory variables explained about 50% of variability of the degree of work intensity.

Table 4. Verification of the statistical significance of the multinomial logistic regression model and the significance of the partial impact of the explanatory variables EAS and HT

Model Fit Statistics		
Criterion	Intercept Only	Intercept and Covariates
AIC	7894.835	5810.644
SC	7919.113	6101.972
-2 Log L	7886.835	5714.644

Testing Global Null Hypothesis: BETA=0			
Test	Chi-Sq	DF	Pr > ChiSq
Likelihood Ratio	2172.20	44	<0.0001
Score	2426.34	44	<0.0001
Wald	1013.25	44	<0.0001

Type 3 Analysis of Effects			
Effect	DF	Wald Chi-Square	Pr > ChiSq
EAS	12	493.4016	<0.0001
HT	32	541.5574	<0.0001

R-Square	0.4933
Max-rescaled R-Square	0.5390

Source: own processing in SAS Enterprise Guide (EU-SILC 2015).

Table 5. Parameter estimates of the multinomial logistic regression model with the explanatory variables EAS and HT

Work Intensity	Intercept	EAS			Household Type							
		unemployed	inactive	retired	1a_at_least_1ch	1adult	2a_1ch	2a_1r	2a_at_least_3ch	2adult_0ch	other_0ch	other_with_ch
1	-1.843	1.042	3.756	2.442	-1.138	-1.832	-0.009	-0.810	0.613	-0.535	1.470	1.672
2	-1.136	2.632	4.724	4.317	-2.430	-14.599	-0.018	-14.583	0.705	-0.507	-0.820	-0.747
3	-3.817	3.614	5.080	4.436	0.209	-1.147	-0.138	-13.703	0.490	-0.335	1.201	1.818
4	-5.350	6.970	8.116	6.729	0.490	0.838	-0.220	1.568	1.047	0.235	-0.499	0.573

Source: own processing in SAS Enterprise Guide (EU-SILC 2015).

On the basis of the estimated parameters (Table 5) of logit functions (8) and used equations (9) we estimated the probabilities of individual degrees of work intensity for individual categories of households (breakdown by economic activity status of the household head and the household type). These probabilities are displayed in Figure 3.

In all types of households we recorded the highest incidence of very high work intensity in those households which are headed by an employed person (Figure 3). We obviously expected this finding. What is interesting, however, is that in some types of households (type 12: two adults with at least three dependent children, type 8: other households without dependent children, type 13: other households with dependent children) headed by an employed person, very high work intensity was only at 50%. From the households headed by an employed person, the households of two adults with at least three dependent children had the highest incidence of average work intensity (30%, while other types of households

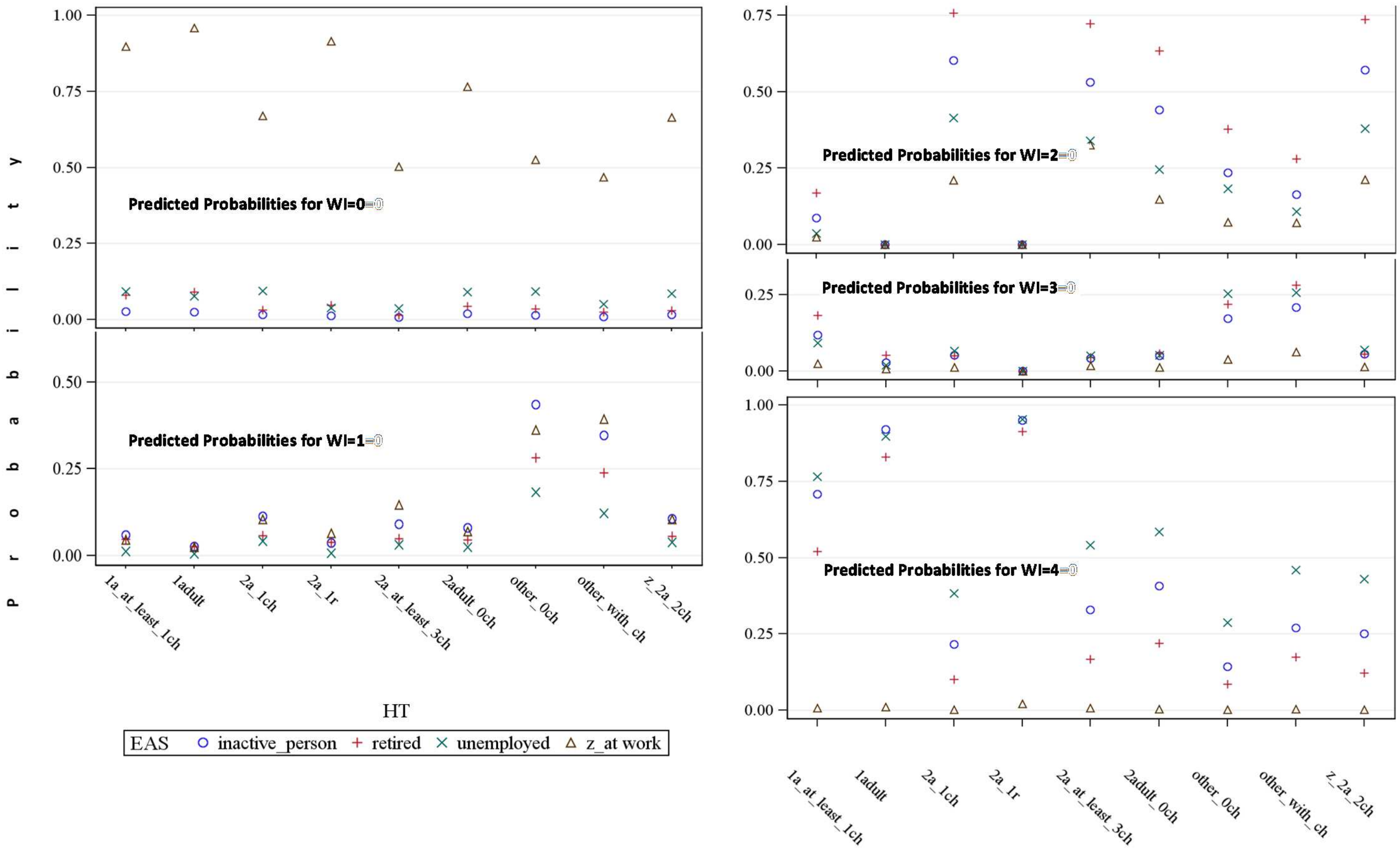

Figure 3. Estimated probabilities of individual degrees of work intensity of Slovak households depending on the status of economic activity of the person at the head of the household and on the household type

Source: own processing in SAS Enterprise Guide (EU-SILC 2015).

where under 25%) and households of type 8: other non-dependent children type 13: other households with dependent children also had the highest incidence of high work intensity (37-38%, while other types of households under 20%). In all types of households, where the person at the head of the household was not employed, so the person at the head of the household was unemployed, inactive, or retired, the rate of very high work intensity was less than 12.5%. In these types of households the following dominated:

- high work intensity (first degree of severity) for Type 8 households: Other households without dependent children and Type 13: Other households with dependent children, if at the head of these households there was an inactive person,
- average work intensity for households of two adults with one dependent child, with two dependent children, with at least 3 dependent children, as well as in the households of two adults without dependent children, if a retired or inactive person was at the head of these households,
- very low work intensity for households headed by an unemployed person (applies to all types of households except for the households of two adults with one dependent child where it was approximately the same percentage of very low and average work intensity (both approximately 38%) and households of type 8: other households without dependent children, where the work intensities were represented by the most uniform (approximately 25% very low, 25% low, 20% medium, 20% high and the rest very high work intensity).

In households headed by a person whose status of economic activity is not employed, high work intensity (severity level 1) and low work intensity (severity level 3) were significantly represented (over 20%) only in households of type 8: other households without dependent children and type 13: other households with dependent children. In other types of households in 2014 these two levels of work intensity were uncommon.

Looking at households with very low work intensity, the worst situation was in households with an unemployed person at the head of the household. In most households, households headed by an inactive person experienced a significantly lower incidence of very low work intensity (approximately 20% lower) than in households with an unemployed person at the head of the household. Exceptions were single-parent households and households of two adults with at least one person aged 65+, where the incidence of very low work intensity was comparable in households not headed by an employed person (in all three categories of economic activity – unemployed, inactive, retired). If the two types of households (one-person households and two-adult households with at least one person aged 65+) were headed by an unemployed person, inactive or retired, the incidence of very low work intensity exceeded 80%, which is the highest incidence of VLWI.

In particular, let us look at households headed by a retired person. For the household type with two adults (with one, two, or three and more dependent children, but also without dependent children), the average work intensity was 65% to 75%. Here it is clear that such a preference for a household with a status as a retiree (under 59) either partially exploited its labour potential or its non-inclusion in the labour market was mostly offset by the second adult of the household. In households with one adult (one-person household or one adult household with at least one dependent child) as well as in households with two adults, of whom at least one person is 65+, dominate very low work intensity (when talking about households headed by a retired person), because they are not compensated by other adults. From these three household types, there is the lowest incidence of VLWI in one adult households and at least one dependent child, where we account for approximately 50% of households with very low work intensity, while in the other two types of households without dependent children it is more than 80% of households.

Analysis of the Interdependence of Economic Activity and Education of the Person at the Head of the Household on the Work Intensity of Slovak Households

The analysis of the multinomial logistic regression model (Table 6) confirms the significance of the impact of a person's education at the head of the household on the work intensity of households, not only when considering the individual impact, if we do not take into account the economic activity of the person at the head of the household (Table 3). Furthermore, we consider also the significance of the partial impact of education of the person at the head of the household when we establish the influence of the status of the economic activity of the person at the head of the household. The two explanatory variables (EAS and Education) together explained approximately 35.5% of the variability of work intensity. In this case, we diagnose a certain degree of multi-collinearity, as the EAS variable specifically explained 33.95%, and the Education variable separately explained 7.98% of the variability of work intensity, which is approximately 6.5 pp more than it was when analysing their joint impact.

Table 6. Verification of the statistical significance of the multinomial logistic regression model and the significance of the partial impact of the explanatory variables EAS and Education

Model Fit Statistics		
Criterion	**Intercept Only**	**Intercept and Covariates**
AIC	7893.683	6547.837
SC	7917.959	6742.046
-2 Log L	7885.683	6483.837

Testing Global Null Hypothesis: BETA=0			
Test	**Chi-Sq**	**DF**	**Pr > ChiSq**
Likelihood Ratio	1401.85	28	<0.0001
Score	1705.96	28	<0.0001
Wald	509.25	28	<0.0001

Type 3 Analysis of Effects			
Effect	**DF**	**Wald Chi-Square**	**Pr > ChiSq**
EAS	12	443.5914	<0.0001
HT	16	69.2282	<0.0001

R-Square	0.3553
Max-rescaled R-Square	0.3881

Source: own processing in SAS Enterprise Guide (EU-SILC 2015).

When comparing Table 4 and Table 6 it is clear that the predictive quality of the model with explanatory variables on the status of economic activity of the person at the head of the household and the type of household (Table 4) is better than the model with explanatory variables on the status of economic activity and the education of the person at the head of the household (Table 6), which confirms not only the coefficient of determination, but also the Akaike information criterion (AIC) and the Schwarz criterion SC (Hair *et al.*, 2010).

Table 7. Parameter estimates of the multinomial logistic regression model with the explanatory variables EAS and Education

Work Intensity	Intercept	EAS			Household Type			
		unemployed	inactive	retired	Less than secondary	Upper secondary	Post secondary	Tertiary 1
1	-1.451	1.183	3.680	2.225	0.873	0.172	0.415	-0.515
2	-1.510	2.482	4.366	3.598	0.726	-0.103	-0.832	0.012
3	-3.755	3.652	4.926	4.180	1.695	0.581	0.602	0.392
4	-5.732	6.603	8.008	6.936	3.053	0.740	0.419	-0.726

Source: own processing in SAS Enterprise Guide (EU-SILC 2015).

Let us look at the estimates of the probabilities of the degree of work intensity obtained on the basis of the multinomial logistic regression model in the two-stage classification of Slovak households according to the status of economic activity and the education of the person at the head of the household (Figure 4). The results confirm that households headed by an employed person have the greatest difficulty in using the work potential of those households whose person at the head of the household has less than secondary education. If the person at the head of the household has less than secondary education, even if he or she is employed, the households of these preferences have a very high degree of work intensity at only 45% and the probability of high work intensity is 25%.

Certainly, in all education groups there are greater problems with the use of work potential if the person at the head of the household is not employed. Households headed by a person with lower secondary education and whose status of economic activity is inactive, retired or unemployed, they hardly ever have very high work intensity. Therefore, 75% of these households have very low work intensity. In households where the person at the head of the household is not employed, we record a relatively high risk of very low work intensity in all education groups. In these households, the probability of very low work intensity of less than 25% is found only in groups of households headed by a person with higher education level (the exception are households headed by an unemployed person with a higher education level of 2nd or 3rd degree). The likelihood of very low work intensity risk for groups of households headed by a person with secondary education (upper secondary or post-secondary education) whose economic activity status is not 'employed' is between 30% and 50%.

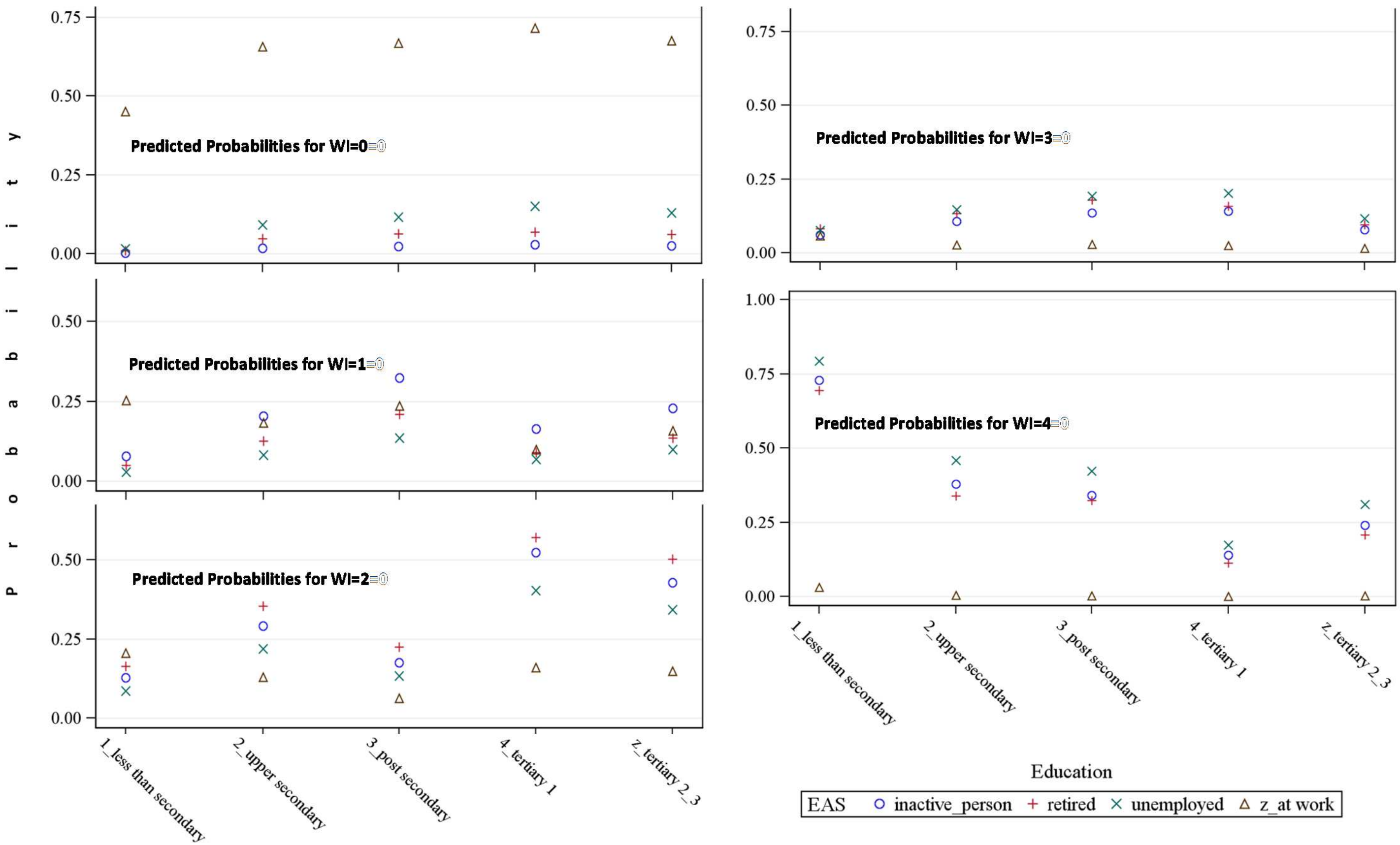

Figure 4. Estimated probabilities of individual degrees of work intensity of Slovak households depending on the status of economic activity and education of the person at the head of the household

Source: own processing in SAS Enterprise Guide (EU-SILC 2015).

CONCLUSIONS

The contingency analysis confirmed that the economic activity of the person at the head of the household, the highest educational attainment of this person, as well as the type of household in 2014 significantly influenced the work intensity of Slovak households. The work intensity of household was naturally determined most by economic activity. By comparing the impact of the other two factors, we considered contradictory results based on contingency analysis and correspondence analysis. While contingency analysis and logistic regression showed a greater impact of the household type, we did not identify any type of household in the correspondence analysis, which would be characterised by very low work intensity, and that the household type causes less disparity in the work intensity of household than the education of the person at the head of the household.

The very low work intensity which defines (quasi-) jobless households is typical for households headed by an unemployed person or a person with less than secondary education. This is the expected result which is consistent with more scientific work. On the other hand, the very high degree of the utilisation of the work potential is characteristic for households headed by an employed person and for households headed by a person with higher education level (this affirmation has been confirmed for all three levels of higher education). While the social inclusion monitor in Europe (Atkinson *et al.*, 2017) says that in 2012 (quasi-) joblessness was typical for households with three or more children, our analysis for 2014 did not confirm this. The exclusion from the labour market in 2014 was the most typical in Slovakia for households without dependent children, where there is no more than one person in productive age, specifically for households of two adults, of whom at least one is aged 65+ and one-person households. In general, their work potential is best used by two adult households with two dependent children or one dependent child. Based on correspondence analysis as well as multinomial logistic regression, we concluded that for households with two adults and at least three children there is a typical medium level of work intensity (utilisation of 45-55% of working potential) and very high degree of work intensity is atypical for them. Even if the head of such a household was an employed person, the use of work potential above 85% was only for 50% of households.

In all types of households, the highest rate of (quasi-) jobless was in households where an unemployed person was at the head of the household. In households with an inactive person, we found a significantly lower rate of very low work intensity in most households (approximately 20% lower) than in households with an unemployed person at the head of the household (except for households with one adult person and households with two adults of whom at least one person is aged 65+). From households in which the person at the head of the household did not have the status of 'employed', exclusion from the labour market was least relevant for households headed by a retired person.

The multinomial logistic model, which resulted in estimates of the probabilities of each degree of work intensity depending on the economic activity and at the same time depending on the education of the person at the head of the household, proved that with an increase in the education of the person at the head of the household in all groups of households broken down by the status of economic activity the predilection of the household increases the likelihood of very high work intensity and it reduces the probability of exclusion from the labour market ((quasi-) joblessness). Interestingly, however, this relationship does not apply to households headed by the person with the highest level of education at tertiary 1 level and by households where the person at the head of the household has a tertiary 2 or tertiary 3 degree of education. Surprisingly, the best results in terms of the utilisation of work potential were achieved by households with a bachelor's degree of higher education, which has been confirmed for all economic activity statuses.

From our point of view, in this article we have considered the most important factor affecting the level of work intensity of the household. The results of the analysis pointed to the categories of households which may be expected to accumulate a number of disadvantages – in terms of the impact of the factors observed. Especially in these categories that emphasis should be placed on monitoring the fulfilment of the national goal of reducing poverty and social exclusion. It would create the conditions for a possible modification, the addition of existent policies and measures.

REFERENCES

AcaStat Software (2015). Applied Statistics Handbook. Retrieved on July 21, 2017 from http://www.acastat.com/statbook/chisqassoc.htm

Allison, P.D. (2012). *Logistic regression using SAS: Theory and application*. Cary: SAS Institute.

Atkinson, A.B., Guio, A., & Marlier, E. (Eds.) (2017). *Monitoring social inclusion in Europe*. Luxembourg: Publications Office of the European Union.

Ayllón, S., & Gábos, A. (2015). *The interrelationships between the Europe 2020 social inclusion indicators* (No. 15/01). Herman Deleeck Centre for Social Policy, University of Antwerp.

Corluy, V., & Vandenbroucke, F. (2017). Individual employment, household employment and risk of poverty in the EU. A decomposition analysis (June 5, 2017). In A.B. Atkinson, A-C. Guio & E. Marlier (Ed.), *Monitoring Social Inclusion in Europe*. Statistical Books Eurostat, Luxembourg: Publications Office of the European Union, 2017. Retrieved on July 21, 2017 from https://ssrn.com/abstract=2981712

Eurostat (n.d.). Income and Living Conditions – List of variables. Retrieved on May 4, 2017 from http://ec.europa.eu/eurostat/web/income-and-living-conditions/methodology/list-variables

Eurostat (2016, August 11). People living in households with very low work intensity. Retrieved on June 29, 2017 from http://ec.europa.eu/eurostat/tgm/refreshTableAction.do?tab=table&plugin=1&pcode=t2020_51&language=en

Eurostat (2017, May 3). Glossary: Persons living in households with low work intensity. Retrieved on July 16, 2017 from http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Persons_living_in_households_with_low_work_intensity

Gerbery, D. (2013). *Nízka intenzita práce a riziko chudoby u pracujúcich v nadväznosti na hodnotenie chudoby a sociálneho vylúčenia* (Publication). Bratislava: Inštitút pre výskum práce a rodiny.

Greenacre, M. (2016). *Correspondence analysis in practice.* New York: Chapman and Hall/CRC.

Guagnano, G., Santarelli, E., & Santini, I. (2013). *Subjective poverty in Europe: the role of household socioeconomic characteristics and social capital* (Working paper No. 113). Retrieved on August 13, 2017 from Università degli Studi di Roma "La Sapienza" website: https://www.memotef.uniroma1.it/sites/dipartimento/files/wpapers/documenti/FullTextWP113.pdf

Hair, J.F., Black, W.C., Babin, B.J., & Anderson, R.E. (2010). *Multivariate data analysis.* New York: Macmillan Publishing Company.

Halleröd, B., Ekbrand, H., & Bengtsson, M. (2015). In-work poverty and labour market trajectories: Poverty risks among the working population in 22 European countries. *Journal of European Social Policy*, *25*(5), 473-488. https://doi.org/10.1177/0958928715608794

Hick, R., & Lanau, A. (2017). *IN – WORK POVERTY IN THE UK: Problem, policy analysis and platform for action* (Rep. No. Final). Retrieved on July 28, 2017 from Cardiff University website: https://orca.cf.ac.uk/103013/1/Hick%20and%20Lanau%20_%20In-Work%20Poverty%20in%20the%20UK.pdf

Horemans, J., Marx, I., & Nolan, B. (2016). Hanging in, but only just: part-time employment and in-work poverty throughout the crisis. *IZA Journal of European Labor Studies*, *5*(1), 5. https://doi.org/10.1186/s40174-016-0053-6

Kis, B.A., & Gábos, A. (2016). Consistent poverty across the EU. *Corvinus Journal of Sociology and Social Policy*, *7*(2), 3-27. https://doi.org/10.14267/issn.2062-087X

Lučkaničová, M., Ondrušeková, I., & Rešovsky, M. (2012). Employment modelling in Slovakia: Comparing logit models in 2005 and 2009. *Economic Annals*, *57*(192), 25-39. https://doi.org/10.2298/EKA1292025L

Mysíkova, M., Večerník, J., & Želinský, T. (2015). The Impact of the Low Work Intensity on Poverty in the Czech Republic and the Slovak Republic. *Journal of Economics*, 63(6), 555-575.

Ramon, C.L., Stroup, W.W., & Freund, R.J. (2010). *SAS for linear models*. SAS Institute.

Rastrigina, O., Leventi, C., & Sutherland, H. (2015). *Nowcasting risk of poverty and low work intensity in Europe* (No. EM9/15). EUROMOD Working Paper.

Řezanková, H., & Želinský, T. (2014). Factors of material deprivation rate in the Czech Republic by household type. *Journal of Economics*, *62*(4), 394-410.

Šoltés, E., & Šoltésová, T. (2016). Occurrence of low work intensity in Slovakia in relation to assessment of poverty and social exclusion. In *The 10th Professor Aleksander Zelias: proceedings [of] international conference on model-ling and forecasting of socio-economic phenomena* (pp. 189-198). Zakopane, Poland: Polska Akademia Nauk.

Watson, D., Maitre, B., & Whelan, C.T. (2012). *Work and Poverty in Ireland: An Analysis of the CSO Survey on Income and Living Conditions 2004-2010* (Rep. No. 3). Retrieved on July 7, 2017 from http://www.esri.ie/pubs/BKMNEXT226.pdf

Whelan, C.T., & Maître, B. (2014). The Great Recession and the changing distribution of economic vulnerability by social class: The Irish case. *Journal of European Social Policy*, 24(5), 470-485. https://doi.org/10.1177/0958928714545444

Authors

The contribution share of authors is equal and amounted to 50% each of them.

Erik Šoltés

Master in Teaching of Subjects: Mathematics – Biology (Comenius University in Bratislava, Slovakia); PhD student in Statistics (University of Economics in Bratislava, Slovakia); habilitation in Quantitative Methods in Economics (University of Economics in Bratislava, Slovakia). His research interests include credibility theory, general linear models, statistical inference, multivariate statistical methods and their application in socio-economic area.

Correspondence to: Ass. Prof. Mgr. Erik Šoltés, PhD., University of Economics in Bratislava, Faculty of Economic Informatics, Department of Statistics, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia, e-mail: erik.soltes@euba.sk

Mária Vojtková

Master in Economic Statistics (University of Economics in Bratislava, Slovakia); PhD student in Statistics (University of Economics in Bratislava, Slovakia); habilitation in Quantitative methods in Economics (University of Economics in Bratislava, Slovakia). Her research interests include measurement of poverty, business demography, analysis of regional disparities in Slovakia, lifelong learning, innovative, growth and human capital tracks in Europe with the use of multivariate statistical methods.

Correspondence to: Ass. Prof. Ing. Mária Vojtková, PhD., University of Economics in Bratislava, Faculty of Economic Informatics, Department of Statistics, Dolnozemská cesta 1, 852 35 Bratislava, Slovakia, e-mail: maria.vojtkova@euba.sk

Acknowledgements and Financial Disclosure

The article was supported by a grant agency of the Ministry of Education, Science, Research and Sport of the Slovak Republic VEGA. Project: VEGA no. 1/0548/16 *The progress of the SR in achieving of the strategy Europe 2020 in the area of poverty and social exclusion.*

Published by the Centre for Strategic and International Entrepreneurship – Krakow, Poland

Ministry of Science and Higher Education Republic of Poland

The copyediting and proofreading of articles in English is financed in the framework of contract No. 799/P-DUN/2017 by the Ministry of Science and Higher Education of the Republic of Poland committed to activities aimed at science promotion.