Inzinerine Ekonomika-Engineering Economics, 2022, 33(2), 132–142

The Risk and Severity of Food Insecurity in V4 Countries: Insight from the Fuzzy Approach

Hanna Dudek

Warsaw University of Life Sciences
Nowoursynowska st. 166, 02-787, Warsaw, Poland
E-mail. hanna_dudek@sggw.edu.pl

crossref http://dx.doi.org/10.5755/j01.ee.33.2.28848

Food Insecurity (FI) is a complex phenomenon, therefore the traditional approach to its analysis, based on the rigid dichotomization between the food-secure and the food-insecure can oversimplify the real picture. The study proposes to consider FI as a degree rather than as an attribute. To do this, it employs a fuzzy approach widely applied in multidimensional poverty analysis. The study aims to identify correlates of FI in the V4 countries using the zero-inflated beta regression model. This model enables to understand the mechanisms behind the risk and the severity of FI in V4. The analysis based on the FIES data collected in the Gallup World Poll for 2018 indicates the role of income, household composition, and social capital as important correlates of FI. The risk of FI was also affected by age, level of education, gender, marital and employment status. Moreover, the study finds that the food insecurity profile exhibits country-specific effects.

Keywords: *Food Insecurity; Food Insecurity Experience Scale; V4 countries; Fuzzy approach; Zero-Inflated Beta Regression; Correlates.*

Introduction

Food insecurity (FI) remains a substantial problem in the world. Thus, one of the Sustainable Development Goals (SDG) established by the United Nations in 2015 is to "end hunger, achieve food security and improve nutrition and promote sustainable agriculture" (United Nations, 2015). The Agenda for Sustainable Development acknowledged the importance of looking beyond hunger towards the aims of ensuring access to safe, nutritious and sufficient food for all people all year round (see Target 2.1 of SDG), and of eradicating all forms of malnutrition (see Target 2.2 of SDG). In order to measure progress achieving Target 2.1 of SDG, the Food and Agriculture Organization of the United Nations (FAO) developed a scale called the Food Insecurity Experience Scale (FIES), a common metric for analysing FI used in most countries around the world. FIES enables to assess for food insecurity according to eight items relating to different FI experiences, from worry about running out of food, compromised dietary quality and quantity, to periods without food and experiencing hunger. The FIES data collected by FAO through the Gallup® World Poll (GWP) enables analysing FI in various sociodemographic groups and reporting on the SDG target 2.1 at a national level.

A number of studies indicate that FI applies not only to low-income countries, but also to middle-income and high-income states, where noticeable percentage of the population does not have a healthy diet (Cafiero *et al.*, 2018; Gundersen & Garasky, 2012; Hossain *et al.*, 2021; Pollard & Booth, 2019; Smith *et al.*, 2017). In particular, recent studies reveal that it still occurs in Europe (Bernaschi, 2020; Garratt, 2020; Grimaccia & Naccarato, 2020; Loopstra, 2020; Zace *et al.*, 2020).

While most research on FI in Europe is focused on the situation in Western European countries, such as Ireland (Ahmadi & Melgar-Quinonez, 2018), Netherlands (Neter *et al.*, 2014), and in the Nordic countries (Borch & Kjærnes, 2016), this paper attempts to shed a light on the food insecurity in four countries of Central Europe: the Czech Republic, Hungary, Poland and Slovakia, known as the Visegrad Group (V4). These four countries are linked by their geographic and geopolitical situation, and a similar level of socioeconomic development. Therefore, there is extensive source literature focusing on various aspects of the living conditions of their inhabitants. This includes studies on the quality of life in V4 (Chrzanowska *et al.*, 2018; Jankiewicz & Pietrzak, 2020), material deprivation (Dudek & Szczesny, 2021), poverty (Su *et al.*, 2020), the labour market (Bieszk-Stolorz & Dmytrow, 2020), price indices (Bialek & Roszko-Wojtowicz, 2021), equivalence scales (Dudek & Chrzanowska, 2020), economic growth (Simionescu *et al.*, 2017), and regional development (Koisova *et al.*, 2019). However, the results of analyses of FAO's FIES data for V4 have not been presented so far. Therefore, this paper attempts to fill this gap in the existing literature regarding food insecurity in the Visegrad Group countries.

The study analyses FI at the microeconomic level. It proposes the use of a fuzzy approach to measure the severity of food insecurity. This approach, borrowed from the literature on multidimensional poverty measurement, enables to cover the extent of food insecurity at the individual level. To identify correlates of the risk and the severity of FI, the zero-inflated beta regression model is employed, never used before in previous analyses of FI. In doing so, this study contributes to the literature in the scope of FI modelling.

The aim of this paper is to describe the profile of food-insecure people in V4. More specifically, the study identifies the socioeconomic and demographic correlates of the risk and severity of FI. In addition, it explores if food insecurity exhibits significant country-specific heterogeneity.

The study is guided by the following research questions: 1) Are the socioeconomic correlates of FI risk and FI severity the same? 2) Is there a country-specific effect explaining the risk and the severity of food insecurity, once all other individual-level correlates are controlled for?

This paper is structured as follows: in its first part the literature review on FI modelling is presented. The second part describes the used data and the key variables. It also contains a presentation of the step-by-step procedure for calculating a fuzzy FI score and the methods of its analysis. The results are described in the following part. Finally, the discussion and conclusions are set out.

Literature

The analysis of FAO's data is based on responses to the eight questions in the Food Insecurity Experience Scale about the individual's experience with food insecurity. The number of affirmative responses is the raw score ranging from 0 to 8. Most of the studies analyse food insecurity using a binary variable based on a raw-score cut-off (Broussard, 2019; Smith *et al.,* 2017). This dichotomous approach applies logit regression, probit regression or linear probability models for binary dependent variables. In the literature different raw-score cut-offs are used (Broussard, 2019; Barlow *et al.,* 2020). However, the authors mostly apply a cut-off of one out of eight (Sinclair et al., 2019; Dudek & Myszkowska-Ryciak, 2020), a cut-off of four out of eight (Smith *et al.,* 2017) and a cut-off of seven out of eight (Smith *et al.,* 2017; Barlow *et al.,* 2020).

Apart from models for binary output, ordered logistic models (Grimaccia & Naccarato 2019), multinomial logistic models (Ben-Davies *et al.,* 2014; Interlenghi & Salles-Costa, 2015) and zero-inflated Poisson regression models (Poczta-Wajda *et al.,* 2020) are also applied. Furthermore, Endeweld and Silber (2017) implemented the tobit model to explain food insecurity score – a composite indicator weighting and aggregating all respondent's responses.

In our opinion, using a composite indicator of FI is an interesting idea because this does not require setting cut-offs when classifying individuals into different food insecurity categories. It should be considered especially in analyses concerning developed countries where a relatively small part of the population experiences any form of food insecurity.

Endeweld's and Silber's (2017) paper has been, to some extent, an inspiration for this study. However, besides the weighting scheme used by these authors, we additionally applied a method that takes into account the problem of the redundancy of information, limiting the influence of sub-indicators which are highly correlated. Moreover, we propose the use of a different econometric methodology. In our study, we model the risk and intensity of FI by applying a two-part model simultaneously estimating both issues.

There are a number of research papers on the food insecurity from a global or continental perspective (Broussard, 2019; Grimaccia & Naccarato, 2019; Saint Ville *et al.,* 2019; Smith *et al.,* 2017), as well as studies describing the situation in one country (Ahmadi & Melgar-Quinonez, 2018; Neter *et al.,* 2014) or the group of countries, such as the Nordic countries (Borch & Kjærnes, 2016) and the sub-Saharan African countries (Na *et al.*, 2019). As for V4, there is a shortage of studies investigating FI. The exceptions include the Dudek (2019), where the European Union Statistics on Income and Living Conditions survey data (EU-SILC) on food deprivation in V4 was used. However, EU-SILC data set provides only one indicator relating to the FI issue – it includes answers to the question whether people are unable to afford to eat meat, chicken, fish (or vegetarian equivalent) every second day. Therefore, the analysis of EU-SILC data does not cover all FI aspects encompassed by FAO's FIES methodology. FAO's approach is based on a well-grounded construct of the experience of FI composed of three domains: uncertainty/anxiety, changes in food quality, and changes in food quantity (FAO, 2020). This paper employs FAO's methodology and presents first research on food insecurity in the Visegrad Group countries applying commonly used worldwide FIES data.

Most researchers across the world indicate the important role of socio-demographic characteristics, such as education, gender, age, marital status, location of dwelling, and household composition as risk factors of FI (Broussard, 2019; Grimaccia & Naccarato, 2020; Magana-Lemus *et al.,* 2016; Smith *et al.,* 2017). Some factors associated with food insecurity may be unique to a certain country or region with particular geographic, socioeconomic and cultural settings. Therefore, there is a need to investigate the situation in various regions across the world. Specifically, the situation in the Visegrad Group countries should be examined, due to the existing gap in the FI literature regarding these Central Europe countries.

Research Methodology

The Data

The study uses Gallup World Poll (GWP) data, including FAO's FIES. The latest available data for all V4 countries refers to 2018, therefore the study analyses this data. Each country's sample size was 1,000 individuals, representative of the resident population aged 15 and older. The survey questions presented in Table 1 were asked to a nationally representative sample through face-to-face interviews. The questions refer to various FI experiences, from less to more severe experiences.

Table 1

Questions in FIES

No.	During the last 12 months, was there a time when, because of lack of money or other resources:	Short reference
(Q1)	You were worried you would not have enough food to eat	WORRIED
(Q2)	You were unable to eat healthy and nutritious food	HEALTHY
(Q3)	You ate only a few kinds of foods	FEWFOODS
(Q4)	You had to skip a meal	SKIPPED
(Q5)	You ate less than you thought you should	ATELESS
(Q6)	You ran out of food	RANOUT
(Q7)	You were hungry but did not eat	HUNGRY
(Q8)	You went without eating for a whole day	WHLDAY

Source: FAO (2020)

Food insecurity manifests itself in a range of experiences, from anxiety about running out of food, compromised dietary quality and reliance on low-cost foods, to not having enough food and going without. Respondents could answer either Yes or No.

Table 2 shows the percentage shares of individuals without any FI experiences, i.e. with negative responses on all FIES questions. Such individuals are unambiguously food-secure.

Table 2

Percentages of Food-Secure Individuals per Country

Country	Percentage	Std. Error	95 % LCI	95 % UCI
V4	86 %	1 %	85 %	87 %
Czechia	89 %	1 %	87 %	91 %
Hungary	83 %	1 %	80 %	86 %
Poland	89 %	1 %	86 %	91 %
Slovakia	84 %	1 %	81 %	86 %

Note: 95 % LCI and 95 % UCI are the lower and upper bounds of 95 % confidence intervals.

The data presented in Table 2 reveals that more than 80 % of individuals in V4 countries were food-secure. Moreover, in Czechia and in Poland there were less individuals experiencing food insecurity than in Hungary and Slovakia.

Access to the Gallup World Poll database enables to explore certain demographic and socioeconomic factors influencing the food insecurity within countries by means of using individual-level characteristics. Thus, the study examines the demographic and socioeconomic features including educational level, gender, age, location of dwelling, and equivalized annual household income expressed in international dollars as potential correlates of FI. Moreover the influence of social capital is taken into account. This is done by using a binary variable which equals one if the individuals feel they can count on their friends and family in times of need.

The Methods: Fuzzy Indicator of Food Insecurity

Food insecurity is a complex, multidimensional problem (Ebadi-Vanestanagh *et al.*, 2019; Hart, 2009; Sisha, 2019). It can be analysed from various methodological points of view (outlined in the Literature section). The study uses the fuzzy approach which is widely applied in multidimensional poverty analysis. To the best of the author's knowledge, the only paper employing a fuzzy methodology for the analysis of food insecurity in the world is (Endeweld & Silber, 2017). Endeweld and Silber (2017) adopted the suggestion made in several papers (Cerioli & Zani, 1990; Cheli & Lemmi, 1995) on multidimensional poverty, proposing a gradual transition from abject food security to definite food insecurity.

In order to obtain a fuzzy measure, the FI items need to be weighted and aggregated. Thus, the FI score for the i-th individual is defined as the weighted sum of eight items corresponding to responses to the FIES questions presented in Table 1. The value of the FI score is achieved as follow:

$$s_i = \sum_{k=1}^{8} w_k d_{ik} \quad (1)$$

where d_{ik} (k=1, 2,…,8) is a binary variable taking the value 1 if the *i*-th individual is food-insecure with respect to the *k*-th item or taking the value 0 if there is a lack of FI with respect to the *k*-th item, w_k is a weight reflecting the relative importance of the *k*-th item, wherein $0 \leq w_k \leq 1$ and $\sum_{k=1}^{8} w_k$ =1. Therefore, the value of the fuzzy indicator of FI is the weighted average across all the FI items.

In the literature on multidimensional poverty there are several weighting methods (Desai & Shah, 1988; Cerioli & Zani, 1990; Betti & Verma, 2008). The most common method is prevalence weighting proposed by Cerioli and Zani (1990):

$$\omega_k = ln \frac{1}{\bar{d}_k} \quad (2)$$

where $\bar{d}_k$ denotes the mean of the binary variable d_{ik} referring to the *k*-th poverty symptom. To sum to one, values (2) are normalized:

$$w_k = \frac{\omega_k}{\sum_{k=1}^{K} \omega_k} \quad (3)$$

where K is the number of poverty symptoms.

This approach assigns a higher weight to relatively infrequent poverty symptoms which are less common among individuals in a given population. Another frequently used method is proposed by Betti and Verma (2008), in which weights are assigned according to the following formula (Betti & Verma, 2008):

$$\omega_k = \omega_k^a \cdot \omega_k^b \quad (4)$$

where the first factor is the coefficient of variation of the *k*-th poverty indicator and the second factor is a measure which gives less weight to poverty indicators more correlated with others in order to reduce redundancy. In the case of binary indicators, the coefficient of variation can be expressed as:

$$\omega_k^a = \sqrt{\frac{1}{\bar{d}_k} - 1} \quad (5)$$

Therefore, as in Cerioli- Zani's (1990) method, this method attributes higher weights to poverty symptoms that are less frequent. The second factor, ω^b in formula (4), is defined in the following manner:

$$\omega_k^b = \left(\frac{1}{1+\sum_{k'=1}^{K} r_{kk'} | r_{kk'} < r^*}\right) \cdot \left(\frac{1}{\sum_{k'=1}^{K} r_{kk'} | r_{kk'} \geq r^*}\right) \quad (6)$$

where: $r_{kk'}$ is the correlation coefficient between two different indicators d_k and $d_{k'}$,

r^* is the predetermined cut-off correlation level,

K is the total number of poverty indicators.

Thus, the method proposed by Betti and Verma (2008) limits the influence of those indicators that are highly correlated with other poverty indicators. Finally, ω_k defined by the formula (4) are normalized to sum to one using formula (3).

Both described weighting methods are widely applied not only in multidimensional poverty research (Panek, 2010; Betti *et al.*, 2013; Tavares & Betti, 2021), but also in quality-of-life analysis (Betti, Soldi, Talev, 2016; Betti, 2016; Betti, 2017; Kwarcinski, & Ulman, 2020), quality of work (Agovino & Parodi, 2014), material deprivation research (Barcena-Martin *et al.*, 2014; Betti *et al.*, 2015; Hildebrand *et al.*, 2017), housing studies (Ulman & Cwiek, 2020), educational mismatch of graduates studies (Betti *et al.*, 2011), the analysis of the innovation processes of companies (Agovino *et al.*, 2017) and the violence against women measurement (Bettio *et al.*, 2020).

In the context of food insecurity analysis, Cerioli-Zani's approach was employed by Endeweld and Silber (2017) for household-level data from Israel. However, according to the author's knowledge, Betti-Verma weighing has not been used so far. In order to reach more robust conclusions, both presented approaches are applied in this study. To compute the same weights for all individuals in a given V4 country, mdepriv – the Stata procedure developed by Pi Alperin and Van Kerm (2014) is applied. In effect, the FI scores with values belonging to the unity interval are obtained. The higher value indicates a higher severity of food insecurity. Furthermore, the risk of FI is analysed, which in this study concerns at least one positive response to FIES questions. In order to gain a deeper insight into the socioeconomic and demographic correlates of the severity and the risk of food insecurity, regression analysis is employed.

The Methods: Model

As the FI scores lie in the closed unit interval [0;1] and many individuals had a value of this core equal to zero, the zero-inflated beta (ZIB) regression model is used to assess the association between FI and various socioeconomic and demographic characteristics. ZIB regression accounts for mass points at zero, assuming that a FI score of 0 occurs through a different process to an FI score higher than zero. It contains two sub-models:

1) a logistic regression model to predict whether or not the FI score equals 0 (zero-inflate),
2) a beta regression model to predict the FI score in the open unit interval (0;1) interval.

Thus, the first sub-model refers to the risk of FI and the second sub-model – to the severity of FI.

ZIB regression enables modelling response variables restricted between 0 and 1 including zero. It assumes the response variable has a mixed continuous-discrete distribution with probability mass at zero. The appropriate mixture density is:

$$BI_0(s,\alpha,\mu,\psi) = \begin{cases} \alpha & \text{if } s = 0 \\ (1-\alpha)f(s,\mu,\psi) & \text{if } s \in (0,1) \end{cases} \quad (7)$$

where α is the probability of observing zero,

$f(s,\mu,\psi)$ is the beta distribution density function defined as:

$$f(s,\mu,\psi) = \frac{\Gamma(\psi)}{\Gamma(\mu\psi)\Gamma((1-\mu)\psi)} s^{\mu\psi-1}(1-s)^{(1-\mu)\psi-1}, \quad (8)$$

Γ is the gamma function,

μ is the mean of the response variable s for $s \epsilon$ (0, 1),

ψ is the scaling factor related to the variance of s, for s ϵ (0, 1).

Denoting by s_1, s_2,..., s_n a random sample from zero-inflated beta distribution, where each s_i has a probability density function (7), the zero-inflated beta regression model can be defined by assuming the relationships for the mixture parameter α and the conditional mean μ (Ospina & Ferrari, 2012):

$$h(\alpha_i) = \boldsymbol{z}_i'\boldsymbol{\gamma} \quad (9)$$

$$g(\mu_i) = \boldsymbol{x}_i'\boldsymbol{\beta} \quad (10)$$

where $\boldsymbol{\gamma}$ and $\boldsymbol{\beta}$ are vectors of unknown parameters to be estimated,

$\boldsymbol{z}_i$ and $\boldsymbol{x}_i$ are vectors of known covariates of i-th individual, (i=1, 2,...,n), which may be identical or partly overlapping (Masserini *et al.*, 2017),

$h(\cdot)$: (0,1) → R, $g(\cdot)$: (0,1) → R, are strictly monotonic and twice continuously differentiable functions.

The vectors of parameters $\boldsymbol{\gamma}$ and $\boldsymbol{\beta}$ of ZIB regression can estimated by maximum likelihood. In this study, the user-contributed command zoib (Buis, 2010) with logit link for $h(\cdot)$ and $g(\cdot)$ is applied to fit the ZIB.

Results and Discussion

In the first stage of the study, the weights assigned to eight items corresponding to each response to FIES questions are computed. The results obtained using the Cerioli-Zani method and the Betti-Verma method are presented in Table 3.

Table 3

The Weights Used in the Analysis

No.	Short reference	The Cerioli-Zani method				The Betti-Verma method			
		CZ	HU	PL	SK	CZ	HU	PL	SK
(Q1)	WORRIED	0.094	0.084	0.090	0.102	0.070	0.052	0.071	0.085
(Q2)	HEALTHY	0.099	0.091	0.096	0.108	0.082	0.078	0.079	0.068
(Q3)	FEWFOODS	0.099	0.088	0.095	0.095	0.073	0.075	0.062	0.077
(Q4)	SKIPPED	0.135	0.144	0.137	0.137	0.112	0.119	0.133	0.126
(Q5)	ATELESS	0.125	0.122	0.113	0.124	0.103	0.116	0.100	0.166
(Q6)	RANOUT	0.128	0.118	0.115	0.128	0.160	0.102	0.107	0.115
(Q7)	HUNGRY	0.148	0.153	0.156	0.150	0.214	0.170	0.178	0.225
(Q8)	WHOLEDAY	0.172	0.201	0.199	0.157	0.188	0.290	0.270	0.139

As shown in Table 3, regardless of the method used, the lowest weights in all countries relate to the first three FIES questions, while the highest – to the last two. The Cerioli-Zani method yields slightly different weights than the Betti-Verma method. This is due to differences in the calculation of weights (see formulas 2-6). The first method uses the normalized logarithm of the inverse of the proportion of the food-insecure individuals. The second method however, takes into account both the relative frequency of the FI items and the correlation among them.

Using the formula (1), the FI score with values ranging from 0 to 1 is determined. A value of 0 means that an individual is unambiguously food-secure, and a value of 1 means that an individual is definitely food-insecure. According to the results presented in Table 2, more than 80 % of individuals in V4 countries were food-secure in 2018. Thus, for these individuals the FI score equals zero. By contrast, it is found that only 26 individuals experienced each FI symptom. In such cases, score values of 1 are replaced by values of 0.999. For those individuals with a greater than zero value of the FI score, the severity of food insecurity is investigated. The mean values of the FI severity are presented in Tables A1 in Appendix. In order to assess the impact of various socioeconomic and demographic factors on the risk and the severity of FI, the parameters of regression models are estimated. The results for two ZIB regression models for the FI score obtained using the Cerioli-Zani method and the Betti-Verma method are shown in Table 4. In these models results for the first sub-model predicting whether or not the FI score equals 0 are the same. On the other hand, estimates for the second sub-model predicting to the severity of FI differ.

Table 4

The Estimates of Zero-Inflated Beta Regression Models

Variable	Logistic regression sub-model for the probability of experiencing of food security		Beta regression sub-model for severity of FI for the FI score obtained using the Cerioli-Zani method		Beta regression sub-model for severity of FI for the FI score obtained using the Betti-Verma method	
	Estimates of γ	***SE***	***Estimates of β***	***SE***	***Estimates of β***	***SE***
Constant	**0.963**	**0.112**	**3.544**	**1.157**	**3.475**	**1.113**
Logarithm of income	**0.492**	**0.166**	**-0.354**	**0.111**	**-0.358**	**0.106**
Number of adults in household	**0.142**	**0.067**	**-0.146**	**0.040**	**-0.143**	**0.039**
Social capital	**1.060**	**0.147**	**-0.466**	**0.131**	**-0.466**	**0.131**
Age	**-0.093**	**0.021**	-0.015	0.022	-0.018	0.022
Squared age	**0.0009**	**0.0002**	0.0002	0.0002	0.0002	0.0002
Woman	**-0.387**	**0.117**	-0.034	0.097	-0.031	0.095
Unemployed	**-1.048**	**0.325**	0.295	0.240	0.286	0.243
Married	**0.556**	**0.137**	-0.011	0.128	0.005	0.127
Education (Ref.: Primary)						
Higher	**1.375**	**0.251**	**-0.082**	**0.021**	**-0.099**	**0.020**
Secondary	**0.804**	**0.162**	0.113	0.098	0.116	0.095
Country (Ref.: Poland)						
Czechia	-0.138	0.172	0.162	0.135	0.191	0.134
Hungary	**-0.410**	**0.174**	0.085	0.120	0.061	0.115
Slovakia	**-0.615**	**0.167**	**0.283**	**0.124**	**0.356**	**0.122**

Note: SE are standard errors of estimated parameters. All reported standard errors are robust to heteroscedasticity. Values in bold denote significant results at a level of 0.05.

The significance of parameter estimates of denotes the significance of the impact of explanatory variables on response variables. Table 4 presents the results for ZIB regression with those explanatory variables which are statistically significant at a level of 0.05 in at least one sub-model. When comparing the results for the risk and the severity of FI, it can be found that some socioeconomic and demographic factors significantly influenced one process but not another. Thus, the answer to the first research question is negative. Specifically, for the risk of FI, all explanatory variables included in ZIB regression are statistically significant at a level of 0.05. However, characteristics such as gender, age, being married and unemployed are not statistically significant correlates of the severity of FI. It means that the risk and the severity of FI are different phenomena, which should be separately modelled by two sub-models.

The estimates for the risk of FI should be interpreted conversely to the results presented in second column in Table 4. This is because, when examining the risk of FI, the probability of a positive answer to at least one of eight FIES questions are considered, whereas the estimation of ZIB regression provides results for the probability of food-security. Therefore, the results of ZIB regression sub-models must be interpreted in the opposite way. As the logistic regression sub-model estimates the probability that an individual is unambiguously food-secure (i.e. the probability of the FI score being zero), a negative estimate of a parameter indicates that the corresponding covariate has a positive effect on the risk of being food-insecure, while a positive coefficient indicates a negative effect. In the beta regression sub-model, a positive estimate indicates an increment in the severity of FI due to growth (or to a change in state) in the covariate, while a negative coefficient shows the opposite. Therefore, with the above remark in mind, the risk and the severity in V4 declines if an income increases. This result is consistent with other studies finding that income is an important correlate of FI (Broussard, 2019; Smith *et al.*, 2017). However, on the one hand, Dudek and Myszkowska-Ryciak (2020) indicate that food insecurity can be experienced also by those not living in income poverty and, on the other hand, some income-poor people can be food-secure. The next crucial correlate is social capital. The results presented in Table 4 reveal that the risk and the severity were lower among the individuals feeling they could count on friends and family in times of need. This finding is largely consistent with previous research (Nosratabadi *et al.*, 2020; Smith *et al.*, 2017) indicating that social capital directly and indirectly improves food security. In particular, Nosratabadi et al. (2020) argue that interaction among people results in sharing food products and information, which facilitates food availability and access to food. Another common correlate for the risk and the severity of FI is the number of adults in an individual's household. However, it is found that the number of children is insignificant in both sub-models. As reported in Table 4, a higher number of adults results in increases in the probability of being food-secure and decreases the severity of food insecurity.

As for the remaining socioeconomic and demographic variables included in the models, it turned out that they are statistically significant only in the zero-inflated regression sub-model.

Specifically, it was found that, according to the ceteris paribus assumption:

- poor school education is associated with an increased risk of FI;
- the risk of FI was higher among women than among men;
- married persons were under less risk of FI that the people with other marital status;
- a higher risk of FI was noted among unemployed persons compared to those with a different employment status;
- age had an inverted U-shaped effect. In other words, respondents were under less risk of FI when they were younger and older than when they were middle-aged.

The results regarding the socioeconomic factors influencing the risk of FI are consistent with other studies to a large degree. In line with previous research (Garratt, 2020; Smith *et al.*, 2017), this study confirms the role of education, current income, gender and age as extremely important factors influencing the risk of FI. Similarly to (Grimaccia & Naccarato, 2020) our results indicate that married persons were under less risk of FI and consistently with Smith et al. (2017) it is found that unemployed persons were under the higher risk of FI. Nevertheless, it is difficult to directly compare the obtained results with the findings of other studies, as different authors used non-identical models in their analyses. In particular, in the models for binary variables, the authors used different thresholds dividing the population into two parts.

In fact, the only research that can be compared with the results relating the severity of FI is (Endeweld & Silber, 2017). In that paper, a tobit regression is implemented for analysis of the fuzzy score obtained via Cerioli-Zani weighting. Endeweld and Silber (2017) found for Israeli data that age and educational level were statistically significant correlates. These results are not fully confirmed in this study analysing V4. Nevertheless, it is worth noting that our findings relating the severity of FI are robust due to the systems of weighting. This study finds that different weighting approaches do not affect the picture of FI.

Apart from the above-mentioned individual-level correlates, the study finds that the country of residence differentiated the risk and the severity of FI once all other individual-level characteristics are controlled for. Therefore, the answer to the second research question is positive. Specifically, Slovaks and Hungarians were on average under higher risk of FI than Poles. In addition, experiencing food insecurity in Slovakia was more severe than in Poland. This finding means that food insecurity resulted not only from each individual's characteristics, but various country-level factors may also influence the risk and the severity of FI. Such differences are associated with the average well-being in given countries (see Table A2). Specifically, compared to Hungary and Slovakia, Poland exhibited a higher value of the Human Development Index and a smaller share of people living in households making ends meet with difficulty. Moreover, median income and expenditures on social protection per inhabitant in Hungary and Slovakia were lower than in Poland and Czechia. Despite the fact that Czechia was the leader among V4 countries in all the mentioned indicators, no statistical difference between Czechia and Poland has been observed. This could be due to the fact that in Poland in 2018 food prices were by far the lowest in the V4 (Main Indicators of the Visegrad Group Countries, 2018).

Strengths, Limitations and Further Research

Although there is an increasing amount of literature on food insecurity in advanced economies, still little is known about the V4 countries in this respect. In particular, analysis based on FAO's FIES data for V4 have not been conducted so far. The use of this data which is validated consistently almost all over the world contributes to the strengths of the study. The analysed samples are nationally representative of the resident, non-institutionalized population aged 15 years and older in each country. Inclusion of FIES to the Gallup World Poll survey enables to investigate the influence of socioeconomic and demographic characteristics on FI experience.

The next strength of this study is a proposal for measuring FI using the fuzzy approach, which enables an analysis of FI as a degree rather than an attribute that is present or absent among individuals in a given population. Therefore, in the first step of the study, the FI score as a composite indicator aggregating all eight FI items is constructed. To achieve more robust results, two different weighting schemes are used in aggregating of the items. As a result, two scores ranging from 0 to 1 are calculated, wherein 0 means that an individual is unambiguously food-secure, and 1 means that an individual is definitely food-insecure, while all intermediate values indicate partial FI. In the second step, to identify the correlates of FI, a regression analysis is conducted. The analysed data indicates the need to use a zero-inflated beta regression model. According to the author's best knowledge, the application of such a model in modelling FI is a novelty, therefore this paper contributes to the literature in the field of FI modelling. Thus, the study proposes a methodological approach to analyze the scientific problem in question. It can serve as a new tool for the analysis of food insecurity. It is expected the paper will inspire other researchers and will have academic implications.

Despite the mentioned strengths, several limitations should be noted. First of all, the study does not include factors which may be interesting but are missing in the GWP database. In particular, it would be worth considering, apart from income, other characteristics relating to the financial situation of individuals. Specifically, including in models such factors relating to assets could provide an interesting insight into the FI profile, as literature shows, savings accumulated in the past enhance the capacity to current consumption, while debts reduce it (Chang, Chatterjee & Kim, 2014; Guo, 2011). Moreover, the cross-sectional nature of the data does not allow identifying the persistence of experiencing of FI. Thus, it is not known whether individuals are permanently food-insecure or whether they experience incidental FI in a given year.

Furthermore, it should be stressed that the fuzzy indicator is a composite indicator, which has advantages and disadvantages. On the one hand, Maggino and Zumbo (2012) argue that an important advantage of composite indicators is that they can overcome problems concerning reliability, precision, accuracy, and validity that are associated with using sub-indicators. Specifically, a latent phenomenon of food insecurity that is not directly observable through one sub-indicator requires the integration of multiple sub-indicators, each corresponding to a particular aspect of FI. On the other hand, composite indicators tend to be marred by problems ranging from the arbitrariness of weights to loss of information in the aggregation process. Thus, they are prone to become black boxes, which may make it difficult for outsiders to understand calculations, assumptions and meanings (Molle & Mollinga, 2003).

Future research is highly advisable to explore the impact of the COVID-19 pandemic on the risk and the severity of FI. Research in such countries as Jordan (Elsahoryi *et al.*, 2020), Peru (Canari-Casano *et al.*, 2021), Mexico (Gaitan-Rossi *et al.*, 2020), Brazil (Tavares & Betti, 2021) and the US (Wolfson & Leung, 2020) revealed that COVID-19 and national lockdowns have a tangible impact on food security. In addition, the first results for Poland indicate that the pandemic resulted in a reduction on food purchases for financial reasons (Kalinowski & Wyduba, 2020). It is likely that the current period of COVID-19 pandemic may exacerbate individual food insecurity and make the problem of FI worse. Thus, as the Visegrad group has been hit hard by the COVID-19 pandemic, there is a need for the consistent monitoring of food insecurity in these countries.

Conclusions

Food insecurity occurs not only in less-developed countries, but also in countries of the European Union. Specifically, the study finds, that 14 % of the Visegrad Group population was at risk of FI. To measure how deep food insecurity was, the severity of FI is investigated. Therefore, the study goes beyond conventional studies based on a binary split between food insecurity and food security. It adopts a fuzzy approach widely applied in multidimensional poverty research. Moreover, it investigates the risk and the severity of FI by the use of a two-part zero-inflated beta regression model simultaneously estimating both issues. Thus, the study proposes a methodological tool to analyze the complex phenomenon of food insecurity. It can help to understand the mechanisms behind the risk and the intensity of FI.

The study uses the 2018 Gallup World Poll dataset, comprised of nationally representative samples of adult individuals in each of the V4 countries, included the eight questions of the Food Insecurity Experience Scale module, as well information on various socioeconomic and demographic characteristics. The Food Insecurity Experience Scale focuses on food-related behaviours and experiences associated with difficulties in accessing food due to resource constraints.

Empirical analysis reveals interesting facts. First, the risk and the severity of FI are different phenomena, which should be separately modelled by two sub-models. Some characteristics were only statistically significant in the risk sub-model, but not significant in the severity sub-model. It is found that the risk of FI was higher among people with lower income, poorly-educated, women, the unemployed, living in one-person-households, middle-aged, not being married, and those feeling they could not count on friends and family in times of need. However, the set of correlates for the severity of FI is much less numerous – it contains individual level characteristics such as income, social capital and the number of adults in a household.

Moreover, pronounced country-specific heterogeneity is observed – Hungary and Slovakia were more under the risk of FI compared to Poland. Exposure to food insecurity was associated with country-level features, such as average well-being, social policy, and economic conditions. However, there was no statistical difference in the risk and the severity of FI between Czechia and Poland. This is a somewhat surprising result, because Czechia achieved better results than Poland taking into account most macroeconomic and well-being indicators. However, to some extent, the explanation for this result may be lower food prices in Poland.

The results help to better understand the profile of food insecurity in the V4 countries. They provide guidelines for prioritizing certain policies by identifying vulnerable groups. Knowledge about socioeconomic correlates of FI is essential to formulate responsible policies dedicated to relieving food insecurity. Monitoring FI can be useful to identify and understand this salient aspect of poverty and to recognize population subgroups with particularly severe conditions. This is crucial in the context of achieving the second Sustainable Development Goal established by the United Nations.

Acknowledgements

The author is grateful to Ms. Meghan Miller from the FAO Food Security and Nutrition Statistics Team for her able assistance and kind support in the FIES data acquisition process.

Annexes

Table A1

The Mean Severity of Food Insecurity

Statistics	The Cerioli-Zani method				The Betti-Verma method			
	CZ	HU	PL	SK	CZ	HU	PL	SK
Mean	0.306	0.323	0.307	0.327	0.273	0.274	0.261	0.305
Std. Error	0.024	0.021	0.021	0.022	0.024	0.020	0.020	0.022
95% LCI	0.259	0.282	0.266	0.285	0.225	0.236	0.222	0.262
95% UCI	0.353	0.363	0.348	0.370	0.320	0.313	0.299	0.349

Table A2

Values of Selected Country-Level Variables in 2018

Country	Food prices	Median income	Difficulty to make ends meet	Social protection	HDI
Czechia	83.9	13,264	11.7	5,589.38	0.898
Hungary	84.5	8,634	22.6	4,080.41	0.850
Poland	69.1	11,546	13.3	4,732.32	0.877
Slovakia	93.6	9,744	17.0	4,132.41	0.858

- Food prices – food price level indices (EU28=100), source Eurostat database (2021);
- Median income – Median equivalised net income (in Purchasing Power Standard (PPS)), source Eurostat database (2021);
- Difficulty to make ends meet – percentage of people living in households making ends meet with difficulty, source Eurostat database (2021);
- Expenditure on social protection (in Purchasing power standard (PPS) per inhabitant), source Eurostat database (2021);
- HDI – Human Development Index, source Human Development Index database (2021).

References

Agovino, M., & Parodi, G. (2014). Identifying the Quality of Work by Fuzzy Sets Theory: A Comparison Between Disabled and Non-disabled Workers. *Social Indicators Research,* 119, 1627–1648. https://doi.org/10.1007/s11205-013-0568-4

Agovino, M., Aldieri, L., Garofalo, A., & Vinci, C.P. (2017). Quality and quantity in the innovation process of firms: a statistical approach. *Quality & Quantity*, 51, 1579–1591 https://doi.org/10.1007/s11135-016-0353-y

Ahmadi, D., & Melgar-Quinonez, H. (2018). Use of the food insecurity experience scale to assess food security status in Ireland, 2014–17: A cross-sectional analysis. *The Lancet*, 392, 16. https://doi.org/10.1016/S0140-6736(18)32868-X

Barcena-Martin, E., Lacomba, B., Moro-Egido, A.I. & Perez-Moreno, S. (2014). Country Differences in Material Deprivation in Europe. *Review of Income and Wealth*, 60, 802–820. https://doi.org/10.1111/roiw.12030

Barlow, P., Loopstra, R., Tarasuk, V., & Reeves, A. (2020). Liberal trade policy and food insecurity across the income distribution: an observational analysis in 132 countries, 2014–17. *Lancet Glob Health*, 8(8):e1090-e1097. https://doi.org/10.1016/S2214-109X(20)30263-1

Ben-Davies, M. E., Kinlaw, A., del Campo, Y. E., Bentley, M, E., & Siega-Riz, A. M. (2014). Risk factors associated with the presence and severity of food insecurity in rural Honduras. *Public Health Nutrition*, 17, 5–13. http://dx.doi.org/10.1017/S1368980013002048

Bernaschi, D. (2020). Food Insecurity in Europe: From the Availability of Food to the Substantive Freedoms in Accessing it. In D. Bernaschi (Ed.), Collective Actions of Solidarity against Food Insecurity. RaumFragen: Stadt – Region – Landschaft (pp. 1-10). Wiesbaden: Springer. https://doi.org/10.1007/978-3-658-31375-3_1

Betti, G., & Verma, V. (2008). Fuzzy measures of the incidence of relative poverty and deprivation: a multi-dimensional perspective. *Statistical Methods and Applications*, 17(2), 225–250. https://doi.org/10.1007/s10260-007-0062-8

Betti, G., D'Agostino, A., & Neri, L. (2011). Educational mismatch of graduates: a multidimensional and fuzzy indicator. *Social Indicators Research*, 103(3), 465–480. https://doi.org/10.1007/s11205-010-9712-6

Betti G., Calik G., & Karakas M. (2013). Multidimensional and Fuzzy Measures of Poverty and Inequality in Turkey at National and Regional Level. In V. Berenger, F. Bresson (Ed.), Poverty and Social Exclusion around the Mediterranean Sea. Economic Studies in Inequality, Social Exclusion and Well-Being, vol 9., (p. 89-108). Boston, MA: Springer. https://doi.org/10.1007/978-1-4614-5263-8_4

Betti, G., Gagliardi, F., Lemmi, A., & Verma, V. (2015). Comparative measures of multidimensional deprivation in the European Union. *Empirical Economics*, 49, 1071–1100. https://doi.org/10.1007/s00181-014-0904-9

Betti, G., Soldi, R., & Talev, I. (2016). Fuzzy multidimensional indicators of quality of life: The empirical case of Macedonia. *Social Indicators Research*, 127(1), 39–53. https://doi.org/10.1007/s11205-015-0965-y

Betti, G. (2016). Fuzzy Measures of Quality of Life: a Multidimensional and Comparative Approach. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems,* 24, 25–37. https://doi.org/10.1142/S021848851640002X

Betti, G. (2017). Fuzzy measures of quality of life in Germany: a multidimensional and comparative approach. *Quality & Quantity*, 51, 23–34. https://doi.org/10.1007/s11135-015-0291-0

Bettio, F., Ticci, E., & Betti, G. (2020). A Fuzzy Index and Severity Scale to Measure Violence Against Women. *Social Indicators Research*, 148, 225–249. https://doi.org/10.1007/s11205-019-02197-7

Bialek, J., & Roszko-Wojtowicz, E. (2021). Dynamics of price level changes in the Visegrad group: comparative study. *Quality & Quantity,* 55**,** 357–384. https://doi.org/10.1007/s11135-020-01021-6

Bieszk-Stolorz, B., & Dmytrow, K. (2020). Influence of Accession of the Visegrad Group Countries to the EU on the Situation in Their Labour Markets. *Sustainability*, *12*(16), 6694. https://doi.org/10.3390/su12166694

Borch, A., & Kjærnes, U. (2016). The Prevalence and Risk of Food Insecurity in the Nordic Region: Preliminary Results. *Journal of Consumer Policy*, 39, 261–274. https://doi.org/10.1007/s10603-016-9316-x

Broussard, N. H. (2019). What explains gender differences in food insecurity. *Food Policy*, 83, 180–194. https://doi.org/10.1016/j.foodpol.2019.01.003

Buis, M. (2010). ZOIB: Stata module to fit a zero-one inflated beta distribution by maximum likelihood. *Statistical Software Components*, S457156, Boston College Department of Economics. https://ideas.repec.org/c/boc/bocode/s457156.html

Cafiero, C., Viviani, S., & Nord, M. (2018). Food security measurement in a global context: the food insecurity experience scale. *Measurement, 116*, 146–152. https://doi.org/10.1016/j.measurement.2017.10.065

Canari-Casano, J. L., Elorreaga, O. A., Cochachin-Henostroza, O., Huaman-Gil, S., Dolores-Maldonado, G., Aquino-Ramirez, A., Giribaldi-Sierralta, J. P., Aparco, J. P., Antiporta, D. A., & Penny, M. (2021). Social predictors of food insecurity during the stay-at-home order due to the COVID-19 pandemic in Peru. Results from a cross-sectional web-based survey. *medRxiv: the preprint server for health sciences*, 2021.02.06.21251221. https://doi.org/10.1101/2021.02.06.21251221

Cerioli, A., & Zani, S. (1990). A Fuzzy approach to the measurement of poverty. In C. Dagum, M. Zenga (Ed.) Income and Wealth Distribution, Inequality and Poverty, Studies in Contemporary Economics, (pp. 272–284). Berlin: Springer Verlag. https://doi.org/10.1007/978-3-642-84250-4_18

Chang, Y., Chatterjee, S., & Kim, J. (2014). Household finance and food insecurity. *Journal of Family and Economics Issues*, 35(4), 499-515. https://doi.org/10.1007/s10834-013-9382-z

Cheli, B., & Lemmi, A. (1995). A 'totally' fuzzy and relative approach to the multidimensional analysis of poverty. *Economic Notes*, 24(1), 115–134.

Chrzanowska, M., Landmesser, J., & Zielinska-Sitkiewicz, M. (2018). Quality of life in the Visegrad group countries - a multidimensional approach. In M. Reiff, P. Gežik (Ed.), Quantitative Methods in Economics. Multiple Criteria Decision Making XIX : proceedings of the International Scientific Conference (pp. 41–49). Bratislava: Letra Edu.

Desai, M., & Shah, A. (1988). An econometric approach to the measurement of poverty. *Oxford Economic Papers*, 40(3), 505–522. https://doi.org/10.1093/oxfordjournals.oep.a041868

Dudek, H., & Chrzanowska, M. (2018). Subjective Equivalence Scales for the Visegrad Group Countries Based on Minimum Income Question. In M. Reiff, P. Gežik (Ed.), Quantitative Methods in Economics. Multiple Criteria Decision Making XIX : proceedings of the International Scientific Conference (pp. 65-71). Bratislava: Letra Edu.

Dudek, H. (2019). Households' food insecurity in the V4 countries: microeconometric analysis. *Amfiteatru Economic*, 21, 377–392. DOI: 10.24818/EA/2019/51/377

Dudek, H., & Myszkowska-Ryciak, J. (2020). The prevalence and socio-demographic correlates of food insecurity in Poland. *International Journal of Environmental Research and Public Health*, 17, 6221. https://doi.org/10.3390/ijerph17176221

Dudek, H., & Szczesny, W. (2021). Multi-Dimensional Material Deprivation in the Visegrad Group: Zero-Inflated Beta Regression Modelling, in G. Betti, A. Lemmi (Ed.), Analysis of Socio-Economic Conditions: Insights from a Fuzzy Multidimensional Approach (pp. 151–165). London and New York: Routledge. https://doi.org/10.4324/9781003053712-10

Ebadi-Vanestanagh, M., Azizi-Lalabadi, M., Jahangiry, L., & Alizadeh, M. (2019). Challenges of Food Insecurity Indicators, Diet Quality and Weight Outcomes in Women: A Cross-Sectional Study. *Preventive nutrition and food science*, 24(4), 393–399. https://doi.org/10.3746/pnf.2019.24.4.393

Elsahoryi, N., Al-Sayyed, H., Odeh, M., McGrattan, A., & Hammad, F. (2020). Effect of Covid-19 on food security: A cross-sectional survey. *Clinical nutrition ESPEN, 40*, 171–178. https://doi.org/10.1016/j.clnesp.2020.09.026

Endeweld, M., & Silber, J. (2017). On Food Security in Israel, Z.-Y. Zhou, G. Wan (Ed.), Food. Insecurity in Asia. Why Institutions Matter (pp.192–256). Tokyo: Asian Development Bank Institute

Eurostat database (2021). https://ec.europa.eu/eurostat/data/database (Accessed 25 March, 2021).

FAO (2003). *Food security: concepts and measurement*, http://www.fao.org/3/y4671e/y4671e06.htm (Accessed 16 February, 2021).

FAO (2008). *An Introduction to the Basic Concepts of Food Security*. United Nations Food and Agriculture Organization: Rome, Italy.

FAO (2020). *Voices of the Hungry*. http://www.fao.org/in-action/voices-of-the-hungry/faq/en/ (Accessed 6 February, 2021).

Ferrari, S. L. P., & Cribari-Neto, F. (2004). Beta regression for modelling rates and proportions. *Journal of Applied Statistics*, 31(7), 799–815. https://doi.org/10.1080/0266476042000214501

Gaitan-Rossi, P., Vilar-Compte, M., Teruel, G., & Perez-Escamilla, R. (2021). Food insecurity measurement and prevalence estimates during the COVID-19 pandemic in a repeated cross-sectional survey in Mexico. *Public health nutrition*, 24(3), 412–421. https://doi.org/10.1017/S1368980020004000

Garcia-German, S., Bardaji, I., & Garrido, A. (2018). Do increasing prices affect food deprivation in the European Union?. *Spanish Journal of Agricultural Research*, 16(1), 1–14. https://doi.org/10.5424/sjar/2018161-11254

Garratt, E. (2020). Food insecurity in Europe: Who is at risk, and how successful are social benefits in protecting against food insecurity? *Journal of Social Policy, 49*(4), 785–809. https://doi.org/10.1017/s0047279419000746

Grimaccia, E., & Naccarato, A. (2019). Food insecurity individual experience: a comparison of economic and social characteristics of the most vulnerable groups in the world. *Social Indicators Research*, 143, 391–410. https://doi.org/10.1007/s11205-018-1975-3

Grimaccia, E., & Naccarato, A. (2020). Food Insecurity in Europe: A Gender Perspective. *Social indicators research*, 1–19. Advance online publication. https://doi.org/10.1007/s11205-020-02387-8

Guo, B. (2011). Household assets and food security: evidence from the survey of program dynamics. *Journal of Family and Economic Issues*, 32(1), 98–110. https://doi.org/10.1007/s10834-010-9194-3

Gundersen, C. G., & Garasky, S. B. (2012). Financial management skills are associated with food insecurity in a sample of households with children in the United States. *Journal of Nutrition*, 142(10), 1865–1870. https://doi.org/10.3945/jn.112.162214

Hart, T. G. (2009). Exploring definitions of food insecurity and vulnerability: time to refocus assessments. *Agrekon,48*(4), 362–383. https://doi.org/10.1080/03031853.2009.9523832

Hildebrand, V. A., Pi Alperin, M. N., & Van Kerm, P. (2017). Measuring and accounting for the deprivation gap of Portuguese immigrants in Luxembourg. *Review of Income Wealth*, 63(2), 288–309. https://doi.org/10.1111/roiw.12210

Hossain, M. B., Long, M. A., & Stretesky, P. B. (2021). Welfare State Spending, Income Inequality and Food Insecurity in Affluent Nations: A Cross-National Examination of OECD Countries. *Sustainability*, *13*, 324. https://doi.org/10.3390/su13010324

Human Development Index (2021). http://hdr.undp.org/en/data (Accessed 25 March, 2021).

Interlenghi, G., & Salles-Costa, R. (2015). Inverse association between social support and household food insecurity in a metropolitan area of Rio de Janeiro, Brazil. *Public Health Nutrition, 18*(16), 2925–2933. doi:10.1017/S1368980014001906

Jankiewicz, M., & Pietrzak, M. B. (2020). Assesment of Trends in the Share of Expenditure on Services and Food in the Visegrad Group Member States. *International Journal of Business and Society*, 21(2), 977–996. https://doi.org/10.33736/ijbs.3306.2020

Kalinowski, S.& Wyduba, W. (2020). Moja sytuacja w okresie koronawirusa. Raport koncowy, Warszawa: Wydawnictwo IRWiR PAN. https://doi.org/10.53098/9788389900609

Koisova, E., Grmanova, E., Skrovankova, K., & Kostrova, J. (2019). Competitiveness of regions in the visegrad group countries. *Inzinerine Ekonomika–Engineering Economics*, 30(2), 203–210. https://doi.org/10.5755/j01.ee.28.5.18204

Kwarcinski, T., & Ulman, P. (2020). Quality of life paradox. Well-being ranking of the selected European countries based on hybrid well-being approach. *Economics and Sociology*, 13(2), 160–180. http://dx.doi.org/10.14254/2071-789X.2020/13-2/12

Loopstra, R. (2020). An overview of food insecurity in Europe and what works and what doesn't work to tackle food insecurity, *European Journal of Public Health*, 30 (5), ckaa165.521, https://doi.org/10.1093/eurpub/ckaa165.521

Loopstra R., Reeves A., & Stuckler D. (2015). Rising food insecurity in Europe. Lancet. 23; 385(9982):2041. https://doi.org/10.1016/S0140-6736(15)60983-7

Magana-Lemus, D., Ishdorj, A., Rosson, P. III. & Lara-Alvarez, J., (2016). Determinants of household food insecurity in Mexico. *Agricultural and Food Economics*, 4(10), 1-20. https://doi.org/10.1186/s40100-016-0054-9

Maggino, F., & Zumbo, B. D. (2012). Measuring the Quality of Life and the Construction of Social Indicators. In K. C. Land, A. C. Michalos, M. J. Sirgy (Ed.), Handbook of Social Indicators and Quality of Life Research (pp. 201–238): Springer Netherlands. http://dx.doi.org/10.1007/978-94-007-2421-1_10

Main Indicators of the Visegrad Group Countries, (2018). https://www.ksh.hu/docs/eng/xftp/idoszaki/ev4_fobbadatok.pdf (Accessed 25 March, 2021).

Masserini, L., Bini, M., & Pratesi, M. (2017). Effectiveness of non-selective evaluation test scores for predicting first-year performance in university career: a zero-inflated beta regression approach. *Quality & Quantity*, 51(2), 693–708. https://doi.org/10.1007/s11135-016-0433-z

Molle, F., & Mollinga, P. (2003). Water poverty indicators: Conceptual problems and policy issues. *Water Policy*, 5, 529–544. https://doi.org/10.2166/wp.2003.0034

Na, M., Miller, M., Ballard, T., Mitchell, D., Hung, Y., & Melgar-Quinonez, H. (2019). Does social support modify the relationship between food insecurity and poor mental health? Evidence from thirty-nine sub-Saharan African countries. *Public Health Nutrition*, 22(5), 874–881. https://doi.org/10.1017/S136898001800277X

Neter, J. E., Dijkstra, S. C., Visser, M., & Brouwer, I. A. (2014). Food insecurity among Dutch food bank recipients: a cross-sectional study. *BMJ Open*, 4(5):e004657–e004657. https://doi:10.1136/bmjopen-2013-004657

Nosratabadi, S., Khazami, N., Abdallah, M. B., Lackner, Z., S. Band, S., Mosavi, A., & Mako, C. (2020). Social Capital Contributions to Food Security: A Comprehensive Literature Review. *Foods*, 9(11), 1650. doi:10.3390/foods9111650

Ospina, R., & Ferrari, S. L. P. (2012). A general class of zero-or-one inflated beta regression models. *Computational Statistics and Data Analysis,* 56(6), 1609–1623. https://doi.org/10.1016/j.csda.2011.10.005

Panek, T. (2010). Multidimensional approach to poverty measurement: Fuzzy measures of the incidence and the depth of poverty. *Statistics in Transition*, 11(2), 361–379.

Pi Alperin, M. N., & Van Kerm, P. (2014). MDEPRIV: Stata module to compute synthetic indicators of multiple deprivation. *Statistical Software Components* S457806, Boston College Department of Economics.

Poczta-Wajda, A., Sapa, A., Stepien, S., & Borychowski, M. (2020). Food Insecurity among Small-Scale Farmers in Poland. *Agriculture, 10*, 295. https://doi.org/10.3390/agriculture10070295

Pollard, C. M., & Booth, S. (2019). Food insecurity and hunger in rich countries-it is time for action against inequality. *International Journal of Environmental Research and Public Health*, 16, 1804. https://doi.org/10.3390/ijerph16101804

Reeves, A., Loopstra, R., & Stuckler, D. (2017). The growing disconnect between food prices and wages in Europe: Cross-national analysis of food deprivation and welfare regimes in twenty-one EU countries, 2004–2012. *Public Health Nutrition*, 20(8), 1414-1422. https://doi.org/10.1017/S1368980017000167

Saint Ville, A., Po, J. Y. T., Sen, A., Bui, A., & Melgar-Quinonez, H. (2019). Food security and the Food Insecurity Experience Scale (FIES): ensuring progress by 2030. *Food Security,* 11(3), 483–491. https://doi.org/10.1007/s12571-019-00936-9

Simionescu, M., Lazanyi, K., Sopkova, G., Dobes, K., & Balcerzak, A. P. (2017). Determinants of economic growth in V4 Countries and Romania. *Journal of Competitiveness*, 9(1), 103–116. https://doi.org/10.7441/joc.2017.01.07

Sinclair, K., Ahmadigheidari, D., Dallmann, D., Miller, M., & Melgar-Quinonez, H. (2019). Rural women: Most likely to experience food insecurity and poor health in low- and middle-income countries. *Global Food Security*, 23, 104–115. https://doi.org/10.1016/j.gfs.2019.04.006.

Sisha, T. A. (2019). Household level food insecurity assessment: Evidence from panel data, Ethiopia. *Scientific African*, 7. 1–9. https://doi.org/10.1016/j.sciaf.2019.e00262

Smith, M. D., Rabbitt, M. P., & Coleman-Jensen, A. (2017). Who are the world’s food insecure? New evidence from the Food and Agriculture Organization's food insecurity experience scale. *World Development*, 93, 402–12. https://doi.org/10.1016/j.worlddev.2017.01.006

Su, W., Betti, G., & Ucar, B. (2020). Longitudinal measures of fuzzy poverty: a focus on Czechia, Hungary and Poland after the crisis. *Quality & Quantity,* 54, 27–41. https://doi.org/10.1007/s11135-019-00933-2

Tavares, F. F., & Betti, G. (2021). The Pandemic of Poverty, Vulnerability, and COVID-19: Evidence from a Fuzzy Multidimensional Analysis of Deprivations in Brazil. *World Development*, 139, 105307. https://doi.org/10.1016/j.worlddev.2020.105307

Ulman, P., & Cwiek M. (2020). Measuring housing poverty in Poland: a multidimensional analysis. *Housing Studies*. https://doi.org/10.1080/02673037.2020.1759515

United Nations. (2015). Sustainable Development Goals https://www.un.org/sustainabledevelopment/sustainable-development-goals/ (Accessed 16 February, 2021).

Wolfson, J. A., & Leung, C. W. (2020). Food insecurity and COVID-19: Disparities in early effects for US adults. *Nutrients*, 12, 1648. https://doi.org/10.3390/nu13030851

Zace, D., Di Pietro, M. L., Caprini, F., de Waure C., & Ricciardi, W. (2020). Prevalence and correlates of food insecurity among children in high-income European countries. A systematic review. *Annali dell’Istituto Superiore di Sanità,* 56(1), 90–98. https://doi.org/10.4415/ANN_20_01_13. PMID: 32242540

Author’s Biography

Hanna Dudek is a professor at the Warsaw University of Life Sciences (Poland). She is a head of the Chair of Econometrics and Financial Engineering at the Institute of Economics and Finance. Her main fields of research include applied econometrics, measurement of food insecurity, multidimensional poverty analysis. She lectures on econometrics and social statistics. She is the author of numerous papers published in scientific journals.

The article has been reviewed.

Received in April 2021; accepted in February 2022.