AgEcon SEARCH
RESEARCH IN AGRICULTURAL & APPLIED ECONOMICS

The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
http://ageconsearch.umn.edu
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.

JEL: Q00, Q02, Q18

***Olha Osypova*[1], *Maryna Horna*[2], *Serhii Vashchaiev*[1], *Yaroslava Ishchuk*[1], *Oksana Pomazun*[1]**

[1]*Kyiv National Economic University named after Vadym Hetman*
[2]*SSI "Institute of Educational Analytics"*
Ukraine

CONVERGENCE OF FOOD CONSUMPTION ACROSS UKRAINIAN REGIONS: APPROACH USING SPATIAL PANEL DATA MODELS

Purpose. *The article studies the convergence between the regions of Ukraine in terms of the basic foodstuff consumption per capita during 2000–2019, taking into account the effects of spatial interaction across regions.*

Methodology / approach. *The convergence analysis between regions of Ukraine is based on the concept of β-convergence which can be tested using spatial econometric models namely spatial autoregressive models and spatial error models. The need for considering spatial interaction can be explained by the fact that regions are characterized by constant interaction with each other. Therefore, region should not be considered as isolated objects in space in empirical research with usage of panel data. Ignoring the spatial interaction between regions and using standard evaluation procedures can reduce the reliability and validity of the obtained results to some extent.*

Results. *The results of our calculation confirm the process of β-convergence of average per capita consumption of all food groups, which means that food consumption in regions with an initial low level of consumption is growing faster than in regions with high initial levels of consumption. Also, as part of the use of spatial econometric models the convergence process was determined to be influenced by spatial interaction between regions while the influence of neighbouring regions has a positive effect on food consumption in particular region.*

Originality / scientific novelty. *The article further develops the main ideas of modeling interregional differentiation based on convergence theory and for the first time, spatial econometric models were used to estimate β-convergence of Ukrainian regions by the levels of consumption of basic foodstuffs.*

Practical value / implications. *The approach proposed by the authors and the obtained results can be used both by state authorities on agrarian policy and food issues, and by enterprises of the agricultural sector in the analysis and forecasting of trends in the consumption of basic foodstuffs at the regional level; when planning the production, processing and delivery of agricultural products, when planning state or regional trade policy in the field of food. At the same time, the inclusion of spatial effects in the model of evaluating convergence will allow policymakers to take into account the geographical features of the convergence process and, accordingly, make more informed decisions to reduce the differentiation of regions of Ukraine by the levels of consumption of basic foodstuffs.*

Key words: *β-convergence, consumption of basic foodstuffs, panel data, spatial autocorrelation, spatial panel data models.*

Introduction and review of literature. A very important area of state policy in Ukraine is ensuring food security as a component of national and economic security of the country. As a whole, the effectiveness of solving this problem reflects the development level of the agro-industrial complex and the country's economical and political independence, stability and ability of the state to meet one of its citizen's needs – the need for food. Providing the population with food products of appropriate quality and in sufficient quantity contributes to a high level of physical and mental activity, maintaining human health at an appropriate level, and reducing social tension in society. The food security problem is particularly acute nowadays under the condition of the economic downturn along with inflation, low level of the population living standards and an increase in social contradictions. After eight years of an international armed conflict, food security and livelihoods in Ukraine remain poor for thousands and even millions people in need in 2022. Also the COVID-19 pandemic led to the rising of food prices, disrupted access to markets, restriction of people's movements across the contact line, reduction in industrial production. All these events complicated the food security situation of the conflict-affected population.

Consumption of certain food types per capita is one of key indicators of the country's food security. The average consumption of food products per capita should meet modern requirements for rational nutrition and ensure full active and healthy life. Significant inter regional differentiation can be quite dangerous due to the threat of various kinds of social conflicts and crises taking into consideration population well-being in particular in terms of food consumption which has developed as a result of various social, economic and historical conditions in different regions. Ukraine can be considered as one of the states where administrative- territorial units (regions) have their own peculiarities and differences in development which are caused by different social, economic and historical conditions. The regions of Ukraine are characterised by both positive and negative phenomena and trends in ensuring their own food security, as well as existing differences in the levels of consumption of basic food products. In this case, the use of the convergence theory allows us to answer the following question: are the existing differences between the regions of Ukraine in terms of food consumption decreasing over time, or on the contrary, is the differentiation of regions in terms of food consumption only increasing over time? It is also interesting to investigate whether spatial interactions between regions affect the process of convergence of Ukrainian regions. In this paper, we attempt to answer these two questions by using spatial econometric models as models for estimating convergence.

The issues of regional economic growth and convergence have been relevant topics of scientific research for several decades. The concept of convergence, based on the neoclassical Solow-Swann growth theory, was formed and became widespread thanks to the works (Mankiv et al., 1992; Barro & Sala-i-Martin, 1992; Barro & Sala-I-Martin, 1995). It is worth noting that most of the early empirical studies on convergence focused on the use of so-called growth regressions using cross-sectional data, less often panel data. At the same time, the presence of spatial interaction between the studied objects was ignored. However, as noted in the works (Meliciani & Peracchi, 2009; Arbia & Piras, 2004), this approach imposes strong a priori restrictions on the parameters of regression models and, as a consequence, can distort real estimates of convergence. Also, Le Gallo and Fingelton in their study (Le Gallo & Fingleton, 2021), devoted to the review of convergence models, confirm the need to take into account spatial interaction in the analysis of regional convergence. In the paper (Meliciani & Peracchi, 2009), an original approach for assessing regional convergence is proposed. The authors use a heterogeneous panel approach that avoids strong a priori restrictions on the parameters of the models. This, in turn, allows us to obtain different model parameters for different regions and take into account the spatial interaction between regions. Also, an increasingly common approach to the analysis of regional convergence is the use of spatial econometric models, which appeared at the intersection of econometrics and regional economics. One of the first scientific papers on spatial econometrics is traditionally considered to be the work "Estimation models for Spatial Autoregressive Structures" by Luc Anselin (Anselin, 1980). Currently, spatial econometric models are successfully used both for analyzing regional data (Zheng et al., 2008; Marques et al., 2014; Osypova et al., 2017; Sartika et al., 2017), and for analysis for groups of countries (Antczak & Suchecka, 2011; Horna et al., 2017; Lukianenko et al., 2016; Matviychuk et al., 2019). There are also many examples of studies that use spatial econometric models in convergence studies. For example, Giuseppe Armani and Gianfranco Piras (Aria & Piras, 2004) showed that taking into account spatial interaction in the convergence analysis significantly improves the estimated values of the convergence rate between European regions. A thorough analysis of convergence between European regions using spatial econometric models was carried out in the studies (Armstrong, 1995; López-Bazo et al., 2004; Fingleton & Lopez-Bazo, 2006; Piras & Arbia, 2007; Rey & Le Gallo, 2009), between regions of the USA – in the studies (Rey & Montouri, 1999; Lim & Kim, 2015). Also, the concept of convergence using spatial econometric models has been discussed not only in the literature on economic growth. In the study (Slander & Ogorevc, 2010) the authors applied a spatial approach to the study of convergence of labor costs across NUTS2 EU regions between 1996 and 2006. In a series of studies (Akarsu & Berke, 2016; Akarsu & Berke, 2020) the authors analyze β-convergence of per capital total electricity consumption across the regions of Turkey in the period 1986–2013 using spatial panel data models and conclude that the use of a spatial approach allows for more accurate estimates of convergence.

The issues of research on convergence in food consumption and food expenditure have also repeatedly become the subject of scientific research. In a study (Herrmann & Roger, 1995), the authors used a cross-section time-series model to analyze the convergence of food costs between OECD countries. The concepts of σ- and β-convergence were used in the work (Gil et al., 1995) in order to find out whether there is a trend towards a single European diet. A similar approach was used by the authors of the work (Regmi & Unnevehr, 2005) to test the presence of convergence in food expenditure among 18 high-income countries of Europe and North America in the period from 1990 to 2004. The work (Wan, 2005) is devoted to testing the presence of convergence in food consumption in rural China using econometric panel data models. The paper (Domazet, 2012) explores the existence of absolute β-convergence of consumption expenditure in the EU-27 countries in the period 2000–2007. As far as we know, most studies used cross-sectional or panel data econometric models to analyze convergence in food consumption. At the same time, we are not aware of works devoted to the study of the convergence of food consumption using spatial econometric methods.

The purpose of the article is to evaluate the convergence between the regions of Ukraine in terms of the basic foodstuff consumption per capita during 2000–2019, taking into account the effects of spatial interaction across regions.

Materials and methods. This section provides a brief overview of the dataset used in the analysis and the theoretical background of the concept of β-convergence and spatial econometric models.

Data. The statistical information source for our study is the data of the State Statistics Service of Ukraine on the average basic foodstuff consumption per capita in the Ukrainian regions in 2000–2019 years (State Statistics Service of Ukraine, 2020). The set of basic foodstuff is determined by the regulatory act of Ukraine (On food security, 2012; On approval of food sets, sets of non-food products and services for major social and demographic groups, 2016) and includes 10 product groups: meat and meat products, in terms of meat including lard and offal (hereinafter meat); milk and dairy products (hereinafter milk); eggs; bread, bread products – bread, pasta, flour, cereals, legumes(hereinafter cereals); potatoes; vegetables and melons food crops (hereinafter vegetables); fruits, berries and grapes without processing into wine (hereinafter referred to as fruits); fish and fish products (hereinafter referred to as fish); sugar; oil.

Exploratory spatial data analysis: spatial autocorrelation and spatial weight matrix. At the first stage of the study it is necessary to establish the spatial dependence presence or spatial autocorrelation in the data. The term "spatial dependence" referred to existence of a functional relationship between that happens at one point in space and that what happens at another place' (Anselin, 1988). Spatial autocorrelation indices are used to detect spatial autocorrelation in regional data. The global spatial autocorrelation index expresses the overall similarity degree between spatially close objects in terms of the value of the studied indicator *Y*. Global spatial autocorrelation indices are designed to detect the presence of a general trend towards clustering in the study area. The local spatial autocorrelation index for each region expresses the similarity degree between this and neighbouring regions by the value of the studied indicator *Y* (Moran, 1948).

Since for the purposes of this work it is enough to detect the presence of spatial effects in general we will focus only on the global index of spatial autocorrelation. The most prominent test to identify global spatial autocorrelation is spatial autocorrelation index designed by Moran (Moran, 1948):

$$I = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\cdot(y_i-\bar{y})(y_j-\bar{y})}{\frac{1}{N}\sum_{i=1}^{N}(y_i-\bar{y})^2\cdot\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}}, \qquad (1)$$

where N is the number of regions;

y_i is the value of the studied variable Y in region i;

y_j is the value of the studied variable Y in region j;

$\bar{y}$ is the average value of the studied variable Y;

w_{ij} is the elements of the spatial weight matrix W.

The weight matrix describes the proximity measure of objects in space and is a square symmetric matrix of size N×N, each element of which (w_{ij}) characterises the proximity degree of objects i and j. The diagonal elements of matrix equal a zero. There are several approaches to constructing a weight matrix, more detailed information about which can be found in the works (Anselin, 1988; Haining, 2003; Cliff & Ord, 1973; Linderhof et al., 2011). In this work we used two of the most common weight matrix types such as contiguity matrix and inverse distance matrix. The non-diagonal elements of the contiguity matrix w_{ij} are calculated in such a way: $w_{ij} = 1$ if regions i and j have a common boundary; $w_{ij} = 0$ if regions i and j do not have common boundaries. The non-diagonal elements of the inverse distance matrix were calculated using the following rule: $w_{ij} = 1/d_{ij}$, where d_{ij} is the distance between the main cities of regions i and j along highways (Drukker et al., 2013). While using contiguity matrix spatial autocorrelation is assumed to take place only between the nearest neighbouring objects in space but inverse distance matrix gives us opportunity to take into account the distance between objects in space (Linderhof et al., 2011). While calculating indices designed by Moran we can use both matrix types in order to understand which type of spatial dependence is suitable for these data. Moran index takes the value from -1 to 1. The value -1 indicates that regions with values of the studied indicator Y above average border with regions where the Y value is lower than average. The value 1 indicates the positive dependence existence: regions in which Y is above average level border each other.

Growth theory and β-convergence model. Convergence theory, based on neoclassical Solow-Swann growth theory, forecasts that a less developed region tends to grow faster than a developed region so that in long- term perspective a less developed region catches up with a developed region. This hypothesis is known as the β-convergence concept (Mankiw et al., 1992; Barro & Sala-i-Martin, 1992; Barro & Sala-i-Martin, 1995) and can be formed as an inverse relationship presence between the growth rate in regions and their initial level of development. In this work the convergence testing was conducted on the basis of a β-convergence model that takes into account panel data structure and can be generalized by the following equation (Piras & Arbia, 2007):

$$ln\left(\frac{y_{i,t}}{y_{i,t-1}}\right) = \alpha_i + \beta\, ln\left(y_{i,t-1}\right) + \varepsilon_{i,t}\ , \qquad (2)$$

where $y_{i,t}$ is basic foodstuff consumption per capita in region i, at some point in time t;

$y_{i,t-1}$ is basic foodstuff consumption per capita in region i at the point in time $t-1$;

a, β are model coefficients, which are to be evaluated;

$\varepsilon_{i,t}$ is random factor of the model.

Negative and statistically significant coefficient β in the model (2) indicates the presence of convergence. It is important to note that model (2) considers regions as isolated objects and does not take into account the influence of regions on each other. As in such works (Slander & Ogorevc, 2010; Rey & Le Gallo, 2009; Abreu et al., 2005; Le Gallo & Fingleton, 2021) is indicated, economic growth of a region can be partly explained by the neighbouring regions growth because of their spatial interaction, so to take into account the spatial dependence on the interregional convergence evaluation we should use spatial economic models.

Spatial econometric models. Spatial econometric models traditionally use two main approaches to define the main characteristics of spatial interaction: the result in one region is influenced by the results in neighbouring regions – spatial autoregressive model (SAR); the result in one region is influenced by random factors of neighbouring regions – spatial error model (SEM) (dos Santos & Faria, 2012; Elhors, 2017). We should analyse the SAR and SEM models to evaluate β-convergence.

In the spatial autoregressive model, the concept of spatial dependence means that the dependent variable is determined not only by a set of exogenous explanatory variables but also by the value of the dependent variable in neighbouring regions. Then the spatial autoregression model for evaluating β-convergence has the following form (Piras & Arabia, 2007; Slander & Ogorevc, 2010):

$$ln\left(\frac{y_{i,t}}{y_{i,t-1}}\right) = \alpha_i + \rho \sum_{j=1}^{n} W \cdot ln\left(\frac{y_{i,t}}{y_{i,t-1}}\right) + \beta\, ln\left(y_{i,t-1}\right) + \varepsilon_{i,t}\ , \qquad (3)$$

where W is spatial weight matrix;

ρ is spatial autoregressive parameter.

The significance and sign of this coefficient make it possible for us to conclude that the dependent variable in a region i is influenced by the values of the dependent variables in neighbouring regions.

The SEM model can be more appropriate in case autocorrelation is considered as an obstacle or inconvenience rather than a significant parameter which means that a random show in a region affects the growth rate in this region and additionally affects neighboring regions. The problem with the SEM model is that it often reflects only the common reflection of regions due to undefined spatially correlated missing variables. Although empirical convergence studies mostly prefer the SEM specification, this model has a weaker theoretical and interpretative meaning than SAR (Fingleton & Lopez-Bazo, 2006). The spatial error model for evaluating β-convergence is given by the following equation (Piras & Arbia, 2007; Slander & Ogorevc, 2010):

$$ln\left(\frac{y_{i,t}}{y_{i,t-1}}\right) = \alpha_i + \beta\, ln\left(y_{i,t-1}\right) + \lambda \sum_{j=1}^{n} W \cdot \varepsilon_{j,t} + \eta_i\ , \qquad (4)$$

where λ is the spatial autocorrelation coefficient of the error term;

η_i is a random factor of the model.

The significance and sign of the coefficient λ makes it possible for us to conclude that the value of the dependent variable in a region i is influenced by the factors which are random and unaccounted in the model for neighbouring regions.

To study the β-convergence of Ukrainian regions in terms of basic foodstuff consumption levels we should use both the spatial autoregressive model and the spatial error model. Also, since we use panel data, the Hausman test (Hausman, 1978) will allow us to make a choice between a fixed- effects model and random- effects model.

Results and discussion. This section provides the results of the assessment of the convergence in the Ukrainian regions in terms of basic foodstuff consumption taking into account the spatial interaction between the regions, and we discuss the obtained results.

The spatial dependence detection traditionally begins with the Moran's index calculation. The dynamics of global Moran's index for the average basic foodstuff consumption per capita in regions of Ukraine in the years 2000–2019 is presented in Table 1 (the neighbour matrix is used as the weight matrix when calculating Moran's index) and Table 2 (the inverse distance matrix is used as the weight matrix when calculating Moran's index).

Table 1

Spatial autocorrelation of basic food groups in Ukrainian regions based on Moran's global index in the years 2000–2019 (contiguity matrix)

Year	Meat	Milk	Eggs	Cereals	Potatoes	Vegetables	Fruits	Fish	Sugar	Oil
2000	0.115	0.651***	0.037	0.284**	0.453***	0.348***	-0.110	0.459***	0.219**	0.571***
2001	-0.005	0.644***	-0.038	0.288***	0.305***	0.222**	-0.039	0.452***	0.344***	0.597***
2002	-0.047	0.630***	-0.136	0.190***	0.534**	0.207**	-0.094	0.492***	0.340***	0.452***
2003	-0.08	0.624***	-0.161	-0.025	0.460***	0.270***	0.086	0.455***	0.637***	0.443***
2004	0.010	0.592***	-0.170	-0.021	0.497***	0.330***	0.136*	0.503***	0.527***	0.528***
2005	0.184**	0.553***	0.073	-0.020	0.423***	0.342***	0.155*	0.461***	0.624***	0.450***
2006	0.220**	0.526***	0.048	0.086	0.503***	0.332***	0.021	0.471***	0.512***	0.342***
2007	0.168*	0.589***	0.039	0.157*	0.518***	0.124*	0.017	0.442***	0.416***	0.182**
2008	0.211**	0.585***	0.118	0.098	0.377***	0.214**	-0.057	0.386***	0.409***	0.387***
2009	0.106	0.519***	0.162*	-0.102	0.446***	0.458***	-0.079	0.437***	-0.058	0.031
2010	0.160*	0.484***	0.262**	-0.265**	0.399***	0.452***	-0.022	0.443***	0.072	-0.092
2011	0.187**	0.510***	0.289***	-0.190	0.396***	0.450***	-0.022	0.450***	-0.079	-0.004
2012	0.225**	0.467***	0.277***	-0.205	0.381***	0.451***	0.054	0.508***	-0.205	0.014
2013	0.196**	0.527***	0.266***	-0.175	0.325***	0.385***	0.020	0.531***	-0.109	0.049
2014	0.245**	0.472***	0.257***	-0.210*	0.375***	0.362***	-0.059	0.422***	-0.127	0.176**
2015	0.127*	0.440***	0.365***	-0.059	0.441***	0.312***	0.005	0.485***	-0.094	0.355***
2016	0.117	0.322***	0.314***	-0.118	0.493***	0.203**	0.012	0.495***	-0.151	0.259**
2017	0.103	0.388***	0.256***	-0.198	0.520***	0.116	0.031	0.481***	-0.206	0.152*
2018	0.174**	0.356***	0.257***	-0.122	0.500***	0.275***	0.048	0.517***	-0.219*	-0.008
2019	0.158*	0.465***	0.275***	-0.053	0.562***	0.224**	0.118	0.569***	-0.158	-0.013

Note. p-value of the significance level of Moran's index in the table is marked as follows: for *p*-value 0.01 – ***, for *p*-value 0.05 – **, for *p*-value 0.1 – *.

Source: State Statistics Service of Ukraine (2020); own calculation.

Throughout the entire study the presence of spatial autocorrelation was diagnosed for such food groups as milk, potatoes, vegetables and fish. A significant spatial interaction impact between regions on the level of meat and eggs consumption can be traced only from 2005 and 2009 years respectively and on the level of sugar and oil consumption until 2008 year. The impact of neighbouring regions on the level of grain and fruit consumption was diagnosed only in some years. If the Moran's index is statistically insignificant the spatial interaction between regions is assumed to be unimportant. However, even in this case taking into account spatial correlation can improve the econometric model characteristics based on regional data (Baltagi & Li, 2004; Robertson & Symons, 1992). The majority of statistically significant Moran's indices are positive which indicates the direct relationship existence: the increase of a certain product consumption in a region can be explained by the increase in consumption of this product in neighbouring regions.

Table 2

Spatial autocorrelation of basic food groups in Ukrainian regions based on Moran's global index in the years 2000-2019 (inverse-distance matrix)

Year	Meat	Milk	Eggs	Cereals	Potatoes	Vegetables	Fruits	Fish	Sugar	Oil
2000	-0.02	0.282***	-0.019	0.013	0.221***	0.135***	-0.063	0.185***	0.095***	0.219***
2001	-0.032	0.292***	-0.054	0.010	0.154***	0.077***	-0.030	0.143***	0.137***	0.219***
2002	-0.051	0.290***	-0.062	0.034*	0.263***	0.093***	-0.044	0.187***	0.174***	0.119***
2003	-0.066	0.291***	-0.062	-0.018	0.201***	0.105***	-0.001	0.169***	0.293***	0.145***
2004	-0.025	0.272***	-0.078	-0.019	0.219***	0.123***	0.012	0.196***	0.244***	0.175***
2005	0.028*	0.257***	-0.002	-0.015	0.214***	0.103***	0.009	0.187***	0.282***	0.131***
2006	0.056**	0.212***	0.003	0.012	0.239***	0.092***	-0.063	0.191***	0.214***	0.082***
2007	0.033**	0.249***	-0.028	0.059**	0.255***	-0.006	-0.078	0.184***	0.193***	0.032*
2008	0.055**	0.264***	0.013	0.018*	0.185***	0.049***	-0.077	0.151***	0.202***	0.073***
2009	0.008	0.221***	0.023*	-0.047	0.212***	0.138***	-0.067	0.160***	0.010	-0.035
2010	0.046**	0.218***	0.061**	-0.083	0.196***	0.128***	-0.035	0.134***	0.028*	-0.049
2011	0.052**	0.229***	0.069***	-0.041	0.210***	0.173***	-0.036	0.150***	0.001	-0.015
2012	0.055**	0.211***	0.057**	-0.032	0.204***	0.201***	-0.006	0.167***	-0.032	-0.017
2013	0.046**	0.217***	0.062**	-0.054	0.174***	0.182***	-0.026	0.159***	-0.016	-0.023
2014	0.057**	0.195***	0.035**	-0.051	0.194***	0.131***	-0.051	0.114***	-0.050	0.007
2015	0.004	0.214***	0.066***	-0.006	0.211***	0.091***	-0.031	0.111***	-0.033	0.082***
2016	-0.015	0.155***	0.038**	-0.019	0.233***	0.062**	-0.035	0.118***	-0.060	0.056**
2017	-0.012	0.175***	0.037**	-0.042	0.257***	0.019*	-0.028	0.109***	-0.080	0.046**
2018	0.025*	0.158***	0.038**	-0.044	0.231***	0.056**	-0.027	0.119***	-0.091	-0.035
2019	0.019*	0.180***	0.054**	-0.022	0.253***	0.038**	-0.014	0.130***	-0.078	-0.034

Note. *p*-value of the significance level of Moran's index in the table is marked as follows: for *p*-value 0.01 – ***, for *p*-value 0.05 – **, for *p*-value 0.1 – *.

Source: State Statistics Service of Ukraine (2020); own calculation.

On the whole, we can draw similar conclusions from the results shown in Table 2. However, as we can see, the Moran's index calculated on the inverse distance matrix basis is significantly lower than similar results obtained on results on the neighbour matrix basis. That is, for our data the spatial relationship primarily exists between regions bordering each other. Therefore, we will use the neighbour matrix as a weight matrix to evaluate β-convergence models in the further works.

β-convergence models were evaluated based on equations (3) and (4) for each main food group. The results obtained are presented in Table 3 (spatial autoregressive models) and in Table 4 (spatial error models). The tables also show the Akaike and the Bayesian information criterion and statistics from the results of the Housman test. At first we should note that the preference is to be given to models with fixed effects according to the results of Hausman test when evaluating β-convergence based on equations (3) and (4) for all basic foodstuff. The tables below show the results of fixed-effect spatial models.

Considering the results of the constructed models we can conclude that the convergence was detected for all groups of basic foodstuff.

Table 3

Convergence of per capita food consumption in Ukrainian regions in the years 2000–2019 (fixed-effect Spatial Autoregressive Model)

Foodstuff	Beta(β)	Rho(ρ)	AIC	BIC	Hausman test
Meat	-0.054^{***} (0.010)	0.658^{***} (0.033)	-1576.108	-1563.741	13.60^{***}
Milk	-0.112^{***} (0.019)	0.663^{***} (0.032)	-1768.346	-1755.979	11.38^{***}
Eggs	-0.159^{***} (0.015)	0.343^{***} (0.044)	-1363.633	-1351.265	3.89^{***}
Cereals	-0.090^{***} (0.019)	0.419^{***} (0.049)	-1660.311	-1647.944	10.33^{***}
Potatoes	-0.325^{***} (0.032)	0.468^{***} (0.041)	-1492.769	-1480.401	23.40^{***}
Vegetables	-0.083^{***} (0.014)	0.444^{***} (0.045)	-1325.712	-1313.345	9.76^{***}
Fruits	-0.085^{***} (0.015)	0.504^{***} (0.042)	-876.635	-864.268	9.56^{***}
Fish	-0.106^{***} (0.017)	0.779^{***} (0.022)	-1046.947	-1034.579	35.72^{***}
Sugar	-0.112^{***} (0.025)	0.589^{***} (0.038)	-1357.332	-1344.965	12.88^{***}
Oil	-0.101^{***} (0.028)	0.590^{***} (0.035)	-608.8449	-596.4775	29.41^{***}

Notes. 1. The significance level of *p*-value: for *p*-value 0.01 – ***, for *p*-value 0.05 – **, for *p*-value 0.1 – *.

2. Standard deviations are in parenthesis under the coefficients.

Source: State Statistics Service of Ukraine (2020); own calculation.

The spatial autoregression parameter which signifies the generalised impact of food consumption in neighbouring regions proved to be positive and statistically significant for all groups of basic foodstuff, that is, it is expected that the consumption of a foodstuff in a particular region will tend to increase with the growth of consumption of this foodstuff in neighboring regions.

Using spatial error models to evaluate β-convergence we also found that convergence which means gradual convergence of regions in terms of consumption levels of major food groups is observed for all major foodstuff. Coefficient λ which characterises the generalised influence of random and unaccounted factors in the model for neighbouring regions proved to be positive and statistically significant for all food groups. Comparing the Akaike and Bayesian criterions for the SAR and SEM models suggests that the spatial error model is better suited for modeling our data. That is, if we consider the convergence taking into account the spatial interaction existence between regions than random shocks that occurred in neighbouring regions are turned out to affect the level of consumption in a particular region and factors that are unaccounted in the model affect consumption in neighbouring regions. As the parameter λ is positive for all models, that is, the influence of neighboring regions has a positive effect on food consumption in a particular region, we can assume that the spatial parameter λ accumulates the influence of such unaccounted indicators in the model as production and income in neighbouring regions. To confirm or refuse this assumption we suggest supplementing our research using conditional convergence model where the above mentioned indicators are included as explanatory factors.

Table 4

Convergence of food consumption per capita in Ukrainian regions in the years 2000–2019 (fixed-effect Spatial Error Model)

Foodstuff	Beta(β)	Lambda(λ)	AIC	BIC	Hausman test
Meat	-0.208^{***} (0.024)	0.741^{***} (0.030)	-1629.469	-1617.102	6.44^{***}
Milk	-0.217^{***} (0.028)	0.698^{***} (0.031)	-1791.077	-1778.709	33.04^{***}
Eggs	-0.267^{***} (0.023)	0.481^{***} (0.046)	-1399.285	-1386.918	9.03^{***}
Cereals	-0.251^{***} (0.035)	0.579^{***} (0.047)	-1698.008	-1685.641	15.28^{***}
Potatoes	-0.316^{***} (0.033)	0.486^{***} (0.045)	-1482.839	-1470.471	28.04^{***}
Vegetables	-0.154^{***} (0.021)	0.501^{***} (0.044)	-1343.234	-1330.867	6.18^{***}
Fruits	-0.256^{***} (0.028)	0.660^{***} (0.039)	-932.8051	-920.4376	14.16^{***}
Fish	-0.359^{***} (0.034)	0.819^{***} (0.021)	-1103.72	-1091.353	41.93^{***}
Sugar	-0.307^{***} (0.038)	0.623^{***} (0.035)	-1399.422	-1387.054	25.05^{***}
Oil	-0.158^{***} (0.042)	0.667^{***} (0.034)	-609.2449	-596.8774	51.83^{***}

Notes. 1. The significance level of *p*-value: for *p*-value 0.01 – ***, for *p*-value 0.05 – **, for *p*-value 0.1 – *.

2. Standard deviations are in parenthesis under the coefficients.

Source: State Statistics Service of Ukraine (2020); own calculation.

Also, the β parameter in the obtained models should be analyzed. The value of the β parameter is higher in spatial autoregressive models than in spatial error models. That is, the convergence rate is lower in spatial autoregressive models. Such results are quite expected and are supported by a number of studies devoted to modeling convergence using spatial panel data models (Abreu et al., 2005; Arbia et al., 2008; Lim & Kim, 2015) and can be interpreted as follows. The β parameter in the spatial autoregressive model represents only the direct marginal effect of increasing the initial consumption level, while the β parameter in the spatial error model accumulates the influence of both the direct marginal effect and indirect effects. In other words, the growth rate of food consumption in a particular region will be affected not only by the external influence of neighboring regions, but also by factors that indirectly affect neighboring regions. This fact may be of interest to policy makers when developing regional agrarian and food policy, and indicates that spatial error models are better suited than spatial autoregressive models for modeling our data.

Conclusions. The convergence analysis of basic food groups consumption in the in the period from 2000 to 2019 is based on the concept β-convergence which is tested using spatial economic models. Currently, there are enough scientific papers that test the presence of β-convergence using spatial econometric models. We can also mention a number of papers devoted to estimating the convergence of food consumption using classical growth regression using cross-sectional data, less often panel data. At the same time, little is known about the use of spatial econometric models to estimate the convergence of food consumption. Therefore, in our paper, we attempted to extend the traditional approach to estimating β-convergence by using spatial econometric models. The advantage of spatial economic models is the fact that they can take into account the circumstance when the regions are not isolated objects as provided by classical economic models. Taking into account and analyzing spatial effects in the process of convergence of regional food consumption allows us to better understand the reasons for the decrease in interregional differentiation of regions by levels of food consumption and can be a source of additional information for policy makers involved in regional economic development and food policy. To estimate convergence, we used two of the most common types of spatial econometric models – spatial autoregressive models and spatial error models. Based on the obtained quantitative results, the following main conclusions can be drawn. At the initial stage of the research, Moran's global indices were calculated to identify the spatial dependence of regions by the levels of consumption of basic foodstuffs. For most foodstuffs (with the exception of cereals and fruits), statistically significant Moran's indices were obtained, that is, the consumption of a foodstuff in the region is somewhat affected by the consumption of this foodstuff in neighboring regions. Positive Moran's indices indicate a positive impact of neighboring regions on the increase in consumption of a particular foodstuff in the region.

Both SAR and SEM models show an absolute process of β-convergence of average per capita consumption of all foodstuffs, which means that food consumption in regions with initial low consumption increases faster than in regions with high initial consumption. The presence of convergence in food consumption indicates that regions tend to have similar diets and similar living standards.

Also, within the framework of using spatial econometric models, it was determined that the process of convergence of regions by the levels of consumption of basic foodstuffs is influenced by spatial interaction across regions. It is found that the influence of neighboring regions has a positive effect on food consumption in a particular region. That is, both the increase in consumption in neighboring regions (SAR model) and factors that are not taken into account in the model that affect consumption in neighboring regions (SEM model) stimulate food consumption in a particular region.

The best specification for all the evaluated models was the spatial error model which takes into account spatial dependences in terms of error. It can be explained by the fact that the spatial coefficient λ accumulates the influence of such indicators as production volumes and income levels in neighbouring regions. It is also obtained for all foodstuffs that the value of the β parameter is lower in spatial error models, this means that the convergence rate is higher in spatial error models. And since the β parameter in the spatial autoregressive model reflects only the direct marginal effect of increasing the initial level of consumption, and the same β parameter in the spatial error model accumulates the influence of both the direct marginal effect and indirect effects, then the food growth rate in a particular region will be affected not only by neighboring regions directly, but also by factors indirectly affecting neighboring regions. That is, in our case, spatial interaction between regions is that food consumption in a particular region is influenced not so much by food consumption in neighboring regions, but by the socio-economic situation in neighboring regions and factors that have an external impact on neighboring regions.

The obtained results and conclusions can be taken into account when planning regional food policy or when planning food production in the regions of Ukraine. Our research can be interesting and provide additional information to policymakers and agribusiness when modeling regional demand for basic foodstuffs; when developing and adjusting plans for the production, processing and delivery of agricultural products, when planning state or regional trade policy in the field of food. Also, from the point of view of state and regional policy, this paper can provide policymakers with some clues about the spatial interaction across regions. When developing and implementing food policy, policymakers should take into account not only the internal capabilities of the region, but also the possible influence of neighboring regions on it. The presence of noticeable spatial interaction across regions underlines the importance of coordinating the activities of regional policymakers and the need to implement comprehensive regional development strategies in the field of food.

Finally, we will outline prospective areas for further research on regional convergence in food consumption. To estimate convergence, we used unconditional convergence model, which is traditionally considered the starting point in the process of modeling β-convergence. Some limitation of unconditional convergence model of is that it does not involve the inclusion of additional factors in the model that can cause the convergence process. First of all, it would be interesting to study the impact of factors such as food production and income levels in the region on the convergence process. Therefore, we consider it promising to use conditional convergence models, where the above-mentioned indicators can be included as explanatory factors. Also, another important area of further research on convergence of regions by the levels of consumption of basic foodstuffs is the use of spatial club convergence models in the case of existence polarized groups of regions by the levels of consumption of basic foodstuffs.

References

1. Abreu, M., de Groot, H. L. F., & Florax, R. J. (2005). Space and growth: a survey of empirical evidence and methods. *Région et Développement*, 21, 13–44. Available at: https://regionetdeveloppement.univ-tln.fr/wp-content/uploads/R21_abreu_al.pdf.

2. Akarsu, G., & Berke, B. (2016). Convergence of electricity consumption in

Turkey: Spatial panel data analysis. https://doi.org/10.2139/ssrn.2875301.

3. Akarsu, G., & Berke, B. (2020). Convergence of electricity consumption in Turkey: spatial panel data analysis. *Panoeconomicus*, 67(2), 241–256. https://doi.org/10.2298/PAN161129007A.

4. Anselin, L. (1980). *Estimation methods for spatial autoregressive structures: a study in spatial econometrics*. Regional science dissertation and monograph series 8. Field of Regional Science, Cornell University, Ithaca, N.Y.

5. Anselin, L. (1988). *Spatial econometrics: methods and models*. Springer Dordrecht. https://doi.org/10.1007/978-94-015-7799-1.

6. Antczak, E., & Suchecka, J. (2011). Spatial autoregressive panel data models applied to evaluate the levels of sustainable development in European countries. *Acta Universitatis Lodziensis. Folia Oeconomica*, 252(1), 21–44. Available at: http://hdl.handle.net/11089/631.

7. Arbia, G., & Piras, G. (2004). Convergence in per-capita GDP across European regions using panel data models extended to spatial autocorrelation effects. *44th Congress of the European Regional Science Association: "Regions and Fiscal Federalism"*, 25th–29th August 2004, Porto, Portugal, European Regional Science Association (ERSA), Louvain-la-Neuve.

8. Arbia, G., Le Gallo, G., & Piras, G. (2008). Does evidence on regional economic convergence depend on the estimation strategy? Outcomes from analysis of a set of NUTS-2 regions. *Spatial Economic Analysis*, 3(2), 209–224. https://doi.org/10.1080/17421770801996664.

9. Armstrong, H. (1995). Convergence among regions of the European Union, 1950–1990. *Papers in Regional Science*, 74(2), 143–152. https://doi.org/10.1111/j.1435-5597.1995.tb00633.x.

10. Baltagi, B. H., & Li, D. (2006). Prediction in the panel data model with spatial correlation: the case of Liquor. Center for Policy Research, 81. Available at: https://surface.syr.edu/cpr/81.

11. Baltagi, B. H., Heun Song, S., Cheol Jung, B., & Koh, W. (2007). Testing for serial correlation, spatial autocorrelation and random effects using panel data. *Journal of Econometrics*, 140(1), 5–51. https://doi.org/10.1016/j.jeconom.2006.09.001.

12. Barro, R. J., & Sala-i-Martin, X. (1992). Convergence. *Journal of Political Economy*, 100(2), 223–251. Available at: https://www.jstor.org/stable/2138606.

13. Barro, R. J., & Sala-i-Martin, X. (1995). *Economic Growth*. McGraw-Hill, New York.

14. Belotti, F., Hughes, G., Mortari, A. P. (2013). *XSMLE – a command to estimate spatial panel models in Stata*. Working paper. CEIS, University of Rome Tor Vergata.

15. Cabinet of Ministers of Ukraine (2016). Resolution of Cabinet of Ministers of Ukraine "On approval of food sets, sets of non-food products and services for major social and demographic groups". Available at: https://zakon.rada.gov.ua/laws/show/656-2000-п#Text.

16. Cliff, A. D., & Ord, J. K. (1981). *Spatial processes: models and applications*.

Pion Limited, London.

17. Cliff, A. D., & Ord, J. K. (1973). *Spatial autocorrelation*. London: Pion.

18. Domazet, A., Sendić, R., & Alić, A. (2012). Convergence analysis of household expenditures using the absolute β-convergence method. *Business Systems Research Journal*, 3(1), 23–29. https://doi.org/10.2478/v10305-012-0003-3.

19. dos Santos, G., & Faria, W. (2012). *Spatial panel data models and fuel demand in Brazil*. Núcleo de Economia Regional e Urbana da Universidade de São Paulo (NEREUS). Available at: http://www.usp.br/nereus/wp-content/uploads/TD_Nereus_10_2012.pdf.

20. Drukker, D. M., Peng, H., Prucha, I. R., & Raciborski, R. (2013). Creating and managing spatial-weighting matrices with the spmat command. *The Stata Journal*, 13(2), 242–286. https://doi.org/10.1177/1536867X1301300202.

21. Elhorst, J. P. (2017). Spatial Panel Data Analysis. In S. Shekhar, H. Xiong, X. Zhou (Eds.), *Encyclopedia of GIS* (pp. 2050–2058). Springer, Cham. https://doi.org/10.1007/978-3-319-17885-1_1641.

22. Figleton, B., & López-Bazo, E. (2006). Empirical growth models with spatial effects. *Papers in Regional Science*, 85(2), 177–198. https://doi.org/10.1111/j.1435-5957.2006.00074.x.

23. Gil, J. M., Gracia, A., & Perez y Perez, L. (1995). Food consumption and economic development in the European Union. *European Review of Agricultural Economics*, 22(3), 385–399. https://doi.org/10.1093/erae/22.3.385.

24. Haining, R. (2003). *Spatial data analysis: theory and practice* (1st ed.). Cambridge University Press, Cambridge. https://doi.org/10.1017/CBO9780511754944.

25. Hausman, J. (1978). Specification tests in econometrics. *Econometrica*, 46(6), 1251–1272. https://doi.org/10.2307/1913827.

26. Herrmann, R., & Roder, C. (1995). Does food consumption converge internationally? Measurement, empirical tests and determinants. *European Review of Agricultural Economics*, 22(3), 400–414. https://doi.org/10.1093/erae/22.3.400.

27. Horna, M., Ishchuk, Ya., & Khalilova, T. (2017). Conditions and factors forming investment attractivenes of Eastern Europe Countries. *International Economic Policy*, 2(27), 131–150. http://iepjournal.com/journals_eng/27/2018_6.pdf.

28. Le Gallo, J., & Fingleton, B. (2021). Regional growth and convergence empirics. In M. M. Fischer, P. Nijkamp (Eds.), *Handbook of regional science* (pp. 679–706). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-662-60723-7_17.

29. LeSage, J., & Fischer, M. (2008). Spatial growth regressions: model specification, estimation and interpretation. *Spatial Economic Analysis*, 3(3), 275–304. https://doi.org/10.1080/17421770802353758.

30. Lim, U., & Kim, D. (2015). Toward sustainable economic growth: a spatial panel data analysis of regional income convergence in US BEA economic areas. *Sustainability*, 7(8), 9943–9959. https://doi.org/10.3390/su7089943.

31. Linderhof, V., Nowicki, P., Leeuwen, E., Reinhard, S., & Smith, M. (2011).

Manual for the tests of spatial econometric model. Spatial Analysis of Rural Development Measures Contract No. 244944. Work Package No. 4. Available at: https://core.ac.uk/download/pdf/29229896.pdf.

32. López-Bazo, E., Vayá, E., & Artís, M. (2004). Regional externalities and growth: evidence from European regions. *Journal of Regional Science*, 44(1), 43–73. https://doi.org/10.1111/j.1085-9489.2004.00327.x.

33. Lukianenko, D., Burmaka, M., & Halakhova, T. (2016). Identification of creative investment in global economy. *International Economic Policy*, 2(25), 7–20. Available at: http://iepjournal.com/journals_eng/25/2016_1_Lukianenko_Burmaka_Galahova.pdf.

34. Mankiw, N. G., Romer, D., & Weil, D. N. (1992). A contribution to the empirics of economic growth. *The Quarterly Journal of Economics*, 107(2), 407–437. https://doi.org/10.2307/2118477.

35. Marques, H., Pino, G., & Horrillo, J. (2014). Regional inflation dynamics using space–time models. *Empirical Economics*, 47(3), 1147–1172. https://doi.org/10.1007/s00181-013-0763-9.

36. Matviychuk, A., Novoseletskyy, O., Vashchaiev, S., Velykoivanenko, H., & Zubenko, I. (2019). Fractal analysis of the economic sustainability of enterprise. *SHS Web of Conferences. Proceedings of the 8th International Conference on Monitoring, Modeling & Management of Emergent Economy*, 65, 06005. https://doi.org/10.1051/shsconf/20196506005.

37. Meliciani, V., & Peracchi, F. (2009). Convergence in per-capita GDP across European regions: a reappraisal. In G. Arbia, B. H. Baltagi (Eds.), *Spatial Econometrics. Studies in Empirical Economics* (pp. 203–222). Physica-Verlag HD. https://doi.org/10.1007/978-3-7908-2070-6_11.

38. Moran, P. A. P. (1948). The Interpretation of statistical maps. *Journal of the Royal Statistical Society: Series B (Methodological)*, 10(2), 243–251. https://doi.org/10.1111/j.2517-6161.1948.tb00012.x N.G.

39. Osypova, O., Ignatova, I., & Shenderivska, L. (2017). The use of spatial regression models to the estimation of demand function. *XXX International conference "Problems of decision making under uncertainties"*. Vilnius, Lithuania, 96–97.

40. Piras, G., & Arbia, G. (2007). Convergence in per-capita GDP across EU-NUTS2 regions using panel data models extended to spatial autocorrelation effects. *Statistica*, 67(2), 157–172. https://doi.org/10.6092/issn.1973-2201/3513.

41. Regmi, A., & Unnevehr, L. (2005). Convergence or divergence in food demand: a comparison of trends in the EU and North America. *11th Congress of the EAAE "The Future of Rural Europe in the Global Agri-Food System"*, (24–27 August 2005). Copenhagen.

42. Rey, S. J., & Le Gallo, J. (2009). Spatial analysis of economic convergence. In T. C. Mills, K. Patterson (Eds.), *Palgrave Handbook of Econometrics* (pp. 1251–1290). Vol. 2. Palgrave Macmillan. https://doi.org/10.1057/9780230244405_27.

43. Rey, S. J., & Montouri, B. D. (1999). US regional income convergence: a spatial econometric perspective. *Regional Studies*, 33(2), 143–156. Available at:

https://web.pdx.edu/~crkl/SEAUG/papers/Rey_RS99.pdf.

44. Robertson, D., & Symons, J. (1992). Some strange properties of panel data estimators. *Journal of Applied Econometrics*, 7(2), 175–189. https://www.jstor.org/stable/2285027.

45. Sartika, W., Susetyo, B., & Syafitri, U. D. (2017). Spatial panel data models of aquaculture production in West Sumatra province with random-effects. *AIP Conference Proceedings*, 1827, 020008. https://doi.org/10.1063/1.4979424.

46. Slander, S., & Ogorevc, M. (2010). Labour cost convergence in the EU: spatial econometrics approach. *Economic Trends and Economic Policy*, 20(122), 27–51. Available at: https://hrcak.srce.hr/file/80468.

47. State Statistics Service of Ukraine (2020). Balances and consumption of basic foodstuffs by the population of Ukraine for 2019. Available at: http://www.ukrstat.gov.ua/druk/publicat/kat_u/2020/zb/07/Zb_bsph2019.pdf.

48. The Verkhovna Rada of Ukraine (2012). Draft of Law of Ukraine "On food security". Available at: http://w1.c1.rada.gov.ua/pls/zweb2/webproc4_1?pf3511=44744.

49. Wan, G. H. (2005). Convergence in food consumption in rural China: evidence from household survey data. *China Economic Review*, 16(1), 90–102. https://doi.org/10.1016/j.chieco.2004.09.002.

50. Zheng, Y. Z., Zhu, J., & Li, D. (2008). Analyzing spatial panel data of cigarette demand: a Bayesian hierarchical modeling approach. *Journal of Data Science*, 6(4), 467–489. https://doi.org/10.6339/jds.2008.06(4).428.

Citation:

Стиль – ДСТУ:

Osypova O., Horna M., Vashchaiev S., Ishchuk Y., Pomazun O. Convergence of food consumption across Ukrainian regions: approach using spatial panel data models. *Agricultural and Resource Economics*. 2023. Vol. 9. No. 1. Pp. 28–43. https://doi.org/10.51599/are.2023.09.01.02.

Style – APA:

Osypova, O., Horna, M., Vashchaiev, S., Ishchuk, Y., & Pomazun, O. (2023). Convergence of food consumption across Ukrainian regions: approach using spatial panel data models. *Agricultural and Resource Economics*, 9(1), 28–43. https://doi.org/10.51599/are.2023.09.01.02.