Country-level Drivers of Severe Material Deprivation Rates in the EU

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Abstract

The severe material deprivation rate indicates the proportion of the population that cannot fulfil at least four of the nine needs identified as basic ones in the European conditions. Due to being an absolute measure, it is very useful for cross-country comparison. This study attempts to identify country-level factors affecting severe material deprivation rate by the use of the GEE methodology which enables to analyse correlated fractional outcome data. It is found that severe material deprivation rate is affected by such factors as: median equivalised disposable income, relative median at-risk-of-poverty gap, long-term unemployment rate, GDP per capita and share of social protection expenditure in GDP. Results reveal that GEE models with cloglog link function exhibit the best goodness of fit. Due to these models imposing non-constant marginal effects, therefore, changes of the severe material deprivation rates depend on levels of country-level factors.

Keywords: *material deprivation, the EU, panel data, fractional output model, GEE*

JEL Classification: C25, I32

Introduction

Poverty is one of the greatest challenges facing mankind today. Its reduction has become one of the most important performance indicators of public policy effectiveness. Although poverty is a universal concept, there is no a widely accepted definition of it. Historically, research studies of poverty has changed perspectives – from narrow concern over the physical and nutritional needs of human beings to include their complex social needs. The definition of poverty

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that is commonly applied to economically advanced societies is referred to as exclusion from ordinary living patterns, customs and activities due to lack of resources (Townsend, 1979; Calandrino, 2003). It is important to stress that research on poverty in most countries relies primarily on household income to capture living standards. However, this approach is not satisfactory for several reasons. One can notice that income is an indirect measure of poverty in the sense that it relates only to resources, not to living standards. Moreover, contemporary income is defined as financial inflows at one point in time, which implies that other resources, such as physical assets and savings, are ignored in the same way as income fluctuations over a longer period of time. Finally, income data suffers from measurement error, especially for households in the bottom and top end of the income distribution (Calandrino, 2003).

Recently, mainly due to the same reasons as mentioned above, awareness of the limitations of conventional income poverty approach has been increasing and heightened attention has been focused on the role which non-monetary measures of deprivation can play in improving measurement and understanding of poverty, and contributing to the design of more effective anti-poverty strategies and policies (Whelan and Maître, 2012). Deprivation indicators enable to measure living standards directly by means of looking at the "enforced lack" of "necessities". The "enforced lack" approach signifies that an item is counted as lacking if it cannot be afforded. It is essential to stress that lack of items is not due to choice and lifestyle preferences but is the result of the enforced lack, i.e., people would like to possess (have access to) the lacked items but cannot afford them (Fusco, Guio and Marlier, 2013).

The contemporary interest in the concept of material deprivation (MD) was initiated by Townsend (1979), who defined deprivation as the lack of socially perceived necessities. Other researchers who further advanced the study of this issue include i.a. Mack and Lansley (1985), Mayer and Jencks (1989), Nolan and Whelan (1996). Supported by pioneering research originated in the late twentieth century, measurement of material deprivation has been commonly used to understand poverty and social exclusion in developed countries, especially in the European Union (EU).

The importance of MD indicators has grown significantly since 2010, as a result of the adoption of the Europe 2020 Strategy on smart, sustainable and inclusive growth, with its five "headline targets" to be achieved by 2020 (Guio et al., 2016; Marlier, Natali and van Dam, 2010). The poverty target is monitored through the headline indicator – "people at risk of poverty or social exclusion", consisting of three sub-indicators covering: severe material deprivation, monetary poverty and very low work intensity.

Severe material deprivation rate (SMDR) is an indicator adopted by the EU Social Protection Committee measuring the percentage of population that cannot afford at least four of the following nine items (Eurostat, 2017):

1) to pay their rent, mortgage or utility bills;
2) to keep their home adequately warm;
3) to face unexpected expenses;
4) to eat meat, fish or a protein equivalent every second day;
5) to go on a week holiday away from home;
6) a television set;
7) a washing machine;
8) a car;
9) a telephone.

It should be stressed that threshold at which people are considered severely materially deprived is a result of convention.[1] What is important is that the list of items and the threshold are the same in all EU countries.

Severe material deprivation rate indicator is very useful for country comparison because, contrary to relative monetary poverty indicators, it reflects absolute aspects of poverty. It should be also underlined that monetary poverty under the Europe 2020 Strategy has been conceived of as relative to a particular country at a particular time. Its measure, known as the "at-risk-of-poverty rate", is the share of people with an equivalised disposable income below threshold, which is set at 60% of the national median equivalised disposable income calculated after social transfers. It does not permit setting a constant benchmark of poverty which would allow comparisons of poverty across time and space (Panek and Zwierzchowski, 2014). According to the Eurostat glossary, at-risk-of-poverty rate does not measure wealth or poverty, but low income in comparison with other residents in that country, which does not necessarily implies a low standard of living (Eurostat, 2017).

For the above-mentioned reasons, the analysis of SMDR indicator is undertaken in our study. Our aim is to shed light on the severe material deprivation rates in the EU Member States over the past eight years, from 2008 up to 2015. The main objective of this study is to identify country-level factors effects on severe material deprivation rates in the EU countries. We contribute to the scarce literature on the effects of various factors on SMDR indicator from a country-level perspective.

In econometric analysis generalized estimating equations (GEE) models are applied. Such models enable to make analysis of correlated panel data for fractional outcome variable. As SMDR is a limited-range variable, it seems reasonable

[1] Taking into account threshold of at least three items one can obtain indicator called material deprivation rate.

to apply GEE approach. To the best of the author's knowledge, in the literature there is no study using these models in analysis of severe material deprivation rates. The paper is organized as follows: The first part presents introduction and comprehensive literature review. The second part describes applied data and methods. The third part presents obtained results. The last part resumes the results and gives some comments.

1. Literature Review

There are numerous studies on determinants of income poverty, while relatively less studies concern the topic of material deprivation. Moreover, some authors have found that these two types of deprivation are not very closely correlated (Acar, Anil, Gursel, 2017; Ayllón and Gábos, 2017; Stávková, Birčiaková and Turčinková, 2012).

Studies on drivers of severe material deprivation are mainly focused on analysis of micro-data describing an individual households' behaviour. The micro-data analyses consider mainly logit or probit models in which the binary variable usually assumes the value of 1 if material deprivation occurs and 0 otherwise.[2] Examples of such researches are provided by Rezanková and Želinský[3] (2014), Šoltés and Ulman (2015), McKnight (2013), Nelson (2012), Bárcena-Martín et al. (2014), Israel (2016), Saltkjel (2018), where the impact of many socio-demographic factors is found – essentially education level, place of residence or biological type of household – and economic factors, such as status on labour market and income situation. What is important, in the four latter mentioned researches, combining micro and macro data, evidence of impact of country-level factors, i.e. GDP per capita and social services is indicated. Moreover, Bárcena-Martín et al. (2014) who apply multilevel models, show that country-specific factors turned out to be much more relevant than individual effects in explaining country differences in material deprivation occurrence.

In macro-data studies, examining relationships of severe material deprivation rates with various correlates, mainly simple tools of two-variable analysis are carried out. Most studies in this field use scatter plots providing two-dimensional visualization of data, simple linear regression or Pearson correlation coefficients. Acar, Anil and Gursel (2017), Kis and Gábos (2016), Nelson (2012), Israel and Spannagel (2013), Whelan and Maître (2012) belong to the group of exemplary researches of such studies presenting evidence of correlation between material

[2] In researches related to material deprivation in EU countries, EU-SILC data is usually used.

[3] It should be also mentioned that that issue of regional differentiation of material deprivation phenomenon in Slovakia and the Czech Republic was examined in Želinský's research (2012).

deprivation rates and various factors. In particular, Acar, Anil and Gursel (2017) and Kis and Gábos (2016) state adverse dependence of GDP per capita; Whelan and Maître (2012) find negative impact of government social expenditure as a percentage of GDP and gross national disposable income per capita; Nelson (2012) points out the role of social assistance benefits levels adverse in decrease of material deprivation rate; Israel and Spannagel (2013) show negative dependence of median of households' equivalent income and positive dependence of households' income inequality.

More advanced macro-data econometric analyses are provided by Blatná (2017), Calvert and Nolan (2012), and Kis, Özdemir and Ward (2015). Blatná (2017) applies Autoregressive Distributed Lag Model (ADL) for analysis of EU material deprivation rates in 2005 – 2015 period. She finds that the EU-28 material deprivation rate in time *t* depends directly on the proportion of people living in households with very low work intensity in the *t* period, being in inverse proportion to those with lower secondary or lower education in the same year *t* and directly dependent on the proportion of people with secondary or lower level of education in the previous year (*t* – 1) respectively. Studies of Calvert and Nolan (2012) and Kis, Özdemir and Ward (2015) use linear panel data models. Calvert and Nolan (2012) show, by means of fixed effects regression models, a substantial role of median income and income inequality in explaining the rate of material deprivation. Moreover, by dividing the sample of countries into three groups classified according to level of median households income and by estimating the models for each group separately, they find out that impact of both variables is statistically significant only in low income countries. Kis, Özdemir and Ward (2015) examine a wide set of potential determinants taking into account average income, social benefits, indicators of income poverty, households' savings rate, employment rate as well as share of young and low educated people in the given country. Their regression results show a significantly positive association with severe material deprivation rate such factors as: indicators of income poverty, the share of young people, while a significantly negative association applies to average households' income, employment rate, and households savings rate.

2. Data and Research Methodology

2.1. Data

Eurostat database is the source of the data for the needs of econometric analysis in this research. In our analysis the time span covered is from 2008 to 2015, and the study encompasses 27 EU Member States, excluding Croatia due to lack of data. Following the related literature (Bárcena-Martín et al. 2014; Blatná, 2017; Calvert and Nolan, 2012; Israel 2016; Kis, Özdemir and Ward, 2015; Nelson, 2012; Saltkjel, 2018), the empirical analysis is based on the following variables:

- the GDP per capita expressed in Purchasing Power Standard (GDP per capita);
- the long-term unemployment rate meaning the number of persons unemployed for 12 months or longer as a percentage of the labour force (L_unemployment);
- the ratio of total expenditure on social protection in relation to GDP (Soc_protection);
- the median equivalised disposable household income expressed in Purchasing Power Standard (Income);
- the relative median at-risk-of-poverty gap being indicator calculated as the difference between the median equivalised net income of persons below the at-risk-of-poverty threshold and the at-risk-of-poverty threshold itself, expressed as a percentage of the at-risk-of-poverty threshold; this threshold is set at 60% of the national median equivalised disposable income of all people in a country and not for the EU as a whole (Poverty_gap);
- Gini index measuring the inequality of income distribution (Gini);
- income quintile share ratio calculated as the ratio of total income received by 20% of the population with the highest income to that received by 20% of the population with the lowest income (S80/20 ratio).

In our study a panel data structure is analysed by use of the generalized estimating equations (GEE) methodology introduced by Liang and Zeger (1986). Such an approach makes it possible to analyse time-correlated limited-range data, referring to the severe material deprivation rates in 2008 – 2015 period.

2.2. Methodology - GEE for Fractional Outcomes

In this section the Generalized Estimating Equations (GEE) approach is shortly described. For more detailed information the following sources are recommended: (Ziegler, 2011) or (Hardin and Hilbe, 2013).

GEE method is traditionally presented as an extension of Generalized Linear Models (GLM) methodology for the analysis of panel data (Hardin and Hilbe, 2013). Fitting a GEE model requires the user to specify (1) the link function to be used, (2) the distribution of the outcome variable, and (3) the correlation structure of the outcome variable (Ballinger, 2004).

Similarly to the GLM, GEE uses a link function, which is a transformation function that allows the mean of the outcome variable y to be expressed as a linear combination of regression coefficients:

$$h(E\left(y_{it}|\boldsymbol{x}_{it}\right)) = \boldsymbol{x}_{it}^{'}\boldsymbol{\beta} \tag{1}$$

where

$\mu(\boldsymbol{x}_{it}) = E\left(y_{it}|\boldsymbol{x}_{it}\right)$ – denotes the mean of the outcome variable *y* conditional on covariates $\boldsymbol{x}$,
$h(\cdot)$ – means a link function,
y_{it} – an outcome referring to severe material deprivation rate of country *i* in year *t*,
$\boldsymbol{x}_{it}$ – denotes a vector of covariates representing the characteristics of country *i* in year *t*,
$\boldsymbol{\beta}$ – a vector of parameters to be estimated.

Because in our study *y* is a fractional outcome, to ensure that μ also belongs to [0, 1] interval, as in (Papke and Wooldridge, 1996) it is assumed that:

$$\mu\left(\boldsymbol{x}_{it}\right) = h^{-1}\left(\boldsymbol{x}_{it}^{'}\boldsymbol{\beta}\right) = G(\boldsymbol{x}_{it}^{'}\boldsymbol{\beta}) \tag{2}$$

where

$G(\cdot)$ – a known function with $0 < \mathrm{G}\left(\boldsymbol{x}_{it}^{'}\boldsymbol{\beta}\right) < 1$ for all $\boldsymbol{x}_{it}^{'}\boldsymbol{\beta} \in R$.

G is the inverse function for the link function *h* indicating how the expected value of the response variable relates to the linear predictor of covariates. For a discussion on link functions in fractional outcome models, see (Smithson and Verkuilen, 2006; Ramalho, Ramalho and Murteira, 2011). In practice functional forms used for *G* are chosen to be a cumulative distribution function (cdf). The most common examples are presented in Table 1.

Table 1

Typical Conditional Mean Specifications for Fractional Response Variables

Specification	**Distribution**	$G(\mathbf{x'}\boldsymbol{\beta}) = \mu$	$h(\mu) = \mathbf{x'}\boldsymbol{\beta}$
logit	Logistic	$\frac{1}{1-exp(-\mathbf{x'}\beta)}$	$ln\left(\frac{\mu}{1-\mu}\right)$
probit	Standard normal	$\Phi\left(\mathbf{x'}\beta\right)$	$\Phi^{-1}\left(\mu\right)$
cloglog	Extreme minimum	$1-exp(-exp(\mathbf{x'}\beta))$	$ln\left(-\ln(1-\mu)\right)$
loglog	Extreme maximum	$exp(-exp(-\mathbf{x'}\beta))$	$-ln\left(-\ln(\mu)\right)$

Source: Own elaboration based on (Ramalho, Ramalho and Murteira, 2011).

The GEE method focuses on average changes in outcome variable over time. The partial effects of a given variable, say X_j, are given by:

$$\frac{\partial E\left(y_{it}|\boldsymbol{x}_{it}\right)}{\partial x_{jit}} = \beta_j g(\boldsymbol{x}_{it}^{'}\boldsymbol{\beta}) \tag{3}$$

where

$$g\left(\boldsymbol{x}_{it}^{'}\boldsymbol{\beta}\right)=\frac{\partial G\left(\boldsymbol{x}_{it}^{'}\boldsymbol{\beta}\right)}{\partial(\boldsymbol{x}_{it}^{'}\boldsymbol{\beta})}$$

x_{jit} – a value of *j*-th explanatory variable for *i*-th country in year *t*.

Hence, significance and direction of the partial effects may be analysed simply by examining significance and sign of β_j (Ramalho and Vidigal da Silva, 2013; Dudek and Szczesny, 2017).

The second step involves specifying distribution of the outcome variable. GEE method permits specification of distributions from the exponential family of distributions, which includes normal, inverse normal, binomial, Poisson, negative binomial, and gamma distributions. In our study the Bernoulli (binomial) family distribution is specified. As in generalized linear models, the variance needs to be defined as a function of the mean:

$$Var\left(y_{it}|\boldsymbol{x}_{it}\right)=\varphi V\left(\mu(\boldsymbol{x}_{it})\right) \tag{4}$$

where

$V(\cdot)$ – a known variance function,

φ – a possible unknown scale or over-dispersion parameter.

Although specification of distribution is important, users do not need to be precise in specification of the variance functions for the parameter estimates (Liang and Zeger, 1986).

The third step involves specification of the form of correlation of responses within subjects in the sample. The GEE is a very flexible approach to handling correlated data structures. Let $\boldsymbol{y}_i=\left(y_{i1},\ldots,y_{iT}\right)^{'}$ represents the outcome variable vector for the *i*-th country, where it is assumed that observations from the same country can depend on each other to some extent, whereas observations from different countries are assumed to be independent. Correlations between components of y_i are represented by so-called working correlation matrix $\mathbf{R}_i\left(\alpha\right)$ that depends on correlation parameter *α*. Note that in the case of balanced data, which are analysed in our study, the correlation structures are *T*x*T*, thus instead $\mathbf{R}_i\left(\alpha\right)$ one can denote working correlation matrix by $\mathbf{R}\left(\alpha\right)$. Liang and Zeger (1986) suggested several structured correlation matrices that can be used to describe pattern of dependency. Popular choices, among others, include:

- exchangeable structure, corresponding to equal-correlation models, where corr(y_{it}, y_{is}) = α for $t \neq s$, $t, s = 1, \ldots, T$;
- autoregressive AR(*p*) structure, defined as the usual correlation matrix for AR(*p*) model, in particular corr(y_{it}, y_{is}) = $\alpha^{|t-s|}$ for $t \neq s$, $t, s = 1, \ldots, T$ for AR(1);

- unstructured, not assuming any pattern for intra-country correlations, where corr(y_{it}, y_{is}) = α_{ts} for $t \neq s$, t, s = 1, …, T;
- independent, where corr(y_{it}, y_{is}) = 0 for $t \neq s$, t, s = 1, …, T.

It should be also noted that specification of the correct form of the correlation of responses increases the efficiency of estimates (Hardin and Hilbe, 2013), but the advantage of GEEs lies in consistent estimation even when the correlation structure is misspecified (Ghisletta and Spini, 2004). The estimates of regression parameters $\boldsymbol{\beta}$ are defined by the solution of the GEE:

$$\sum_{i=1}^{n} \frac{\partial \boldsymbol{\mu}'}{\partial \boldsymbol{\beta}} Var\left(\boldsymbol{y}_i\right)^{-1}\left(\boldsymbol{y}_i - \boldsymbol{\mu}_i\right) = 0 \tag{5}$$

where

$$\boldsymbol{\mu}_i = E\left(\boldsymbol{y}_i\right)$$

$$Var\left(\boldsymbol{y}_i\right) = \varphi \boldsymbol{A}_i^{\frac{1}{2}} \mathbf{R}_i\left(\alpha\right) \boldsymbol{A}_i^{\frac{1}{2}}$$

$\mathbf{R}_i\left(\alpha\right)$ – working correlation matrix,

$\boldsymbol{A}_i$ – diagonal matrix with $V\left(\mu(\boldsymbol{x}_{it})\right)$ along the diagonal.

Typically, moment estimates are used for estimation of usually unknown parameters φ and α.

GEE models have a number of attractive properties for applied researchers. They facilitate regression analyses of limited range outcome variable, in particular – a fractional output variable. GEE approach focuses on average changes in outcome variable over time and assesses the impact of covariates on these changes. The advantage of GEE is that only the mean structure and specification of the covariance structure need to be defined. GEE models have become popular in various fields of science. In particular, they have been applied in microeconomic research (Hwang, Chung and Ku, 2013; Gerthofer et al., 2016; Thomsen, Rose and Kronborg, 2016) as well as in macroeconomic studies (Miles, 2000; Price and Elu, 2014; Magazzino and Mantovani, 2014). GEE estimation has been incorporated into many major statistical software packages. In our study xtgee command implemented in Stata program is applied.

3. Results and Discussion

Quite stable level of average in the EU severe material deprivation rate in 2008 – 2015 period is observed, changing from 8% to 10%. However, SMDR significantly varied from country to country. In particular, in 2008 the lowest level of rate of severe material deprivation was in Luxembourg (0.7%) and the highest in Bulgaria (41.2%). In 2015 Bulgaria appeared repeatedly as the worst country with 34.2% value of severe material deprivation rate, while the lowest level among the EU countries was 0.7% in Sweden. During the period in question the proportion of the severe materially deprived population decreased in 14 countries and increased in 13 countries. It is important to emphasize that for most countries small changes were observed. The most distinct drop between 2008 and 2015 refers to Romania and Poland, which reduced their share of severely materially deprived people by about 10 percentage points, whereas the biggest decrement relates to Greece (growth of 11 p.p.) reflecting the falling material living conditions in this country. Table 2 presents basic descriptive statistics of severe material deprivation rates.

T a b l e 2

Descriptive Statistics of Severe Material Deprivation Rate in the EU Countries

Statistics	2008	2015	2008 – 2015
Minimum	0.7	0.7	0.5
Mean	9.6	9.5	10.4
First quartile	2.0	4.4	4.5
Median	5.9	6.4	6.7
Third quartile	17.9	13.9	12.8
Standard deviation	9.4	7.8	9.4
Maximum	41.2	34.2	45.7

Source: Own elaboration.

Results in Table 2 show that severe material deprivation rates exhibited a very wide dispersion across countries in the EU.

On the basis of values of inter-quartile range and standard deviation it was concluded that dispersion in 2015 was smaller than in 2008. Levels of the quartiles provide a clearer picture of SMDR indicator distribution. In particular, in about the quarter of the EU countries proportion of the severe materially deprived population did not exceed 2% in 2008 and 4.4% in 2015, moreover in about half of the sample countries, SMDR indicator was smaller than 5.9% in 2008 and 6.4% in 2015. On the other hand, in about the quarter of the EU countries severe material deprivation rates were greater than 9.4% and 7.8% respectively at the beginning and at the end of the analysed period. There was no clear division between the countries that joined the EU in 2004 or later (EU-15) and the so-called old EU countries (EU-12). However, it must be admitted that most of the EU-12 countries were in the group of countries with lower than average level of SMDR indicator in the EU. The exceptions were only Greece, Italy and Portugal.

In order to indicate factors that may affect the severe material deprivation rates, many models with different sets of regressors were considered in our study. For each model, the goodness of fit was evaluated using the root-mean-square--error (RMSE), the mean absolute error (MAE) and the value of pseudo-R^2, wherein the pseudo-R^2 was calculated as the square of the correlation between actual and fitted values of outcome variable and, thus, it is comparable across models (Ramalho and Vidigal da Silva, 2013).

The paper presents the results of estimates of chosen models with good fit. Due to strong dependency of the SMDR values on their values in the previous year, in the estimated GEE models AR(1) working correlation matrices are applied. This is also supported by analysis of statistical significance of parameters and values of goodness of fit measures.

The first model includes gross domestic product (GDP) per capita, the long--term unemployment rate and the ratio of total expenditure on social protection to GDP. The results comparing linear model (corresponding to the Gaussian GEE with identity link function) and binomial GEE models with different link functions are shown in Table 3.

T a b l e 3

Results of Estimation of Model 1

Variables	**Binomial GEE with link function:**				**Gaussian GEE**
	logit	probit	cloglog	loglog	identity link funct.
GDP per capita	–0.043* (0.013)	–0.023* (0.007)	–0.045* (0.012)	–0.007* (0.003)	–0.003* (0.001)
L_unemployment	6.602* (0.836)	3.199* (0.427)	5.505* (0.757)	2.658* (0.332)	0.473 (0.271)
Soc_protection	–2.576* (0.859)	–1.739* (0.430)	–2.691* (0.751)	–0.936* (0.471)	–0.203* (0.107)
Constant	–0.679 (0.634)	–0.331 (0.292)	–0.599 (0.537)	–0.498* (0.224)	–0.316* (0.224)
RMSE	0.020	0.020	0.019	0.022	0.023
MAE	0.040	0.041	0.038	0.046	0.051
Pseudo-R^2	0.651	0.645	0.678	0.602	0.515

Source: Own elaboration; Robust[4] standard errors in parentheses; * means statistical significance at 0.05.

According to the signs of estimated parameters presented in Table 3, the increment in the expected values of the severe material deprivation rate was influenced by the increase in long-term unemployment and the decrease of GDP per capita and the percentage share of expenditures on social protection in GDP. These findings are in line with prior research in the field, for example (Whelan and Maître, 2012; Nelson, 2012; Kis, Özdemir and Ward, 2015).

[4] For all models the vce(robust) option in Stata is applied. It means that the Huber/White/ sandwich estimator of variance is used in place of the default conventional variance estimator.

Long-term unemployment may affect life opportunity to earn income (Bárcena--Martín et al., 2014) and – in consequence – difficulties in meeting basic needs. As indicated by Martínez and Navarro (2015), long-lasting lack of work and labour precariousness tend to generate situations of persistently low income, more associated with material deprivation than transitory episodes of a fall in income. Greece can be an example in this regard. In this country in 2008 – 2015, an increase in long-term unemployment was accompanied by a rise of a severe material deprivation rate.[5]

As regard to the GDP per capita, some researchers note that it might be interpreted as a general economic affluence reflecting many other socioeconomic variables, therefore indicating the average material welfare of a society (Dewilde, 2008; Bárcena-Martín et al., 2014). Thus, in more affluent countries severe material deprivation rates tend to be lower. In particular, SMDR declined quite strongly in Member States experiencing strong growth of the GDP per capita. The case of Poland is illustrative – the severe material deprivation rate was on a declining trend in 2018 – 2015, while the GDP per capita had an upward tendency.

Our results provide robust empirical evidence of a negative association between the ratio of total expenditure on social protection to GDP and SMDR, indicating that poverty can be reduced by redistributive policies. Thus, social assistance should be part of the programmes to counteract material deprivation in the EU. As Nelson (2012) points out, severe material deprivation is less prevalent in countries with more elaborate social assistance programmes. Generally, severe material deprivation is widespread in Central and Eastern Europe, where social assistance benefit levels are fairly low. Estonia is an exception, where relatively low rate of the severe material deprivation goes together with relatively low ratio of total expenditure on social protection to GDP and moderate levels of long-term unemployment as well as GDP per capita. It is also important to highlight that in Southern European countries, especially in Italy which was deeply hit by the economic downturn, despite the fact that expenditure on social protection relative to GDP was near 30% in 2011 – 2015, the SMR exceeded the EU average level.

Comparing the goodness of fit of models presented in Table 3, one can find that the best goodness of fit exhibits the model with cloglog link function, whereas the worse one – Gaussian GEE identity link function corresponding to the linear model. Therefore, in the next step of our study we analyse the results of the first of these models.

[5] Conclusions and assertions about individual countries are based on direct analysis of Eurostat data.

In order to assess quantitative changes in the expected values of the SMDR corresponding to the increase in macroeconomic drivers, we compute marginal effects according to the formula (3). Table 4 shows results for the various quartiles of a given regressor, assuming the value of other explanatory variables being at the median level.

Table 4

The Marginal Effects for Model 1 with Cloglog Link Function

	First quartile	Second quartile	Third quartile
GDP per capita	–0.004* (0.002)	–0.003* (0.001)	–0.002* (0.001)
L_unemployment	0.383* (0.046)	0.410* (0.052)	0.457* (0.064)
Soc_protection	–0.227* (0.075)	–0.200* (0.060)	–0.176* (0.046)

Source: Own elaboration; Robust standard errors in parentheses; * means statistical significance at 0.05.

As the GDP per capita is expressed in thousands of PPS and the SMDR, L_unemployment and Soc_protection are the numbers from (0, 1), assuming the long-term unemployment rate and the ratio of total expenditure on social protection to the GDP to be on their median levels, we can interpret that an increase of GDP per capita by 1000 PPS is accompanied by a drop of the expected value of the severe material deprivation rate:

- by 0.4 percentage point (pp) if the GDP per capita was on the level of its first quartile,
- by 0.3 percentage point in the case of the second quartile,
- by 0.2 percentage point if the GDP per capita was on the level of its third quartile.

On the other hand, assuming the long-term unemployment rate and the GDP per capita to be anchored on the median levels of their distributions, one percentage point increase of the ratio of total expenditure on social protection to the GDP reduced the expected values of the severe material deprivation rate by appropriately 0.227 pp, 0.200 pp and 0.176 pp. Analogously, 1 percentage point growth of the long-term unemployment rate affects expected values of the SMDR by respectively 0.383 pp., 0.410 pp. and 0.457 pp. depending on the quartile of long-term unemployment rate.

These results mean that changes of the expected values of SMDR altered by increment of the GDP per capita were smaller in more developed countries than in poorer ones. Likewise, after controlling for the GDP per capita and the long-term unemployment rates, effects of changes were smaller in countries with more generous social policy. On the other hand, the higher the long-term unemployment rate, the higher change of the expected value of the severe material deprivation rate.

In the next model, we consider variables directly related to the income situation of households as regressors. Table 5 presents the results of estimates of model 2 including the median equivalised disposable household income and the relative median at-risk-of-poverty gap as regressors. It should be explained here in more detail that the second indicator is defined as the median income poverty gap in the country population as a proportion of the country's poverty threshold. Thus, it informs about the depth of income poverty, which quantifies just how poor the poor are.

T a b l e 5

Results of Estimation of Model 2

Variables	Binomial GEE with link function:				Gaussian GEE
	logit	probit	cloglog	loglog	identity link function
Income	–0.124* (0.021)	–0.062* (0.011)	–0.121* (0.200)	–0.043* (0.009)	–0.009* (0.001)
Poverty_gap	5.522* (1.980)	3.089 * (1.111)	4.659* (1.752)	0.569* (0.212)	0.110 (0.062)
Constant	–1.983* (0.610)	–1.220* (0.327)	–1.920* (0.563)	–0.440* (0.154)	0.196* (0.044)
RMSE	0.051	0.051	0.051	0.060	0.063
MAE	0.035	0.035	0.034	0.038	0.042
Pseudo-R^2	0.708	0.701	0.711	0.663	0.584

Source: Own elaboration; Robust standard errors in parentheses; * means statistical significance at 0.05.

As might be expected, the median equivalised disposable household income plays a substantial role in explaining the severe material deprivation rate. In line with the literature (Calvert and Nolan, 2012; Israel and Spannagel, 2013; Kis, Özdemir and Ward, 2015) a significantly negative relationship is observed. Thus, in countries with high median income, more households were able to afford basic items than in low income countries. However, controlling for median income, the relative median at-risk-of-poverty gap is also statistically significant and positively associated with severe material deprivation rate. An example in this respect is Italy, where the severe material deprivation rate was on a rising trend in 2011 – 2015, while the median income was almost unchanged, but the relative median at-risk-of-poverty gap grew. It means that a worsening situation of the Italian poor resulted in more people being unable to afford basic items. It is also worth noting that in Bulgaria and Romania – countries with the highest levels of SMDR and the lowest median income in the EU – the depth of income poverty was among the highest in the EU.

Similarly to model 1, one can state that binomial GEE models for fractional outcome variables are better fitted to the data than the linear model. Again, the model with the complementary log-log (cloglog) specification turns out to be slightly better than models with logit or probit link function. As the pseudo-R^2 values exceed 0.7, then both regressors seem to well explain differences of the severe material deprivation rates. Finding that disposable income and the relative median at-risk-of-poverty gap are important determinants for the severe material deprivation rates, we focus on the extent to which changes in these factors are followed by changes of the SMDR. Unlike linear model, marginal effects in binomial GEE with cloglog link function depend on the levels of explanatory variables. Thus, in Table 6 we present as examples the results for each quartiles of one regressor, assuming the value of remaining explanatory variables being at the median level.

T a b l e 6

The Marginal Effects for Model 2 with Cloglog Link Function

	First quartile	Second quartile	Third quartile
Income	–0.014* (0.004)	–0.007* (0.001)	–0.005* (0.001)
Poverty_gap	0.242* (0.083)	0.270* (0.103)	0.325* (0.145)

Source: Own elaboration; Robust standard errors in parentheses; * means statistical significance at 0.

Owing to the fact that the SMDR and the relative median at-risk-of-poverty gap are the numbers from (0, 1), the median equivalised disposable household income is expressed in thousands of PPS and assuming the relative median at-risk-of-poverty gap to be on its median level, an increase of median income by 1000 PPS is accompanied by a decrease of the expected value of the severe material deprivation rate:

- by 1.4 percentage point if the median equivalised income was on the level of its first quartile,
- by 0.7 percentage point in the case of the second quartile,
- by 0.5 percentage point if the median equivalised income was on the level of its third quartile.

It means that the decrease of expected value of the severe material deprivation rate altered by increment of the median disposable income was smaller in more wealthy countries than in poorer ones. According to the quartiles of the relative median at-risk-of-poverty gap, while assuming median equivalised income to be on its median level, one percentage point growth of the median relative income poverty gap affects expected values of the SMDR by respectively 0.242 pp, 0.270 pp. and 0.325 pp. As a consequence, after controlling for the median disposable income, the higher the depth of income poverty, the higher increase effects of changes of the expected value of the severe material deprivation rate.

It should also be noted that the inequality of income distribution exhibits positive impact on the SMDR. However, variables regarding indices measuring the inequality of income distribution have not been included to any of the two presented models because neither Gini index nor income quintile share ratio was statistically significant. Nonetheless, it must be stressed that we achieved statistically significant positive relationship taking into account models with only one explanatory variable referring to each of these indices. Thus, rising inequality within a country led to the higher risk of severe material deprivation.

To summarise, we find that all explanatory variables together seem to fulfil their role very well in explaining between-country differences in severe material deprivation rate. Moreover, we observe analysed country-level effects to head in the expected direction. Thus, our findings provide both plausible and substantively interpretable results.

Conclusion

Material deprivation indicators measure households' living standard by focusing on the affordability of nine items referring to needs to be considered as basic ones in the EU conditions. The items typically reflect common perceptions of what are essential necessities. This paper aims at taking a closer look at severe material deprivation rate indicating the proportion of a country population that cannot fulfil at least four of the nine needs. It attempts to reveal a broader picture of these needs in the EU member states and to examine the economic drivers behind the changes observed. The paper evaluates the impact of main drivers derived from the literature by the use of generalized estimating equations methodology. The application of GEE models makes it possible to analyse time-correlated fractional outcome data. As severe material deprivation rates refer to limited-range panel data it seems reasonable to use GEE models.

It is observed that the severe material deprivation rate shows a very wide dispersion across countries in the EU. On the one hand are the Nordic countries and Luxembourg with less than 4% of the SMDR, while on the other hand is Bulgaria with over 30% proportion of the severe materially deprived population in the whole 2008 – 2015 period.

We find that the drivers derived from literature on material deprivation are significant and are characterised by the expected signs. First of all, income situation of households plays an important role in explaining the severe material deprivation rate. Moreover, the increment in the expected values of the SMDR was influenced by the increase in long-term unemployment and the decrease of the GDP per capita and the percentage share of expenditures on social protection in

GDP. Our results show that high differentiation in severe material deprivation rate across the EU can be partly explained by levels of examined factors. In particular, the Nordic countries and Luxembourg combine the lowest levels of the SMDRs in the EU with good social protection, high GDP per capita and low long-term unemployment rate. On the other hand, in Bulgaria – country with the highest level of severe material deprivation rate in the EU – GDP per capita as well as ratio of total expenditure on social protection to the GDP were the lowest in the EU.

Our findings suggest that the severe material deprivation rate cannot only be reduced by simply raising the average household income. Thus, action should be taken in the areas of social protection and improving the efficiency and effectiveness of support of poor households.

Obtained results of econometric analysis suggest that differences of SMDR across European countries can be explained from macro-level perspectives. The estimated models are quite well fitted to the data. Moreover, we find that GEE for a fractional outcome variable exhibit better goodness of fit than linear models. Thus, marginal effects depend on values of explanatory variables. This finding is a certain contribution to the literature on the severe material deprivation rates, whereas as yet linear models have been commonly applied.

In conclusion, it is important to emphasize that our research on the material deprivation issue will be continued. In the coming period, we are planning to extend our research including microeconometric analysis of the households' data. It seems that there is a need to investigate not only incidence, but also the depth of severe material deprivation. Thus, modelling of a number of deprivation items belongs to important future directions. Examining persistence of deprivation among various groups of households is another interesting topic. Such future researches would enable a deeper insight into the material deprivation issue in the European Union countries.

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