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# CHANGES IN FOOD DEMAND IN THE EU MEMBER STATES AND SELECTED OECD COUNTRIES: THE IMPACT OF DISPOSABLE INCOME, UNEMPLOYMENT, AND INFLATION

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**Abstract.** This study focuses on consumption patterns: as societies get richer, their attitude toward the level and structure of consumption changes. Unemployment and inflation might influence consumption patterns. This paper aims to analyze the impact of unemployment and inflation on the convergence of food demand in households in the EU Member States and selected OECD countries from 1995 to 2019. The analysis of β-conditional convergence proved that the convergence of the share of food expenditure was positively conditioned by the unemployment level and negatively by the disposable income, but with no inflation influence. While in club convergence of more developed economies, with a higher inflation level comes a higher share of disposable income spent on food.

**Keywords:** convergence, disposable income, inflation, food expenditure, spatial analysis, sustainable consumption, unemployment.

**JEL Classification:** D31, E21, E24, E31, P46.

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## 1. Introduction

Nowadays, there is an ongoing debate on sustainable development worldwide. Such a concept clearly means to focus on three pillars: economic, social, and environmental development at the same time. However, one should note that such a process cannot only concern countries as separate entities. If that were the case, there would be even more inequalities worldwide, especially in terms of income. Hence, ensuring sustainable development as a global action framework is crucial to monitor different countries' performance and track their progress toward achieving the Sustainable Development Goals set by the 2030 United Nations Agenda for Sustainable Development. The ideal situation would be for countries to grow their economies in a sustainable way, and at the same time, initially, poorer nations would have faster economic growth rates than wealthier ones, which would mean a catching-up process occurs. This economic phenomenon, called convergence, occurs in countries/regions through different mechanisms, i.e., technology transfer, capital flow, international trade, globalization, institutional development, human capital and its flow, economic policies, etc. Economic convergence affects many aspects of socioeconomic activities in the economy. One of them concerns changes in the level and structure of household consumption. This paper, in particular, is interested in food demand since it is an essential part of numerous sustainable development aspects, including: economic stability (i.e., food scarcity, supply chain), societal impact (food security), and environmental concerns (sustainable production and trade). Interestingly, according to Engel's law, when households become richer, they tend to spend relatively less on food (as a share of their total budget) in their overall expenditure structure.

On top of that, it is vital to analyze different economic factors that might affect changes in food demand. Therefore, this paper formulates an attempt to investigate whether unemployment and inflation (as they are two critical macroeconomic phenomena) have any influence on changes in food demand in the EU Member States and selected OECD countries from 1995 to 2019.

Apart from this primary aim, this study also sets the following objectives:

1. This study is to find out whether there are any spatial dependencies and interactions among the considered countries in the share of household food expenditure and related macroeconomic issues (inflation, unemployment), and if so:
   1.1. what kind of dependencies exist when considering a common land border neighborhood;
   1.2. what kind of dependencies exist when considering ecological development similarity neighborhood.
2. This paper is to determine whether there is any influence of economic development (GDP per capita similarity) on the share of household food expenditure and related macroeconomic issues (inflation, unemployment).

## 2. Literature review

One of the main goals for any country is to achieve progress in socioeconomic development. The ideal situation would be that initially poorer countries will eventually catch up with wealthier ones. It would mean the economic convergence process occurs (Amable, 1993; Barro et al., 1991; Barro & Sala-i-Martin, 1997; Szczepańska-Woszczyna et al., 2022). Changes in the level and structure of household consumption are the side effects of that convergence.

There are many important economic aspects for households to consider, including: income (dependent on taxes and government transfers), inflation, employment, budget management (consumption, savings, investments, debts), housing (owing or renting a house or an apartment), pension planning, and more (Herzberg-Druker & Stier, 2019; Kaplan & Schulhofer-Wohl, 2017; Qi et al., 2022; Seefeldt, 2015; Tabner, 2016; Vivel-Búa et al., 2019). Hence, food expenditure accounted for 17% of the average OECD household budget in 2023, so it remains an essential category of household spending (Arend et al., 2024).

According to Engel's law, when an average household income increases, the average share of food expenditure in total household expenditure drops (Anand et al., 2015; Loeb, 1955; Pope, 2012; Zimmerman, 1932). Numerous studies analyzed the share of food expenditure from different perspectives: food security (Amrullah et al., 2019), disposable income (Perthel, 1975), inequalities (Borkotoky & Unisa, 2018), trends and dynamics (Jankiewicz & Pietrzak, 2020), life expectancy (Li et al., 2021), and convergence (Healy, 2014; Jankiewicz, 2019; Liang et al., 2024; Regmi & Unnevehr, 2005).

Moreover, one should note that the environmental context is also vital and should be taken into consideration since it is part of the United Nations' 2030 Agenda for Sustainable Development, particularly concerning the concept of sustainable consumption (Sénit, 2020; Seyfang, 2009; Xiao & Li, 2011). The previous study in this area examined the convergence of household food expenditure, including disposable income and ecological situation, indicated by ecological footprint. The main results of that study reveal that (1) the convergence process occurred in disposable income and food expenditure; (2) in western and northern countries in Europe, the proportion of total expenditure allocated to food was comparatively lower than in central and eastern Europe; (3) there were stronger spatial effects between countries with similar ecological situation than between bordering countries (Grodzicki & Jankiewicz, 2022).

Hence, this paper continues researching this topic by adding new macroeconomic insights. It considers the aspects of unemployment and inflation that might impact consumption patterns (Nordhaus, 1975). Therefore, evaluating how these economic phenomena can affect food demand is crucial.

Numerous studies focus on unemployment and food expenditure. Elsner (1999) assumed that food expenditure is generally lower for unemployed than employed households. Aguiar and Hurst (2005) determined that, on average, unemployed people experienced a 19% decline in total food expenditure. Another study also confirmed that changes in the unemployment rate influence food expenditure, and, in particular, a one percentage point increase in the unemployment rate results in a roughly 1.1% drop in food consumption (Campos & Reggio, 2015). In the Spanish case, the unemployment effect on food expenditure amounted to 2.9% in the boom period and 4.5% in the crisis period (Antelo et al., 2017). However, these studies considered food expenditure in absolute terms, and none focused on its share in total spending.

Inflation is also crucial when analyzing a household's food expenditure. Out of all types of expenditures, inflation generally tends to hit the spending on food the most. However, once severe inflation occurs, people are more likely to reduce their total spending, but food expenditure is one of the few items likely to change. Zhang (2012), in the example of the Chinese economy, found that housing expenditures are the most significant cause of the decline in consumption due to increasing inflation. That is because the policy supports households with housing subsidies, predominantly low-income households. The second most significant decrease in expenditure is for transportation, since people tend to travel less. The third category of household expenditure reduction is food along with miscellaneous goods and services. Based on the analysis of the impacts of inflation on the distribution of household consumption expenditures in the US, Taylor (2022) revealed that expenditures for housing, transportation, gasoline and oil, and personal insurance experienced the most significant impact from inflation. Therefore, when an economy is experiencing an increasing inflation rate, the government could implement subsidies for food expenditure, following the example of the housing policy (Zhang, 2012). However, there is a lack of research on the impact of inflation on the portion of total household expenditure spent on food.

## 3. Methodology and data

This research considers data characterizing households' food expenditure shares in the final expenditures, the disposable income per capita, inflation measured by the Consumer Price Index (CPI), and the unemployment rate. For data availability reasons, the period of 1995–2019 is adopted as the time range of the study. Also, the research is provided at the country level for the same reason. The food expenditure comparable data for lower aggregation levels in the European Union are unavailable. All data come from the European Statistical Office (EUROSTAT) database (https://ec.europa.eu/eurostat/data/database). The data relating to food expenditure and disposable income were obtained through calculations, but the values of CPI come directly from the database mentioned above.

Disposable income, inflation, and unemployment are the most crucial phenomena influencing household expenditures. Based on Engel's Law, food expenditure shares decrease with increased disposable income (Aykaç, 2018; Benda-Prokeinová et al., 2017). Becoming richer results in a fall in food expenditure, so the unemployment rate rises, and CPI growth causes an increase in the households' food expenditure shares (Akinboade et al., 2016; Dilanchiev & Taktakishvili, 2021).

The first step of the study concerns an analysis of the spatial dependence in the formation of additional processes conditioning the convergence process – the unemployment rate and Consumer Price Index (CPI). In this case, Moran's test based on Moran's I statistics, verifying the spatial autocorrelation, is used (Moran, 1950; Schabenberger & Gotway, 2005). The test statistic takes the following form:

$$I = \frac{1}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \cdot \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left[y_i - \bar{y}\right]\left[y_j - \bar{y}\right]}{\frac{1}{n}\sum_{i=1}^{n}\left[y_i - \bar{y}\right]^2} = \frac{n}{S_0} \cdot \frac{\boldsymbol{z}^T \boldsymbol{W} \boldsymbol{z}}{\boldsymbol{z}^T \boldsymbol{z}}, \tag{1}$$

where $y_i$ indicates the observed value of the phenomenon in the i$^{th}$ region, $\boldsymbol{z}$ is a column vector with elements $z_i = y_i - \bar{y}$, $S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}$ denotes a sum of the corresponding elements of the weights matrix, and $n$ is the number of regions.

In this study, two neighborhood matrices are used. The first defines the neighborhood as the occurrence of a common land border (first-order contiguity matrix) – $\boldsymbol{W}1$, while the second is based on the ecological development similarity – $\boldsymbol{W}2$ (Grodzicki & Jankiewicz, 2022; Jankiewicz & Szulc, 2021). When there is no neighbor for some territorial unit (for example, islands based on W1 matrix), the value of the spatially lagged variable for this unit equals zero. The ecological similarity matrix is employed because the consumer's behaviors significantly affect the formation of the ecological footprint. In turn, the geographical neighborhood matrix is used due to the relevance of the proximity of units in the analysis of dependencies resulting from the First Law of Geography (Tobler, 1970).

Spatial connection matrices allow for interactions between neighbors in the convergence models presented below.

Firstly, the spatio-temporal conditional convergence model with the differentiated intercept (to determine the individual characteristics of states) is considered. The general form of the model is as follows:

$$\ln\left(Y_{i,t}\right)=\beta_{0i}+\beta_1\ln\left(Y_{i,t-1}\right)+\beta_2\ln\left(X_{1i,t}\right)+\beta_3\ln\left(X_{2i,t}\right)+\beta_4X_{3i,t}+\varepsilon_{i,t},\tag{2}$$

where $Y_{i,t}$ is the share of the food expenditure of households in i$^{th}$ country in time $t$, $X_{1i,t}$, $X_{2i,t}$ and $X_{3i,t}$ indicate the explanatory variable, respectively: the level of disposable income per capita of households, the unemployment rate, and the Consumer Price Index (CPI). Moreover $\varepsilon_{i,t}$ is a random component instead $\beta_{0i}, \beta_1, \beta_2, \beta_3, \beta_4$ – structural parameters of the model.

The Lagrange Multiplier (LM) tests (Breusch & Pagan, 1980; Engle, 1984) in the basic and robust versions are conducted to determine the character of spatial interactions. The role of LM tests is to provide a supposition about the nature of spatial dependence. This study adopts a general-to-specific approach to choose the best model with a spatial factor. Therefore, at the beginning, the model proposed by Manski is estimated (Manski, 1993). This model contains the spatially lagged dependent variable – $\boldsymbol{W}\ln\left(Y_{i,t}\right)$, spatially lagged exogenous variables – $\boldsymbol{W}\ln\left(X_{1i,t}\right)$, $\boldsymbol{W}\ln\left(X_{2i,t}\right)$, $\boldsymbol{W}X_{3i,t}$ and spatially lagged error term – $\boldsymbol{W}\left(\eta\right)_{i,t}$ takes the following form:

$$\ln\left(Y_{i,t}\right)=\beta_{0i}+\beta_1\ln\left(Y_{i,t-1}\right)+\beta_2\ln\left(X_{1i,t}\right)+\theta_2\boldsymbol{W}\ln\left(X_{1i,t}\right)+\beta_3\ln\left(X_{2i,t}\right)+\theta_3\boldsymbol{W}\ln\left(X_{2i,t}\right)+$$
$$\beta_4X_{3i,t}+\theta_4\boldsymbol{W}X_{3i,t}+\tilde{n}\,\boldsymbol{W}\ln\left(Y_{i,t}\right)+\eta_{i,t},\tag{3}$$

Based on this general model, in the following step, the models with a narrower structure are considered until the best model is selected. In the second step, three simpler models were created by assumptions: (i) $\lambda=0$, (ii) $\rho=0$, and (iii) $\theta_2=\theta_3=\theta_4=0$ are estimated. The assumptions (i), (ii), and (iii) change the Manski model into the spatial Durbin (SDM) model, spatial Durbin error (SDEM) model, and spatial autoregressive combined (SAC) model, respectively (Elhorst, 2014; Fingleton & López-Bazo, 2006). The mentioned models take the following forms:

$$\ln\left(Y_{i,t}\right)=\beta_{0i}+\beta_1\ln\left(Y_{i,t-1}\right)+\beta_2\ln\left(X_{1i,t}\right)+\theta_2\boldsymbol{W}\ln\left(X_{1i,t}\right)+\beta_3\ln\left(X_{2i,t}\right)+\theta_3\boldsymbol{W}\ln\left(X_{2i,t}\right)+$$
$$\beta_4X_{3i,t}+\theta_4\boldsymbol{W}X_{3i,t}+\tilde{n}\,\boldsymbol{W}\ln\left(Y_{i,t}\right)+\eta_{i,t};\tag{4}$$

$$\ln\left(Y_{i,t}\right)=\beta_{0i}+\beta_1\ln\left(Y_{i,t-1}\right)+\beta_2\ln\left(X_{1i,t}\right)+\theta_2\boldsymbol{W}\ln\left(X_{1i,t}\right)+\beta_3\ln\left(X_{2i,t}\right)+$$
$$\theta_3\boldsymbol{W}\ln\left(X_{2i,t}\right)+\beta_4X_{3i,t}+\theta_4\boldsymbol{W}X_{3i,t}+\eta_{i,t},$$
$$\eta_{i,t}=\lambda\boldsymbol{W}\left(\eta\right)_{i,t}+\varepsilon_{i,t};\tag{5}$$

$$\ln\left(Y_{i,t}\right)=\beta_{0i}+\beta_1\ln\left(Y_{i,t-1}\right)+\beta_2\ln\left(X_{1i,t}\right)+\beta_3\ln\left(X_{2i,t}\right)+\beta_4X_{3i,t}+\rho\boldsymbol{W}\ln\left(Y_{i,t}\right)+\eta_{i,t},$$
$$\eta_{i,t}=\lambda\boldsymbol{W}\left(\eta\right)_{i,t}+\varepsilon_{i,t}.\tag{6}$$

The final step of simplifying models is the estimation of the spatial autoregressive (SAR) model, spatial error (SE) model, and spatial lag of X (SLX) model that is created by adopting assumptions: (iv) $\lambda=0\wedge\theta_2=\theta_3=\theta_4=0$, (v) $\rho=0\wedge\theta_2=\theta_3=\theta_4=0$ and (vi) $\lambda=0\wedge\rho=0$, respectively. The Eqs. (–(9) describe the formulas of the SAR, SE, and SLX models, respectively:

$$\ln\left(Y_{i,t}\right)=\beta_{0i}+\beta_1\ln\left(Y_{i,t-1}\right)+\beta_2\ln\left(X_{1i,t}\right)+\beta_3\ln\left(X_{2i,t}\right)+\beta_4X_{3i,t}+\rho\boldsymbol{W}\ln\left(Y_{i,t}\right)+\eta_{i,t};\tag{7}$$

$$\ln\left(Y_{i,t}\right)=\beta_{0i}+\beta_1\ln\left(Y_{i,t-1}\right)+\beta_2\ln\left(X_{1i,t}\right)+\beta_3\ln\left(X_{2i,t}\right)+\beta_4X_{3i,t}+\eta_{i,t},$$
$$\eta_{i,t}=\lambda\boldsymbol{W}\left(\eta\right)_{i,t}+\varepsilon_{i,t};\tag{8}$$

$$\ln\left(Y_{i,t}\right)=\beta_{0i}+\beta_1\ln\left(Y_{i,t-1}\right)+\beta_2\ln\left(X_{1i,t}\right)+\theta_2\boldsymbol{W}\ln\left(X_{1i,t}\right)+\beta_3\ln\left(X_{2i,t}\right)+$$
$$\theta_3\boldsymbol{W}\ln\left(X_{2i,t}\right)+\beta_4X_{3i,t}+\theta_4\boldsymbol{W}X_{3i,t}+\eta_{i,t}. \quad (9)$$

The estimated models are compared mainly based on the statistical significance of spatially lagged parameters, economic interpretation, and the presence of spatial autocorrelation in residuals. Moreover, the Akaike Information Criterion (AIC) is a complementary tool for making decisions about the final model. Generally, the model is better when it is characterised by a lower value of AIC.

In the next step of the investigation, the club-convergence models are estimated and verified. The analyzed regions are divided into two regimes based on the GDP per capita level in the period considered. The division is done with cluster analysis using the Ward method (Murtagh & Legendre, 2014; Ward, 1963). The Ward method belongs to the hierarchical clustering method. In the beginning, all territorial units are recognized as separate clusters. Based on the dissimilarity measure (Euclidean distance), the less dissimilar objects are agglomerated in new clusters, deleting the agglomerans, or agglomerated clusters. Then, the values of dissimilarity measures are calculated for the newly built cluster. The steps of the algorithm are repeated while the variance within clusters is minimized (Murtagh & Legendre, 2014).

For determined subgroups, the club-convergence models are considered. In this case, the switching regression absolute and conditional models are studied. The general form of the absolute convergence model is as follows:

$$\ln\left(Y_{i,t}\right)=\sum_h\beta_{0i}^h+\beta_1^h\ln\left(Y_{i,t-1}^h\right)+\varepsilon_{i,t}, \quad (10)$$

where $Y_{i,t-1}^h$ is the share of the food expenditure of households in i$^{th}$ country from h$^{th}$ regime in time $t$ – 1. The following equations characterize the conditional convergence process without (11) and with (12) spatial dependence:

$$\ln\left(Y_{i,t}\right)=\sum_h\beta_{0i}^h+\beta_1^h\ln\left(Y_{i,t-1}^h\right)+\beta_2^h\ln\left(X_{1i,t}^h\right)\beta_{0i}+\beta_3^h\ln\left(X_{2i,t}^h\right)+\beta_4^hX_{3i,t}^h+\varepsilon_{i,t}; \quad (11)$$

$$\ln\left(Y_{i,t}\right)=\sum_h\beta_{0i}^h+\beta_1^h\ln\left(Y_{i,t-1}^h\right)+\beta_2^h\ln\left(X_{1i,t}^h\right)\beta_{0i}+\beta_3^h\ln\left(X_{2i,t}^h\right)+\beta_4^hX_{3i,t}^h+\eta_{i,t},$$
$$\eta_{i,t}=\lambda\boldsymbol{W}\left(\eta\right)_{i,t}+\varepsilon_{i,t}. \quad (12)$$

In the models $X_{1i,t}^h$, $X_{2i,t}^h$ and $X_{3i,t}^h$ indicate the explanatory variables for i$^{th}$ country from h$^{th}$ regime in time $t$, instead $\boldsymbol{W}\left(\eta\right)_{i,t}$ denotes a spatial lag of an error term.

Based on the estimated models, the elementary characteristics of the convergence process, namely the speed of convergence and half-life statistics (Arbia, 2006) are quantified with the Eqs. (13)–(14) expressed as:

$$b=-\ln\beta_1, \quad (13)$$

$$t_{half-life}=\frac{\ln\left(2\right)}{b}. \quad (14)$$

## 4. Empirical results

Firstly, the spatial autocorrelation based on Moran's *I* statistics for an additional explanatory variable – the unemployment rate – is tested (Table 1). The spatial dependence between territorial units in the case of the unemployment rate is a crucial factor due to, for instance, the free movement of human capital.

**Table 1.** The results of Moran's spatial autocorrelation test

| Year | ***W*1** | | ***W*2** | |
|---|---|---|---|---|
| | *I* | p-value | *I* | p-value |
| 1995 | 0.0514 | 0.2984 | –0.2164 | 0.0881 |
| 1996 | 0.0363 | 0.3301 | –0.2246 | 0.0783 |
| 1997 | –0.0432 | 0.4854 | –0.1878 | 0.1292 |
| 1998 | –0.0811 | 0.3983 | –0.2022 | 0.1107 |
| 1999 | 0.0268 | 0.3565 | –0.1482 | 0.2071 |
| 2000 | 0.1724 | 0.1124 | –0.1369 | 0.2298 |
| 2001 | 0.2073 | 0.0761 | –0.1224 | 0.2606 |
| 2002 | 0.1496 | 0.1349 | –0.1102 | 0.2888 |
| 2003 | 0.1637 | 0.1163 | –0.1125 | 0.2820 |
| 2004 | 0.1438 | 0.1369 | –0.0640 | 0.4121 |
| 2005 | 0.1141 | 0.1766 | 0.0317 | 0.3071 |
| 2006 | 0.0319 | 0.3401 | 0.1400 | 0.0973 |
| 2007 | –0.0678 | 0.4287 | 0.1888 | 0.0519 |
| 2008 | –0.2474 | 0.1068 | –0.0967 | 0.3238 |
| 2009 | 0.1931 | 0.0829 | –0.0892 | 0.3409 |
| 2010 | 0.2656 | 0.0367 | –0.0443 | 0.4712 |
| 2011 | 0.1147 | 0.1843 | 0.1066 | 0.1493 |
| 2012 | 0.0580 | 0.2812 | 0.2097 | 0.0322 |
| 2013 | 0.0458 | 0.3032 | 0.2714 | 0.0092 |
| 2014 | 0.0094 | 0.3859 | 0.2608 | 0.0111 |
| 2015 | 0.0422 | 0.3084 | 0.2288 | 0.0198 |
| 2016 | 0.0740 | 0.2373 | 0.1692 | 0.0524 |
| 2017 | 0.0649 | 0.2539 | 0.1136 | 0.1171 |
| 2018 | 0.0514 | 0.2781 | 0.0491 | 0.2464 |
| 2019 | 0.0854 | 0.2076 | 0.0084 | 0.3626 |

It is worth noting that the positive global spatial autocorrelation was observed only in 2010, considering the neighborhood with the common land border between states (W1 matrix). Regarding ecological similarity, the statistically significant dependence between neighbors was noted from 2012 to 2015. The remaining Moran statistics have p–values above the adopted significance level of 0.05. That means there is a lack of relevant dependence between neighbors regarding the unemployment rate.

Table 2 shows the results of the estimation and verification of the conditional convergence model for the share of food expenditure of households. In the Tables A1–A2 attached in Appendix, the basic descriptive statistics of explanatory variables are provided to show no collinearity between them. Moreover, slight deviations from the normal distribution in the case of variables X1 and X2 are observed, but this imperfection is leveled out with the estimated logarithms of variables in the models.

**Table 2.** The results of the estimation and verification of the conditional convergence model

| Parameter | Estimate | Std. Error | t Statistics | p-value |
|---|---|---|---|---|
| $\beta_1$ | 0.7989 | 0.0200 | 39.9460 | 0.0000 |
| $\beta_2$ | –0.0228 | 0.0058 | –3.9030 | 0.0001 |
| $\beta_3$ | 0.0106 | 0.0034 | 3.1000 | 0.0020 |
| $\beta_4$ | 0.0000 | 0.0000 | 0.5900 | 0.5552 |
| $R^2$ = 0.9999 | | | | |
| Moran test | $\boldsymbol{W}1$ | | $\boldsymbol{W}2$ | |
| $I$ | 0.1607 | | 0.1768 | |
| p-value | 0.0000 | | 0.0000 | |
| *LM* tests | | | | |
| | Statistics | p-value | Statistics | p-value |
| $LM_{err}$ | 23.8418 | 0.0000 | 38.2697 | 0.0000 |
| $LM_{lag}$ | 0.0026 | 0.9595 | 5.5663 | 0.0183 |
| $RLM_{err}$ | 31.3122 | 0.0000 | 32.7368 | 0.0000 |
| $RLM_{lag}$ | 7.4730 | 0.0063 | 0.0333 | 0.8551 |
| $b$ | 22.45% | | | |
| $t_{half\text{-}life}$ | 3.09 | | | |

*Note*: $\beta_1$ – time lag of dependent variable; $\beta_2$ – disposable income per capita; $\beta_3$ – unemployment rate; $\beta_4$ – consumption price index.

Statistically significant parameter $\beta_1$ confirms the correctness of the estimated model. Moreover, its value, positive and less than one, indicates the occurrence of the convergence process. Current inequalities can be reduced by half in more than three years. It results from convergence speed, which is around 22.5% annually. Parameter $\beta_2$ denotes the negative impact of the increase in disposable income on the share of food expenditure. In turn, an increase in the unemployment rate causes an average increase in the dependent variable level (positive and statistically significant parameter $\beta_3$). There is no influence of inflation on the share of food expenditure convergence.

The results of Moran's test indicate the presence of spatial autocorrelation in the model residuals, regardless of the neighborhood matrix used. Moreover, the Lagrange Multiplier tests prove that the spatial error model is better than the spatial lag model in the case of both connection matrices. Therefore, it can be supposed that in the further step of the research, models with the spatial shift of the error term will be better than models with the spatial shift of the endogenous variable.

Choosing an appropriate model with a spatial factor begins with estimating the general Manski model containing all types of spatial shifts. Table 3 presents the results of the estimation and verification of general models. The convergence model extended by spatial dependence based on the geographical proximity (***W***1) contains a significant parameter only for the impact of omitted or random processes (λ). The remaining spatial parameters are not relevant. In turn, in the case of ecological similarity (matrix ***W***2), both the λ and ρ parameters are statistically significant, as well as one of the parameters describing the influence of exogenous variables ($\theta_2$). It is worth noting that the parameter $\beta_3$ lost validity compared to the base model. This is the undesirable property of modelling that takes into account economic theory. Moreover, residuals in models for both neighborhood types (geographical and ecological) do not show spatial autocorrelation, considering the Moran's I statistics. In the following step, the reduction of the models shown in Table 3 into SDM, SDEM, and SAC is considered (see the results of estimation and verification in Appendix Table A3).

In the case of the ***W***1 matrix, after reducing the general model, there are models obtained with significant parameters for spatially lagged variables (except for $\theta_3$ and $\theta_4$, which are irrelevant in all estimated models). Nevertheless, spatial autocorrelation in the residuals occurs for the SDM model, which makes this model worse than the rest. Models SDEM and SAC are similar in quality, but the advantage of the SAC model is the lower value of the Akaike criterion. For the ***W***2 matrix, choosing the best model among SDM, SDEM, and SAC is easier. There, the spatial Durbin error model surpasses the rest because in the SDM, spatial autocorrelation in the residuals occurs, and in the SAC model, the parameter ρ is not statistically significant. Therefore, in the first step of reducing the general model, the SAC for the ***W***1 matrix and the SDEM for the ***W***2 matrix are recommended as the best.

**Table 3.** The results of the estimation and verification of the Manski conditional convergence model

| Parameter | ***W***1 | | | ***W***2 | | |
|---|---|---|---|---|---|---|
| | Estimate | Std. Error | p-value | Estimate | Std. Error | p-value |
| $\beta_1$ | 0.8021 | 0.0194 | < 2.2e-16 | 0.7850 | 0.0202 | < 2.2e-16 |
| $\beta_2$ | –0.0417 | 0.0076 | 0.0000 | –0.0355 | 0.0068 | 0.0000 |
| $\theta_2$ | 0.0155 | 0.0101 | 0.1261 | 0.0277 | 0.0090 | 0.0021 |
| $\beta_3$ | 0.0082 | 0.0035 | 0.0178 | 0.0063 | 0.0036 | 0.0748 |
| $\theta_3$ | 0.0068 | 0.0052 | 0.1877 | 0.0097 | 0.0057 | 0.0926 |
| $\beta_4$ | 1.37E-05 | 2.77E-05 | 0.6203 | 8.63E-06 | 2.71E-05 | 0.7502 |
| $\theta_4$ | 2.64E-05 | 2.56E-05 | 0.3040 | 0.0001 | 0.0001 | 0.1445 |
| ρ | –0.0471 | 0.0296 | 0.1113 | 0.0704 | 0.0331 | 0.0332 |
| $l$ | 0.2212 | 0.0379 | 0.0002 | 0.1731 | 0.0435 | 0.0433 |
| Moran's *I* | –0.0214 | | 0.2914 | –0.0182 | | 0.2837 |
| AIC | –3156.8000 | | | –3163.3000 | | |

*Note*: $\beta_1$ – time lag of dependent variable; $\beta_2$ – disposable income per capita; $\beta_3$ – unemployment rate; $\beta_4$ – consumption price index, ρ – spatial shift of the dependent variable, λ – spatial shift of the residual component, $\theta_2$, $\theta_3$, $\theta_4$ – spatial shifts of disposable income, unemployment rate, and consumption price index, respectively.

The next stage of the study involves the reduction of the SDM, SDEM, and SAC models into the Spatial Autocorrelation (SAR) model, Spatial Error (SE) model, and spatial lag of X (SLX) model (please see the results of their estimation and verification in Appendix Table A4). For both neighbourhood matrices, the spatial error model is chosen because of spatial autocorrelation in the residuals of the SAR and SLX models.

Finally, there are two models for the ***W***1 matrix – SAC and SE – and also two models for the ***W***2 matrix – SDEM and SE. Among them, this study applies the one based on the AIC values and economic reasons.

For comparison of the utility of spatial models (SAR, SE, SDM, SAC, SDEM, Manski), the Akaike criterion (AIC) values are collected in Table 4. For the ecological neighborhood matrix (***W***2), the value of AIC is the lowest for the spatial Durbin Error Model (SDEM), so this model can be seen as better than the others. However, as the final model, the study applies the spatial Error Model (SE) due to economic reasons (the lack of significance of the impact of the unemployment rate, including spatial shifts of exogenous variables) and also a slight difference in AIC value. In turn, for the ***W***1 matrix (describing the geographical neighborhood), the SAC model is the best based on the AIC criterion. This model is presented as the final conditional convergence model for the ***W***1 matrix.

Therefore, the spatial error model estimation and verification results for matrices ***W***1 and ***W***2 are presented in Table 5.

Statistically significant parameter $\lambda$ in both models confirms the relevance of the connections between neighboring states in the case of food expenditure convergence. Moreover, the ecological similarity shows a slightly lower strength of the spatial relationship ($\lambda = 0.2423$ for ***W***2 matrix). It means that the random processes or processes not included in the model from countries with similar ecological development have a lower impact on food expenditure in the individual unit than in countries in the direct geographical neighborhood. But the strength of the spatial relationship based on geographical proximity is lowered by the influence of the level of food demand from neighbouring countries (the negative estimation of parameter $\rho$). Therefore, the common impact of spatially lagged variables is higher for ecological similarity. The effect of the additional explanatory variables is the same as in the case of the non-spatial convergence model.

Estimates of the parameter $\beta_1$ in the spatial models, a slight acceleration of the convergence process is considered, considering the ecological neighborhood and a slight slowdown with the use of ***W***1 matrix. The speed of convergence for these models is 23.76% and 22.88%, respectively.

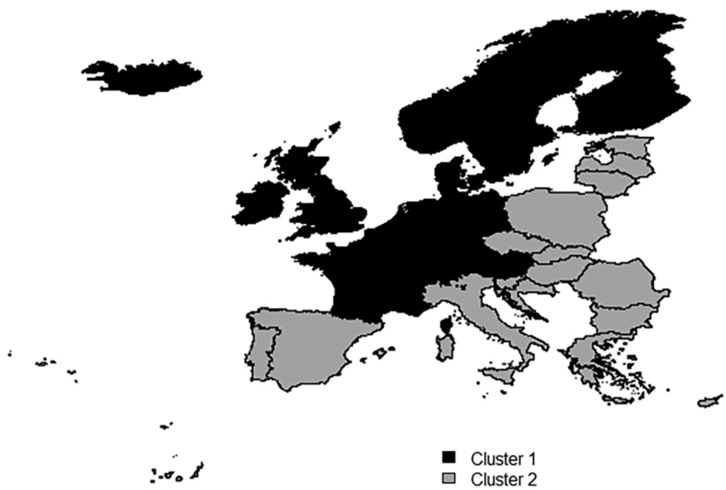
**Table 4.** The results of the comparison of spatial models – Akaike criterion

| ***W***1 matrix | | | | | | | |
|---|---|---|---|---|---|---|---|
| Model | LM | SAR | SE | SDM | SAC | SDEM | Manski |
| AIC | –3131.4 | –3129.4 | –3150.4 | –3143.5 | –3159.5 | –3157.9 | –3156.8 |
| ***W***2 matrix | | | | | | | |
| Model | LM | SAR | SE | SDM | SAC | SDEM | Manski |
| AIC | –3131.4 | –3134.7 | –3162.4 | –3155.2 | –3161.1 | –3164.3 | –3163.3 |

**Table 5.** The results of the estimation and verification of the spatial conditional convergence models

| Parameter | ***W*1** | | | ***W*2** | | |
|---|---|---|---|---|---|---|
| | Estimate | Std. Error | p-value | Estimate | Std. Error | p-value |
| $\beta_1$ | 0.7955 | 0.0199 | 0.0000 | 0.7885 | 0.0200 | 0.0000 |
| $\beta_2$ | –0.0402 | 0.0070 | 0.0000 | –0.0281 | 0.0061 | 0.0000 |
| $\beta_3$ | 0.0087 | 0.0034 | 0.0115 | 0.0091 | 0.0034 | 0.0075 |
| $\beta_4$ | 4.04E-06 | 0.0000 | 0.8782 | 0.0000 | 0.0000 | 0.7507 |
| $\rho$ | –0.0817 | 0.0203 | 0.0001 | – | – | – |
| $I$ | 0.2547 | 0.0388 | 0.0000 | 0.2423 | 0.0415 | 0.0000 |
| pseudo-$R^2$ | 0.9929 | | | 0.9929 | | |
| Moran test | | | | | | |
| $I$ | –0.0244 | | | –0.0258 | | |
| p-value | 0.2635 | | | 0.2031 | | |
| AIC | –3159.5000 | | | –3162.4000 | | |
| $b$ | 22.88% | | | 23.76% | | |
| $t_{half\text{-}life}$ | 3.03 | | | 2.92 | | |

*Note*: $\beta_1$ – time lag of dependent variable; $\beta_2$ – disposable income per capita; $\beta_3$ – unemployment rate; $\beta_4$ – consumption price index, $\rho$ – spatial shift of the dependent variable, $\lambda$ – spatial shift of the residual component.




*Note*: Cluster 1: Austria, Belgium, Denmark, Finland, France, Germany, Iceland, Ireland, Luxembourg, Netherlands, Norway, Sweden, Switzerland, United KingdomCluster 2: Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Greece, Hungary, Italy, Latvia, Lithuania, Malta, Poland, Portugal, Romania, Slovakia, Slovenia, Spain.

**Figure 1.** Spatial differentiation of determined regimes

In the next step of the study, club convergence is applied. Ward Clustering divided countries into two groups regarding GDP per capita similarity. Figure 1 presents the spatial differentiation of the determined regimes resulting from cluster analysis.

Regimes create two spatially consistent areas. In the first cluster, countries of Northern and northwestern Europe are included. The remaining territorial units (from the southern and southeastern parts of the considered area) are classified into the second group.

Table 6 presents the results of the estimation and verification of the absolute club convergence model. A difference in the parameters $\beta_1^1$ and $\beta_1^2$ denotes that the convergence process occurs faster in the group of higher developed economies (R1). The speed of inequality reduction is higher by almost six percentage points (17.91% for R1 countries and 12.10% for the second regime). It causes the time needed to reduce inequalities by half to be longer, about 2 years in less developed economies. That can result from a more homogenous and more stable character of states in the first cluster.

Moran's test points out the presence of spatial autocorrelation in the model residuals. Moreover, LM tests show that the SE model is better than SAR (spatial autoregressive) in describing the spatial connections between states (for both types of the connection matrix). Thus, Table 7 presents the results of estimating and verifying the absolute club-convergence model in the spatial context.

The statistically significant parameter λ confirms the relevance of connections between neighboring countries in the household's food expenditure. A higher estimate for the SE model with the ***W***1 matrix denotes a higher similarity in the food spending between units with a similar level of environmental development than in neighboring units directly in the

**Table 6.** The results of the estimation and verification of the absolute club convergence model

| Parameter | Estimate | Std. Error | t Statistics | p-value |
|---|---|---|---|---|
| $\beta_1^1$ | 0.8361 | 0.0236 | 35.4030 | 0.0000 |
| $\beta_1^2$ | 0.8861 | 0.0124 | 71.5780 | 0.0000 |
| $R^2$ = 0.9999 | | | | |
| Moran test | ***W***1 | | ***W***2 | |
| $I$ | 0.1609 | | 0.1678 | |
| p-value | 0.0000 | | 0.0000 | |
| *LM* tests | | | | |
| | Statistics | p-value | Statistics | p-value |
| $LM_{err}$ | 23.8870 | 0.0000 | 34.4870 | 0.0000 |
| $LM_{lag}$ | 3.6693 | 0.0554 | 10.3933 | 0.0013 |
| $RLM_{err}$ | 20.2832 | 0.0000 | 24.9952 | 0.0000 |
| $RLM_{lag}$ | 0.0655 | 0.7980 | 0.9015 | 0.3424 |
| | R1 | | R2 | |
| $b$ | 17.91% | | 12.10% | |
| $t_{half\text{-}life}$ | 3.87 | | 5.73 | |

*Note*: $\beta_1^h$ – time lag of dependent variable in h$^{th}$ regime.

**Table 7.** The results of the estimation and verification of the spatial absolute club convergence model

| Parameter | ***W*1** | | | ***W*2** | | |
|---|---|---|---|---|---|---|
| | Estimate | Std. Error | p-value | Estimate | Std. Error | p-value |
| $\beta_1^1$ | 0.8458 | 0.0241 | 0.0000 | 0.8365 | 0.0239 | 0.0000 |
| $\beta_1^2$ | 0.8832 | 0.0133 | 0.0000 | 0.8838 | 0.0128 | 0.0000 |
| $l$ | 0.1715 | 0.0389 | 0.0000 | 0.2279 | 0.0420 | 0.0000 |
| pseudo-$R^2$ | 0.9925 | | | 0.9926 | | |
| Moran test | | | | | | |
| $I$ | –0.0162 | | | –0.0236 | | |
| p-value | 0.3428 | | | 0.2248 | | |
| AIC | –3127.0000 | | | –3135.5000 | | |
| | R1 | | R2 | R1 | | R2 |
| $b$ | 16.75% | | 12.42% | 17.85% | | 12.35% |
| $t_{half\text{–}life}$ | 4.14 | | 5.58 | 3.88 | | 5.61 |

Note: $\beta_1^h$ – time lag of dependent variable in h[th] regime, λ – spatial shift of the residual component.

space (same as in the case of non-club convergence). Including spatial connections speeds up the convergence process in the group of less developed states. In turn, the time needed to reduce current inequalities by half became slightly longer (compared with the non-spatial model) in countries with a higher GDP per capita, considering the geographical neighborhood. The desirable characteristic of both models is the lack of spatial autocorrelation in residuals.

Finally, the effect of including additional explanatory variables is considered along with the estimation and verification of conditional club-convergence spatial models. The results are presented in Table 8.

The different effects of the processes conditioning the convergence of food expenditure depending on the state's cluster are worth noting. The significant influence of changes in the disposable income and the unemployment rate in the second group (parameters $\beta_2^2$ and $\beta_3^2$) causes the convergence to speed up in this cluster. The convergence speed increased from 12.42% to 21.81% and from 12.35% to 23.15% for models with ***W***1 and ***W***2 matrix, respectively. This results in the lower value of $t_{\text{half-life}}$ statistics for the second regime states than in the first group of economies (different than in the absolute convergence). The non-relevance of the disposable income had an impact on the higher developed economies (parameter $\beta_2^1$). That can result from reaching such an income level where the share of food expenditure does not increase (according to Engel's law). In turn, a significant influence of the inflation rate is observed, which is different from that of the second cluster.

Similarly, as in the case of absolute convergence, the ecological neighborhood exhibits higher strength than the geographical neighborhood (based on the higher estimate of parameter λ in the model with ***W***2 than ***W***1 matrix). Moreover, consideration of the spatial connections allows for reducing the residual spatial autocorrelation.

**Table 8.** The results of the estimation and verification of the spatial absolute club convergence model

| Parameter | ***W*1** | | | ***W*2** | | |
|---|---|---|---|---|---|---|
| | Estimate | Std. Error | p-value | Estimate | Std. Error | p-value |
| $\beta_1^1$ | 0.8328 | 0.0329 | 0.0000 | 0.8055 | 0.0324 | 0.0000 |
| $\beta_2^1$ | –0.0090 | 0.0117 | 0.4398 | –0.0176 | 0.0112 | 0.1169 |
| $\beta_3^1$ | 0.0148 | 0.0057 | 0.0088 | 0.0132 | 0.0056 | 0.0192 |
| $\beta_4^1$ | 0.0048 | 0.0013 | 0.0004 | 0.0035 | 0.0013 | 0.0081 |
| $\beta_1^2$ | 0.8040 | 0.0244 | 0.0000 | 0.7934 | 0.0242 | 0.0000 |
| $\beta_2^2$ | –0.0239 | 0.0072 | 0.0008 | –0.0269 | 0.0071 | 0.0002 |
| $\beta_3^2$ | 0.0093 | 0.0043 | 0.0300 | 0.0085 | 0.0042 | 0.0413 |
| $\beta_4^2$ | 0.0000 | 0.0000 | 0.6686 | 0.0000 | 0.0000 | 0.7751 |
| $l$ | 0.1751 | 0.0388 | 0.0000 | 0.2276 | 0.0420 | 0.0000 |
| pseudo-$R^2$ | 0.9929 | | | 0.9930 | | |
| Moran test | | | | | | |
| $I$ | –0.0180 | | | –0.0242 | | |
| p-value | 0.3247 | | | 0.2490 | | |
| AIC | –3155.1000 | | | –3161.6000 | | |
| | R1 | | R2 | R1 | | R2 |
| $b$ | 18.30% | | 21.81% | 21.63% | | 23.15% |
| $t_{half\text{-}life}$ | 3.79 | | 3.18 | 3.20 | | 2.99 |

*Note*: $\beta_1^h$ – time lag of dependent variable in h$^{th}$ regime, $\beta_2^h$ – disposable income in h$^{th}$ regime, $\beta_3^h$ – unemployment rate in h$^{th}$ regime, $\beta_4^h$ – consumption price index in h$^{th}$ regime, λ – spatial shift of the residual component.

## 5. Policy implications and discussion

This paper contributes to the ongoing debate on the consequences of economic growth and its impact on food demand and ecological aspects. This paper contributes to the current state of knowledge in food demand studies, broadening the horizons with additional vital variables in this phenomenon. Not only does it analyze the disposable income but it also includes unemployment and inflation as factors that might contribute to changes in food expenditure. It is essential to understand all the connections between the different variables in this puzzle in order to make the necessary choices in formulating socioeconomic policy. Having these three crucial aspects in one research on food expenditure enriches the current debate on a broader topic: sustainable consumption. Understanding the connection between those factors is important for shaping economic policies that align with social progress and environmental protection.

The results indicate that the convergence process of the share of food expenditure occurred in the considered countries from 1995 to 2019. The analysis of convergence was conducted for both cases: common land border (***W*1**); and ecological development similarity

(***W***2). In both criteria, ***W***1 and ***W***2, the convergence was positively conditioned by the unemployment level and negatively by the disposable income, and there was no impact of inflation. When society gets richer and richer, it tends to spend less disposable income on food, on average. Although their spending on food might increase in absolute terms, their share of food expenditure would eventually decrease. That might be caused by many factors that influence consumer spending behaviors, and as a result, people tend to spend more money on higher-order goods. When unemployment increases, so does the share of disposable income spent on food. In times of uncertainty, when there is a growing unemployment level, people tend to save money. People who have already lost jobs very often cannot afford to pay the bills and buy food, so their share of disposable income spent on food increases. Surprisingly, the inflation rate did not have any impact on household choices in terms of food expenditure in the studied countries.

This study is indeed crucial for policymakers as it underlines the need for targeted policy actions depending on the economic situation. Especially during the economic slowdown and growing unemployment, food policy should be much more focused on implementing tools to make food more affordable. In turn, when an economy is in the expansion phase, and as long as society gets richer and richer, relatively low food prices should no longer be at the heart of food policy. Global leaders should also think of enhancing a higher level of economic growth in less developed countries. That is because the analysis of club convergence for both ***W***1 and ***W***2 proved that in the group of initially wealthier economies, the convergence is faster, which can be attributed to the more homogenous character of that group. Changes in disposable income and the unemployment rate sped up the convergence in the cluster of relatively less developed countries. Thus, their leaders should address these aspects in their policies by promoting actions that would increase disposable income and reduce the unemployment rate. In the group of more developed economies, disposable income had no influence on the food expenditure convergence. It might not be surprising since, according to Engel's law, these countries could reach a particular level of disposable income from which the share of food expenditure does not rise.

Contrary to the results from non-club conditional convergence, here, the inflation rate positively impacted considered convergence but only in the first cluster (in the second one, the parameter is not statistically significant). It means that in more developed economies, the higher the inflation, the higher the share of disposable income spent on food. It may be because the society in wealthier economies does not necessarily change its food consumption patterns as the price increases. Meanwhile, in less developed economies, people tend to change their food expenditure patterns (by searching for substitutes, discounts, etc.) as the price rises. Lastly, it is worth mentioning that spatial connections allow for reducing spatial autocorrelation of residuals and that the ecological neighborhood tends to have higher strength than the geographical neighborhood.

Comparing this research with other studies, using spatial models in food demand analysis is a new approach. Hitherto, causality analysis has been applied to analyze the relationship between consumption and its major determinants, such as unemployment and inflation. Therefore, adding a spatial aspect is the main advantage and strength of this study. Moreover, the main economic relationships related to household consumption, as in the other studies, were confirmed.

## 6. Conclusions

The paper touches on a very significant issue of food demand, which affects society as a whole. The level of disposable income drives certain human behaviors. This study focused on the changes in the share of household food expenditure caused by not only changes in disposable income but also two major macroeconomic phenomena: unemployment and inflation. In addition, it also offered a spatial model that examines two kinds of neighborhoods: a common land border and similarity in ecological development. The analysis applied the β-convergence model to see if, initially, worse-performing countries grow at a faster rate than the best ones. That would eventually allow the poorer ones to catch up with the rich ones, so it will equalize the chances and decrease (or even end) inequalities and disparities.

The study forms an essential consideration not only for academia but also for business and policymakers, as it concerns the food demand that can be affected by different economic dimensions, such as unemployment and inflation. Producers need to know what to produce, as changes in food demand (the type of food, its quantity) may appear as the disposable income of households increases or decreases. Policymakers ought to react and intervene when they see the problem with reducing food price affordability.

Further research on this topic might include a different spatial consideration (e.g., analysis of various regional units), examination of the COVID-19 pandemic period, and other determinants of households' food demand (e.g., educational level or cultural conditions).

## Author contributions

Authors declare that they have contributed this paper equally. T. G. and M. J.: conceptualization, investigation, resources, formal analysis, writing – original draft. T. G.: validation, project administration. M. J.: methodology, software, data curation, visualization.

## Disclosure statement

The authors declare that they have no conflict of interest.

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## APPENDIX

**Table A1.** The descriptive statistics of the explanatory variables used in the research

| Measure | Mean | Median | Minimum | Maximum |
|---|---|---|---|---|
| X1 | 14037 | 13738 | 771.98 | 47549 |
| X2 | 8.2737 | 7.205 | 1.81 | 27.47 |
| X3 | 4.7971 | 2.1305 | -4.4781 | 1058.4 |
| Measure | Standard deviation | Volatility | Skewness | Kurtosis |
| X1 | 8761.5 | 0.62417 | 0.73968 | 0.56717 |
| X2 | 4.3806 | 0.52947 | 1.3354 | 2.0521 |
| X3 | 39.594 | 8.2538 | 25.491 | 673.04 |

**Table A2.** The correlation matrix between explanatory variables used in the research

| | X1 (Disposable income) | X2 (Unemployment) | X3 (CPI) |
|---|---|---|---|
| X1 (Disposable income) | 1 | –0.4159 | –0.1094 |
| X2 (Unemployment) | –0.4159 | 1 | 0.0451 |
| X3 (CPI) | –0.1094 | 0.0451 | 1 |

**Table A3.** The results of the estimation and verification of the SDM, SDEM, and SAC models

| Parameter | ***W***1 | | | ***W***2 | | |
|---|---|---|---|---|---|---|
| | SDM | SDEM | SAC | SDM | SDEM | SAC |
| $\beta_1$ | 0.7971 (0.0000) | 0.8058 (0.0000) | 0.7955 (0.0000) | 0.7662 (0.0000) | 0.7911 (0.0000) | 0.7899 (0.0000) |
| $\beta_2$ | –0.0439 (0.0000) | –0.0412 (0.0000) | –0.0402 (0.0000) | –0.0398 (0.0000) | –0.0339 (0.0000) | –0.0299 (0.0000) |
| $\theta_2$ | 0.0433 (0.0000) | 0.0267 (0.0002) | – | 0.0429 (0.0000) | 0.0129 (0.0218) | – |
| $\beta_3$ | 0.0084 (0.0202) | 0.0082 (0.0186) | 0.0087 (0.0115) | 0.0064 (0.0786) | 0.0065 (0.0638) | 0.0083 (0.0075) |
| $\theta_3$ | 0.0047 (0.3523) | 0.0064 (0.2147) | – | 0.0074 (0.0171) | 0.0107 (0.0709) | – |
| $\beta_4$ | 7.24E-06 (0.7914) | 1.24E-05 (0.6522) | 4.04E-06 (0.8782) | 1.71E-06 (0.9491) | 1.56E-05 (0.5689) | 7.68E-06 (0.7508) |
| $\theta_4$ | 3.12E-05 (0.2116) | 2.77E-05 (0.2726) | – | 4.54E-05 (0.4498) | 0.0001 (0.0649) | – |
| $\rho$ | 0.0729 (0.0053) | – | –0.0817 (0.0001) | 0.1455 (0.0000) | – | –0.0183 (0.3428) |
| $l$ | – | 0.1758 (0.0000) | 0.2547 (0.0000) | – | 0.2506 (0.0000) | 0.2613 (0.0000) |
| Moran's *I* | 0.0952 (0.0038) | –0.0176 (0.3281) | –0.0244 (0.2635) | 0.0588 (0.0203) | –0.0253 (0.2078) | –0.0258 (0.2031) |
| AIC | –3143.5 | –3157.9 | –3159.5 | –3155.2 | –3164.3 | –3161.1 |

**Table A4.** The results of the estimation and verification of the SAR, SE, and SLX models

| Parameter | ***W***1 | | | ***W***2 | | |
|---|---|---|---|---|---|---|
| | SAR | SE | SLX | SAR | SE | SLX |
| $\beta_1$ | 0.7988 (0.0000) | 0.8019 (0.0000) | 0.8026 (0.0000) | 0.7866 (0.0000) | 0.7885 (0.0000) | 0.8007 (0.0000) |
| $\beta_2$ | –0.0227 (0.0006) | –0.0239 (0.0000) | –0.0422 (0.0000) | –0.0192 (0.0013) | –0.0281 (0.0000) | –0.0312 (0.0000) |
| $\theta_2$ | – | – | 0.0264 (0.0007) | – | – | 0.0126 (0.0398) |
| $\beta_3$ | 0.0106 (0.0015) | 0.0098 (0.0040) | 0.0085 (0.0230) | 0.0119 (0.0004) | 0.0091 (0.0075) | 0.0068 (0.0766) |
| $\theta_3$ | – | – | 0.0052 (0.3186) | – | – | 0.0088 (0.1234) |
| $\beta_4$ | 1.66E–05 (0.5445) | 1.38E-05 (0.6082) | 8.82E-06 (0.7552) | 1.58E-05 (0.5630) | 8.39E-06 (0.7507) | 1.11E-05 (0.6934) |
| $\theta_4$ | – | – | 3.12E-05 (0.2274) | – | – | 0.0001 (0.2817) |
| $\rho$ | 0.0010 (0.9604) | – | – | 0.0439 (0.0208) | – | – |
| $l$ | – | 0.1726 (0.0000) | – | – | 0.2426 (0.0000) | – |
| Moran's *I* | 0.1597 (0.0000) | –0.0171 (0.3335) | 0.1659 (0.0000) | 0.1368 (0.0000) | –0.0258 (0.2031) | 0.1828 (0.0000) |
| AIC | –3129.4 | –3150.4 | – | –3134.7 | –3162.4 | – |