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LOCAL DIMENSIONS OF REGIONAL INCOME INEQUALITIES IN THE 2010S - GEOGRAPHICAL PROXIMITY BASED EXPERIENCES FROM HUNGARY

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Abstract

In this paper, we look at how geographical proximity influences settlement income trends in the period following the 2008 economic crisis. In the first part of the paper, we highlight the general impact of geographical proximity effects on socio-economic processes, followed by a discussion of the spatiality of income inequality phenomena in Hungary.

The income inequality analyses are carried out using spatial econometric methods: global and local spatial autocorrelation (Global and Local Moran I, Getis-Ord General G, Getis-Ord Gi*), kernel density estimation, and 'spaceless' Markov-, Spatial- and LISA Markov chains expressing income mobility. Our LISA Markov chain analysis is experimentally based on the Getis-Ord Gi* categories, which, to the best of our knowledge, is unique in the spatial econometric income inequality literature.

The results show that spatial income processes in the 2010s are related to both Myrdal's theory of cumulative causality and Richardson's theory of polarization reversal. In a period of income expansion, territorial income spillovers are limited and localised, and in practice reinforce the contiguous central region west of the capital, while peripheral regions are not significantly dissolved and in many cases are re-enforced. The results of the period under review highlight that Hungary is still a transitional country in terms of spatial inequalities.

Keywords: Local Moran I, Getis-Ord Gi*, income distribution, centre-periphery

INTRODUCTION

In the period following the regime change, the socio-economic transformation of the Central and Eastern European region can be described by very clear spatial features (Gorzelak, 1997; Leibenath et al, 2007; Rechnitzer et al. 2008, Szabó & Farkas, 2014; Smetkowski 2014; ESPON 2012, 2014). Compared to the previous period (socialism), new and novel phenomena (innovations, transnational corporations, foreign direct investment, international competition, metropolisation, economic restructuring, the emergence of infocommunications, etc.) have significantly modified and are still modifying the spatial structure of each country (Enyedi 2004; Lux, 2012; Nemes Nagy, 2009; Nölke−Vliegenthart, 2009; Capello−Perucca, 2013, Smetkowski, 2018; Lengyel, 2021).

In explaining these phenomena, as well as development and backwardness, spatial parameters such as geographical length, distance from capitals, other centres and western borders, access to higher transport infrastructures (motorways, trans-European networks) and neighbourhood effects are again having an independent and reinforced explanatory power. (Gorzelak, 2001; Győri & Mikle, 2017; Jakobi, 2018).

Hungary's territorial disparities also reveal the socio-economic effects of the above spatial parameters. The central and north-western regions (the Central Hungary and the Central and Western Transdanubian regions), which are well served by the creative destruction[1] (Schumpeter 1942) and are well served by accessibility and location, account for more than two-thirds of Hungary's gross domestic product, while the other regions are members of the lowest income convergence club in the European Union (European Commission, 2017; Immarino et al, 2017). The main spatial features are not only visible at the large scale, but also at the lower territorial levels (Lukovics & Kovács, 2011; Pénzes & Demeter, 2021; Faluvégi, 2020).

In our paper, we focus on geographical proximity and the role of neighborhood proximity among the above phenomena. Tobler's (1970) first law of geography, according to which ‘everything is related to everything else, but near things are more related than distant things’, has been/is manifested in many socio-economic dimensions in the Hungarian context. Such regionalising phenomena in Hungary include, for example, different labour market characteristics (employability, unemployment, adult education), the level of education of the population, income status, health status, economic activities, entrepreneurial activity, socio-economic development, or the population of foreign origin (Alpek–Tésits, 2019; Lőcsei, 2010; Hajdú & Koncz, 2022; Pénzes et al, 2018; Tóth & Nagy, 2013; Pénzes et al, 2014; Egri & Kőszegi, 2016; Egri, 2017; Szakálné Kanó, 2017; Jeneiné Gerő et al, 2021; Kincses & Tóth, 2019; Jakobi, 2018; Farkas & Kovács, 2018).

The aim of our study is the analysis of income inequalities in Hungary based on spatial proximity effects, during which we describe in detail the local mechanisms of the spatial organization of income structure and its spatial changes in the conjunctural period following the 2008 economic crisis.

THEORETICAL BACKGROUND

In the last two or three decades, the issues of regional income inequalities have appeared prominently both in academic research and in economic and regional policy ideas (Barro,

[1] „…process of industrial mutation that continuously revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one.” (Schumpeter 1942)

1991; Quah, 1996; Komlósi, 2014). The topic aroused keen interest in Central and Eastern Europe, including Hungary, at the time of the regime change and in the subsequent period (Nemes Nagy & Németh, 2005; Németh & Kiss, 2007; Capello & Perucca, 2013; Smętkowski, 2018). The development of regional income inequality trends, the factors shaping inequalities and growth/convergence, as well as the positioning of certain types of settlements in a privileged position (the most backward, or a certain circle of cities), the change in their situation, the transformation of certain sample areas following regime change are all prominent research trends in Hungary and in Central and Eastern Europe (Paas et al., 2007; Czaller, 2016; Molnár et al., 2018; Lengyel & Kotosz, 2018).

International convergence studies examining income catch-up and territorial convergence point out that although income differences may decrease, convergence is not an automatic mechanism (Barro, 1991; Karahasan, 2020). Using the Markov chain model, Quah (1996) points out that regions with the same initial conditions converge and form specific clubs, the differences between which can become permanent. In other words, multiple spatial equilibrium states can be observed.

The spillover effects resulting from geographical proximity play a significant role in the formation of convergence clubs (Le Gallo, 2001; Bufetova, 2016; Karahasan, 2017; Karahasan, 2020). The assumption that territorial economies are independent of each other has long been untenable, as technological transfers, knowledge spillovers, labour migration, institutional spillovers, and economic crises testify to the fact that economies 'interact' with each other and are actually spatially dependent on each other (Varga, 2009; Czaller, 2016).

The spatiality and spatial interactions of economic and social phenomena (and to a significant extent neighbourhood effects) can be interpreted as the interaction of centrifugal and centripetal forces, as well as in the context of their feedback (Varga, 2009). This was explained by several classic and new models, presenting the main spatial relationships of agglomerations, center-periphery relations, urbanization, transport infrastructure, sectoral linkages, other forms of local characteristics, innovation, economic growth and development (Marshall, 1920; Myrdal, 1957; Pottier, 1963; Boudeville, 1968; Lausén, 1973; Richardson, 1980; Faragó, 1995; Krugman, 1991; Haggett, 2006; Crescenzi, Rodriguez & Pose, 2008; Panico & Olivella, 2009; de Bok & van Oort, 2011; Lengyel, 2021).

Le Gallo (2001) points out that areas close to higher-income regions have a greater chance of moving up (catch-up) within the income distribution, while in the case of poor neighbours, falling behind is typical. Several authors have used global and local spatial autocorrelation methods (Moran I, Getis Ord Gi*) and Markov chain analysis based on spatial categories to highlight the local persistence or mobility of the spatial income situation in the EU, the US and Mexico (Le Gallo & Ertur, 2000; Fischer & Stirbock, 2006; Gutiérrez & Rey, 2013; Le Gallo & Fingleton, 2013; Smetkowski, 2014; Ayouba & Le Gallo, 2019). The results all showed marked center-periphery relations in the examined spaces.

The role of geographical proximity in income inequality (with a special focus on Hungary)

In studies of regional income inequality in Hungary, the effects of geographic proximity are clearly evident, both explicitly and implicitly. Nemes Nagy and Németh (2005) use the values of the income of neighbouring sub-regions as the factors that determine the distribution of income between 1988 and 2003. In the regression models, the spatial dimension can be defined as a clear phenomenon accompanying the socio-economic transformation, and the authors explain this by the regionalising centre-periphery phenomenon. Csite and Németh (2007) show the β-convergence of the HDI[2] (Human Development Index) at the sub-regional level after the regime change (1994-2005). A significant contribution to this is made by geographical proximity, which, according to the authors, also reflects spatial differentiation. Czaller (2016) presented the conditional β-convergence of gross value added at the sub-regional level for the period 1993-2012. Its results show that the external economies of scale and the free mobility production of factors contributed to rapid convergence. Pannon Elemző et al. (2013) use spatial econometric methods to analyse the impact of EU support schemes on territorial cohesion (the economic strength of settlements[3]). Among the aid schemes implemented, spill-over effects (i.e. developmental effects on neighbours) are only observed for R&D and higher education aid and for aid to enterprises. The analysis also shows that developments in the Central Hungary region, while further increasing the weight of the central region, are also spilling over to other parts of the country, positively influencing the economic value added of the small regions. The territorial competitiveness analysis of Tóth and Nagy (2013) draws attention to the fact that spillover effects are not automatic in the proximity of large cities, and the catchment areas of competitive county seats tend to show a competitive disadvantage in many cases, rather than supporting each other. The detection of convergence clubs in income inequality in Hungary is implicit in most cases: on the one hand, different levels of the settlement hierarchy form independent and stable clubs, and on the

[2] HDI is a composite index that includes dimensions of decent living standards (income), education and healthy life (UNDP 1990).
[3] For a disaggregated version of the GDP indicator at a lower territorial level, see Csite-Németh (2007).

other hand, districts and counties composed of settlements may form income and income inequality clubs (Dusek, 2006; Németh & Kiss, 2007; Pannon Elemző et al., 2013; Pénzes, 2019). Dusek (2006), for example, used the spatial moving average method to illustrate local income groups at the settlement level based on spatial similarities between the regime change and the millennium period (metropolitan agglomerations, outer and inner peripheries, etc.). Németh and Kiss (2007), analysing the trends of internal income inequality in small regions, show that levelling, stagnating and differentiating spaces are clearly regionalised on the basis of geographical proximity. Pénzes and co-authors (2014) described the variation in spatial clubs of per capita income between 1988 and 2012 using settlement level "layers" of local autocorrelation for different periods. Egri (2020) explains the temporal variability of incomes (1988-2017) in Békés County by various factors (settlement size, distance dependence, initial income level, etc.). The author uses a spatial lag maximum likelihood regression model to demonstrate the spatially embedded substantive nature of the process. In addition, by comparing the average pattern of spatial inequality and spatial divergence, the author also shows the spatial spread and backwash effects in income structure.

From the above, it is clear that in Hungary, even at the lower territorial levels, there are forces acting in the direction of spatial income clubbing, which shape the spatial distribution of the phenomenon under study with different amplitudes.

In this paper, we aim to highlight the linkages of Hungarian income inequality processes at the settlement level based on geographical proximity. Our research seeks to answer the following questions:

Research Question (1) How does spatial proximity contribute to inequalities in income mobility/stability at the settlement level? In other words, in our paper we assume that geographical proximity not only influences static income positions, but also fundamentally affects dynamics (contributing to catching-up and lagging behind.)

Research Question (2) Do income (convergence) clubs appear as a result of movements in settlement incomes? In our study, we hypothesise that income mobility resulting from geographical proximity 'pushes' neighbouring settlements towards club formation. In this way, similarities in the spatial pattern of settlement income positions can be discovered, which are ordered by neighbourhood effects.

Research Question (3) To what extent can settlement level income clubs based on neighbourhood relations be considered stable? Our hypothesis is that income trends in Hungary (following the 2008 economic crisis) typically change the spatial configuration of incomes.

DATA AND METHODS

Answers to the research questions will be given using ETSDA (Exploratory Time-Space Data Analysis) and ESTDA (Exploratory Space-Time Data Analysis). The two acronym methods differ in their 'origin', in that they extend from the analysis of temporal processes to space (ETSDA), or they add the time dimension to the spatial modelling (ESTDA) (Rey 2019). The methods we use include the classic and spatial Markov chains for ETSDA and the Moran I, Local Moran I, Getis-Ord local Gi* and LISA[4] Markov chains for ESTDA. The relationship between the research questions/hypotheses and the methodology can be seen in Tab. 1.

Table 1 The relationship between research questions/hypotheses and applied methods in the study

Research questions/ hypotheses	Applied Methods	Applied software(s)
1.	Global Moran I, Local Moran I, Kernel density estimation, classic and spatial Markov chain	GeoDa, ArcGIS, Stata, IBM SPSS, own calculation
2.	Getis-Ord Gi*	ArcGIS
3.	LISA Markov chain based on Getis-Ord Gi*	own calculation based on ArcGIS outputs

Source: Authors' own construction

The key feature of the analyses is geographical proximity, which is described using spatial autocorrelation methods. The global approach is used to explore the average pattern of income in the Hungarian settlements. This is illustrated using Global Moran's I (Anselin, 1995; Tóth, 2014).

$$I = \frac{n}{2A}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\delta_{ij}(y_i-\bar{y})(y_j-\bar{y})}{\sum_{i=1}^{n}(y_i-\bar{y})^2},$$

where

- n is the number of spatial units indexed by i and j,
- y is the variable of interest (income per capita),
- $\bar{y}$ is the mean of y,
- A is a matrix of spatial weights with zeroes on the diagonal,
- and the δ_{ij} coefficient is 1 if i and j are neighbours and 0 otherwise.

[4] Local indicators of spatial association.

If I > -1/(n-1), the spatial autocorrelation correlation is positive, if I < -1/(n-1), the autocorrelation correlation is negative. If I = -1/(n-1), there is no autocorrelation between the territorial units. In our study, we used distance weight (K-nearest neighbours, distance band, kernel) and contiguity weight (queen, rook) matrices to operationalize neighbourhood relations.

The spatial pattern of incomes was examined using Hot spot analysis, the Getis-Ord local Gi* statistic (Getis & Ord, 1992; Anselin & Rey, 2014; Vida, 2016). The resulting z- and p-values show where high and low income settlements are clustered in Hungary. The formula is as follows:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \bar{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}}$$

where:

- $\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}$ és $S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2}$.
- x_j is the x variable in j settlement,
- n is the number of spatial units,
- w_{ij} is a matrix of spatial weights.

According to the Getis-Ord statistics, a higher than average income value (positive z-score, Gi*>1.96) indicates a 'hot spot', a lower than average value (negative z-score, Gi*<-1.96) indicates a 'cold spot', while -1.96 <Gi*<1.96 indicates non-significant spaces. Unlike the Local Moran I statistic, the Getis-Ord approach does not take into account spatial outliers.

The density-based approach of the convergence kernel aims to capture the evolution of the distribution of per capita income between settlements over time. From this point of view, convergence occurs when the shape of the cross-sectional distribution becomes unimodal over time. In this nonparametric framework, the appearance of multiple modes is usually associated with the existence of convergence clubs (Quah 1996), which contradicts general and unique convergence (Karahasan 2017).

Danny T. Quah (1996) used the classical Markov chain method to study income convergence because of the limitations of traditional β- and σ-convergence analyses. In this case, the method, by using transition probability matrices with stochastic properties, contributes to the description of the detection of the movement of settlements from one period to another. For the basic Markov chain, we used a panel approach, categorising each settlement according to the annual change. The analysis is based on 22,078 transitions. To discretise the state space, we used the equal number of observations option, dividing the settlements into five equal parts, with 20 per cent of the settlements belonging to each income class. This forms the five income classes of the Markov model. The bottom 20 percent make up the first income class, and the top 20 percent make up the fifth.

Mobility (and its presentation) is an important criterion and objective of the study, so the related indicators are also presented. The stability index provides information on the stability of the process - on the probability of remaining in the given category. The higher its value, the greater the chance of 'non-movement', i.e., in terms of income inequalities, of low-level convergence (Monfort 2020). The same phenomenon is expressed in a different way by the mobility or Shorrocks index (Shorrocks 1978). The so-called ergodic (invariant, stationary) distribution assumes a state where the distribution does not change any more, it can be interpreted as a future resting point (long-term equilibrium state) (Monfort, 2020; Le Gallo & Fingleton 2013). The rate at which the initial distribution presumably approaches the long-term equilibrium state can also be determined. This is called the half-life of the chain, which expresses how much time is required from the initial distribution to reach half of the equilibrium state (Monfort, 2020; Shorrocks, 1978).

Pearson's Q and Likelihood Ratio (LR) tests were used to examine spatial heterogeneity and temporal stationarity (Bickenbach & Bode, 2003), to determine whether or not the investigated phenomenon can be considered homogeneous in space and time. Both tests point to the significance of the correlations. (Larger values indicate significant outputs.)

An important question is how spatial interactions (knowledge, information, technology, trade, capital and labour movements, economies of scale, transfer payments, etc. (Rodríguez, Pose, & Tselios, 2015) due to geographical proximity contribute to income inequalities, such as mobility, or centre-periphery relations, or possible polarisation (Pellegrini, 2002). The spatial Markov matrix transforms the two-dimensional transition matrix into a three-dimensional one by using the initial static income values of the neighbouring observation units. The model assumes that the neighbourhood environment has an impact on a given spatial unit, contributing to catching-up or even to lagging behind, i.e. movement between transitions (Le Gallo 2001; Bickenbach & Bode, 2003). The so-called spatial conditioning was done along five categories (quintiles): poorest, below median, median income, above median, rich neighbours. The analysis of mobility is again based on the panel database.

Last but not least, the LISA Markov model is used to analyse the dynamics of the spatial dependence of incomes. The method allows us to describe the movements of local positions over the period considered. The technique is originally based on the quadrants of the Moran scatter plot, which give the possible states of the Markov chain (Rey, 2019` Le Gallo & Fingleton, 2013; Kotosz, 2016). In our article, we experimentally analyze the spatial dependence of incomes with the Getis-Ord local Gi* statistic, also with the help of the LISA Markov chain, in order to find out how local income inequalities change in space and time. Spatial clusters based on local statistics can also be interpreted as convergence clubs (Le Gallo & Ertur, 2000; Fischer & Stirböck, 2006; Rey, 2019; Gutiérrez & Rey, 2013). During the analysis, we use the panel approach again. The annual changes form the transition probability matrix of the LISA Markov chain. (22,078 observations.)

The above methods allow to study how the income performance of a settlement can be explained by its geographical environment and point to the role of space in the emergence of possible income convergence clusters (Le Gallo, 2001; Le Gallo & Fingleton, 2013; Karahasan, 2020).

The data source is the National Spatial Development and Planning Information System database. The basic indicator for income inequality at the settlement level is taxable income per capita. Like GDP, this indicator has a number of shortcomings and limitations (Major & Nemes Nagy, 1999; Kiss, 2007), but should be treated as an important dimension of socio-economic development.

It is assumed that the different geographical proximities observed in the Hungarian settlement space are also reflected in the dynamics of personal income and have a marked influence on the spatial structure of income. The focus of the study is the growth period following the economic crisis (2012-2019). After the crisis, from 2012, constant growth is typical in Hungary.

The spatial framework of the analyzes is the settlement level (there are 3155 settlements in Hungary). Annex 1 describes the Hungarian administrative classification and main spatial structure characteristics.

RESULTS

The role of spatial proximity in income inequalities

To answer the first research question, we first analyze the stability and mobility of spatial income inequalities. To operationalise the neighbourhood relations, we first tested the spatial dependence of per capita income using several spatial weight matrices. Since the analysis covers several years, we finally decided to use the most elementary weight matrix: the first-order queen matrix. Thus, the settlements included in the analysis are those that shared a border section with a settlement or were contiguous at a common point.

First, the spatial and temporal stability of the spatial autocorrelation of the phenomenon under study was examined. For this task, we used the Global and Local Moran I values and z-scores. (Tab. 2.) The Moran's I value shows an almost similar average pattern between 2012 and 2019, and the very high and statistically significant z-scores suggest that similar income values are clustered in space. Thus, in the period under review, settlements with high per capita taxable incomes in neighbouring settlements, also have high incomes, while those with low incomes in their neighbourhood, have low incomes.

The stability of this phenomenon over time and space is clearly confirmed by the results of correlation analysis on Local Moran I values expressing the nature and extent of neighborhood similarity. (Second half of Tab.2.)

The Spearman rank correlation coefficient is above +0.96 at all time points and is always highly significant ($p < 0.001$). The relationship between the initial and final period Local Moran I values is slightly weakened, but the result still shows a very close and statistically robust relationship. These results suggest that no really significant changes in the income spatial pattern can be expected.

Table 2 The main characteristics of the global spatial autocorrelation at settlement level (2012-2019)

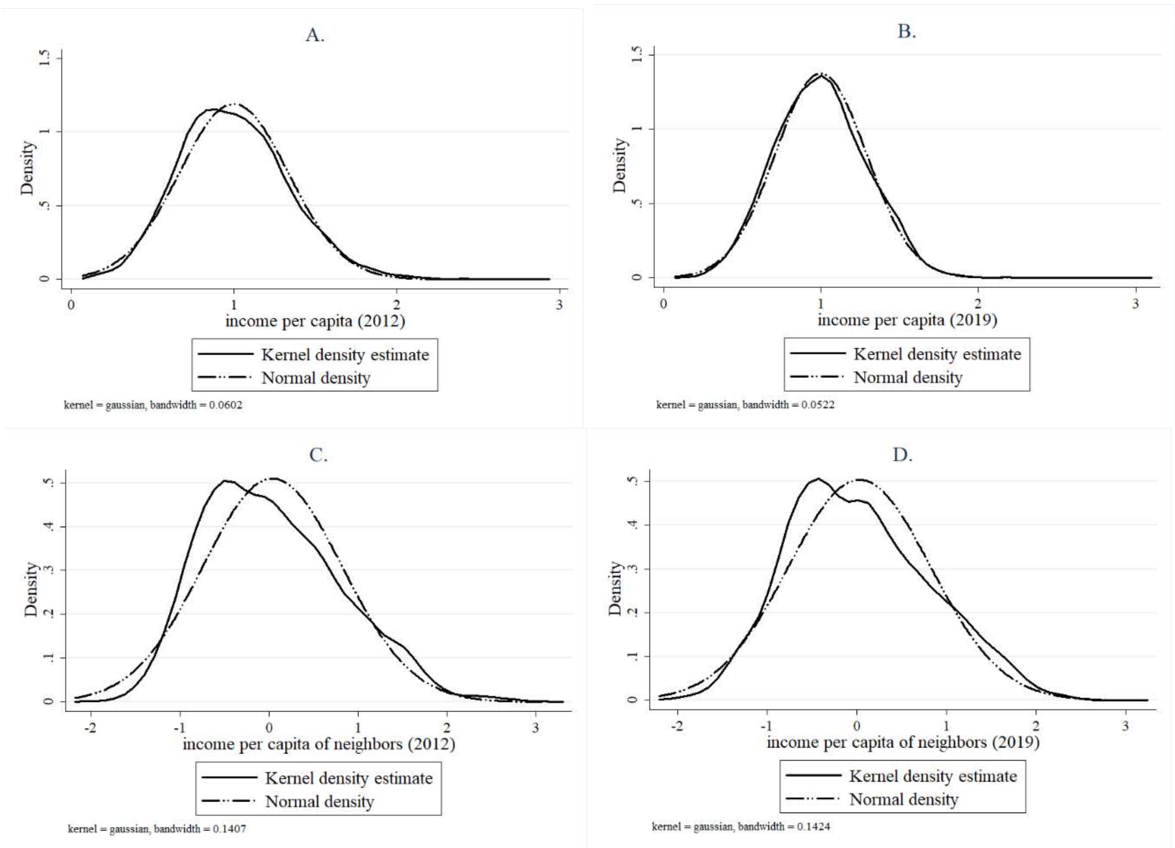
	Moran I	**z-score**	**standard deviation (I)**	**period**	**Spearman's rho**
2012	0.584***	54.93	0.0106	-	-
2013	0.552***	50.08	0.0110	2012-2013	0.968***
2014	0.569***	52.57	0.0108	2013-2014	0.972***
2015	0.564***	52.75	0.0107	2014-2015	0.962***
2016	0.585***	54.78	0.0107	2015-2016	0.966***
2017	0.571***	52.91	0.0108	2016-2017	0.969***
2018	0.565***	53.00	0.0107	2017-2018	0.971***
2019	0.597***	56.03	0.0106	2018-2019	0.968***
-	-	-	-	2012-2019	0.849***

Note: Spearman's rank correlation coefficient shows the relationships between Local Moran I values per year. Spatial weight matrix: first-order queen. *** Significant at the - 0.001 level. The value of -1/(n-1) is -0.0003 in all cases.
Source: Authors' own construction

To analyse the income distribution and its spatial context, the kernel estimation method was used to determine the distribution functions of relative per capita income and neighbourhood income values. (Fig. 1.) Based on the kernel density function for the initial (2012) and final (2019) income dates, the convergence phenomenon can be observed. (The A. and B. parts of Fig. 1.) The method does not reveal any income convergence clubs at the settlement level, and there are no significant changes in the distributions. Both kernel distributions clearly approach the normal distribution, clubs with exceptional income performance do not appear at any time.

However, the income position of the settlements is explained in a relevant way by their geographical proximity, especially near the median values. (C. and D. parts of Fig. 1.) The exception is the position of the most developed settlements (above one and a half times the national average). It is important to highlight that, in addition to the general convergence, there is a clear polarization of neighbourhood incomes in 2019 (especially around median incomes and above-average performance, there are marked club formation). Density estimations clearly show the differences between settlement and neighbourhood income situations, but not how they interact (especially the effects of neighbourhood). We therefore move on to spatial Markov chain methods.

Figure 1 Kernel density estimations of settlement and neighbourhood incomes (2012, 2019)



Note: Settlement neighbourhood incomes are based on the first-order queen matrix.
Source: Authors' own construction

The first local (spatial Markov-) matrix analyses the impact of geographical proximity on settlement income inequality and convergence. For the analysis, in addition to the original ('spaceless') Markov matrix, five 5x5 spatially conditioned transition probability matrices are created. These are intended to indicate the likelihood that a given settlement will remain or move in income clusters relative to the national average, by controlling for the income categories of its neighbours. The results obtained should be interpreted as a function of the original transition matrix, which does not take into account geographical proximity (Le Gallo 2001, Bickenbach & Bode 2003).

By including the neighbour's values from the initial period (2012), the results clearly provide a more complex picture of the settlement level income convergence processes. (Tab. 3.). The related test statistics (Q = 501.67 and LR = 463.52; with 32 degrees of freedom, p<0,000) show that the spatial context cannot be excluded from the explanation of income mobility at the settlement level, the income convergence significantly related to geographical proximity. The values indicate that the income classes of the original matrix differ significantly from the same rows of the spatially conditioned matrices, that is, for each income class, the difference is statistically robust.

Table 3 Spatial transition probability matrices of settlements (2012-2019)

income class	no. of observations	transition probabilities					homogeneity tests		
		1	2	3	4	5	d.o.f.	Qi; Q	LR
1	4406	*0.904*	0.096				4	*79.19*	*75,55*
2	4400	0.069	*0.811*	0.120			8	*74.30*	*72,87*
3	4391		0.094	*0.806*	0.100		8	*111.41*	*100,20*
4	4395			0.101	*0.822*	0.077	8	*90.28*	*87,05*
5	4400				0.088	*0.912*	4	*146.49*	*127,85*
					whole matrix		32	*501.67*	*463.52*
Spatial lag 1. (poorest neighbours)									
1	2361	*0.938*	0.062				1	*65.92*	*34,95*
2	1252	0.081	*0.843*	0.076			2	*34.29*	*27,58*
3	507		0.148	*0.785*	0.067		2	*24.28*	*19,84*
4	205			0.171	*0.751*	0.078	2	*11.67*	*9,45*
5	66				0.258	*0.742*	1	*24.01*	*16,35*
					whole matrix		8	*160.17*	*108.17*
Spatial lag 2. (neighbours with below median income)									
1	1241	*0.882*	0.118				1	*9.45*	*6,30*
2	1461	0.068	*0.832*	0.099			2	*8.98*	*6,39*
3	1104		0.106	*0.837*	0.057		2	*31.20*	*27,03*
4	471			0.144	*0.796*	0.059	2	*12.36*	*10,17*
5	120				0.225	*0.775*	1	*28.85*	*20,42*
					whole matrix		8	*90.83*	*70.30*

Table 3 (continued)

Spatial lag 3. (neighbours with median income)									
1	557	*0.855*	0.145				1	*18.00*	*13,75*
2	1044	0.064	*0.778*	0.158			2	*18.96*	*13,24*
3	1376		0.079	*0.820*	0.101		2	5.12	3,72
4	1092			0.120	*0.832*	0.048	2	*21.58*	*18,00*
5	326				0.181	*0.819*	1	*37.91*	*27,66*
					whole matrix		8	*101.57*	*76.37*
Spatial lag 4. (neighbours with above median income)									
1	221	*0.814*	0.186				1	*21.50*	*16,48*
2	536	0.054	*0.759*	0.187			2	*26.57*	*20,57*
3	1136		0.083	*0.794*	0.123		2	*10.61*	*7,51*
4	1486			0.093	*0.840*	0.067	2	5.02	3,47
5	1017				0.127	*0.873*	1	*24.80*	*17,03*
					whole matrix		8	*88.50*	*65.06*
Spatial lag 5. (rich neighbours)									
1	26	*0.769*	0.231				1	*5.47*	4,07
2	107	0.065	*0.738*	0.196			2	*6.05*	5,08
3	268		0.063	*0.701*	0.235		2	*58.78*	*42,11*
4	1141			0.063	*0.813*	0.124	2	*65.68*	*45,97*
5	2871				0.054	*0.946*	1	*117.34*	*46,39*
					whole matrix		8	*253.33*	*143.62*

Note: d.o.f. - Degree of freedom, Qi, Q - Pearson's Q-test per row and per matrix, LR - Likelihood ratio. In italics, significant test statistic values at the 0.05 level or above are shown. The matrix shows a stationary distribution over time. Cells that take a value of zero to two decimal places have been removed from the matrix. For transition probabilities, any deviation from 1.0 is due to rounding.
Source: Authors' own construction

Most of the individual rows of the transition probability matrices with different spatial lags differ significantly from the national average mobility probabilities. (Columns Qi, Q and LR in Tab. 3 show this, most of the values are highly significant.)

The table also clearly shows that the effects of geographical proximity vary significantly across the national settlement space. Settlements with lower-income neighbours have a much lower chance of catching up than similar rows in the 'spaceless' basic matrix. For example, with the poorest neighbours, the probability of moving up the income class of the least developed (p_{12}[5]) is only 6.2 percent, compared to 9.6 percent for the original matrix. In addition, the push back effect is significant for lower-income neighbours.

For neighbours below median income, the probability of being left behind in the most advanced category (p_{54}) is 22.5 per cent, compared to a base case of only 8.8 percent. The reverse is also true, with significantly higher chances of catching up and lower chances of lagging behind in an above-median spatial environment. The proximity of rich neighbours significantly increases the catching-up chances of the poorest income class (from 9.6 percent

[5] p represents the probability of the movement, the first number represents the row, while the second represents the column.

to 23.1 percent [p_{12}], which Karahasan [2017] calls the 'hinterland effect'), while significantly decreases the lagging behind (fifth income class: 5.4 per cent versus 8.8 percent, [p_{54}]). Overall, with one or two exceptions, the relationship can be considered almost linear in terms of catching-up and lagging behind levels for different geographical proximities. Neighbourhood effects also have a clear impact on stability. Poorer neighbours tend to conserve low income settlements (while more developed ones are downwardly mobile), while the same phenomenon is reversed for richer neighbours.

Table 4 Main values of mobility and convergence by different spatial lags (2012-2019)

	Hungary	spatial lags				
		1.	2.	3.	4.	5.
stability	0.851	0.812	0.825	0.821	0.816	0.794
mobility	0.186	0.235	0.219	0.224	0.230	0.258
half-lives (year)	15.368	10.313	8.916	11.145	8.269	7.784

Source: Authors' own construction

Spatial conditioning clearly accelerates income mobility compared to the 'spaceless' model, irrespective of neighbourhood positions, and the phenomenon is particularly striking for half-lives. (Tab. 4.) According to the calculation, in each income neighbourhood, processes are more mobile and faster than the national average (since all mobility, stability, and half-life times differ from the national average). The extent to which each micro-regional environment can affect income convergence is also an important question for the movement. As can be seen from Tab. 4, it is the environments at the extremes (i.e. the poorest, but especially the richest) that are characterised by the most dynamic impact mechanism. (The high value of mobility, as well as the aggregated Q and LR test results in Table 3, indicate this.)

In other words, the most significant forces of mobility associated with income convergence in the period under study essentially support, maintain or reinforce polarization (centre-periphery relations). The results of the analysis show a picture of strong and spatially differentiated mechanisms of action in settlement income convergence (and development), which is locally significant everywhere, with one or two exceptions. In other words, settlement convergence and its main components (catching-up, stagnation, lagging behind) are closely linked to neighbourhood proximity effects and cannot be understood without them.

Pessimism about catching up is realistic for settlements in the lowest income clusters and micro-environments, while upward mobility is much more likely in the (most) wealthiest neighbourhoods. The results in Tab. 3 and Annex 2 show that there are spatial multiple equilibria for settlement incomes, and these vary according to geographical context. Thus, the results in fact also provide evidence that spatial interactions lead to income convergence clusters in the spatial structure of Hungary. This is supported by both the initial and ergodic distributions, which show a relative majority of settlements corresponding to spatial proximity. (Annex 2.) The invariant distributions that can be predicted from the movements observed over the period under study do not indicate significant changes, and the spatial distributions based on geographical proximity and income convergence clubs will persist in the future.

The results on the dependence of settlement development on neighbouring spaces draw attention to the importance of spatial development based on spatial interactions, which have a fundamental influence on the success of economic development interventions at the local-regional level. The issue is particularly sensitive in relation to the lowest income neighbourhood clusters.

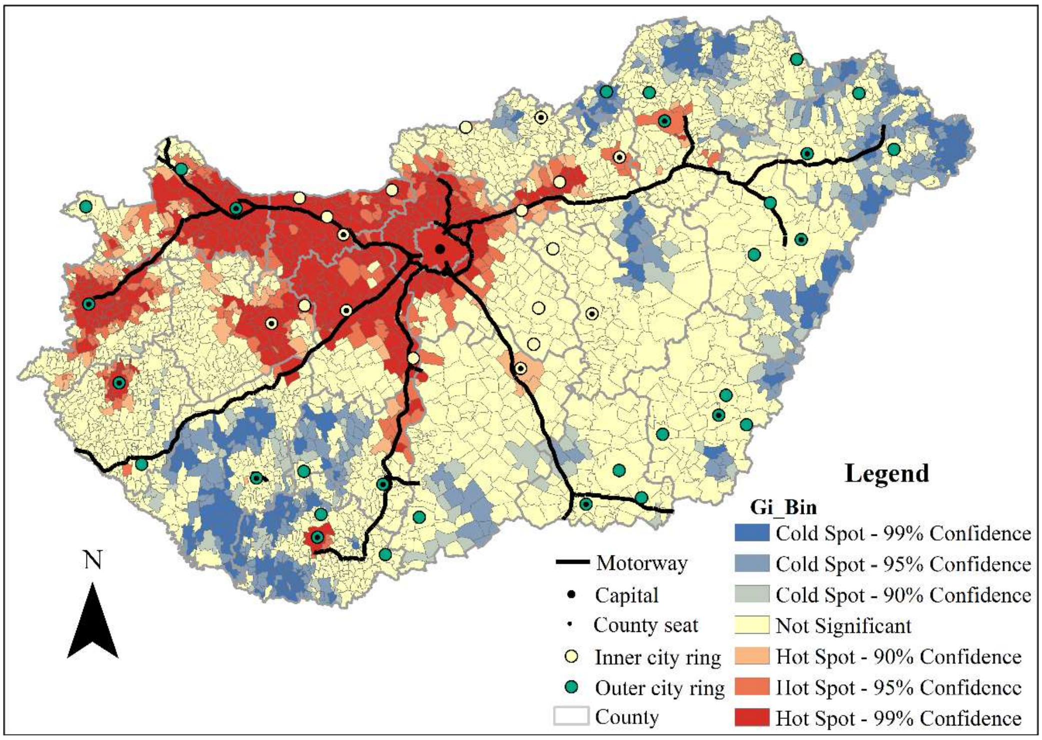
Income (convergence) clubs as results of movements in settlement incomes

The second research question refers to the emergence of income mobility clubs in Hungary as a result of geographical proximity.

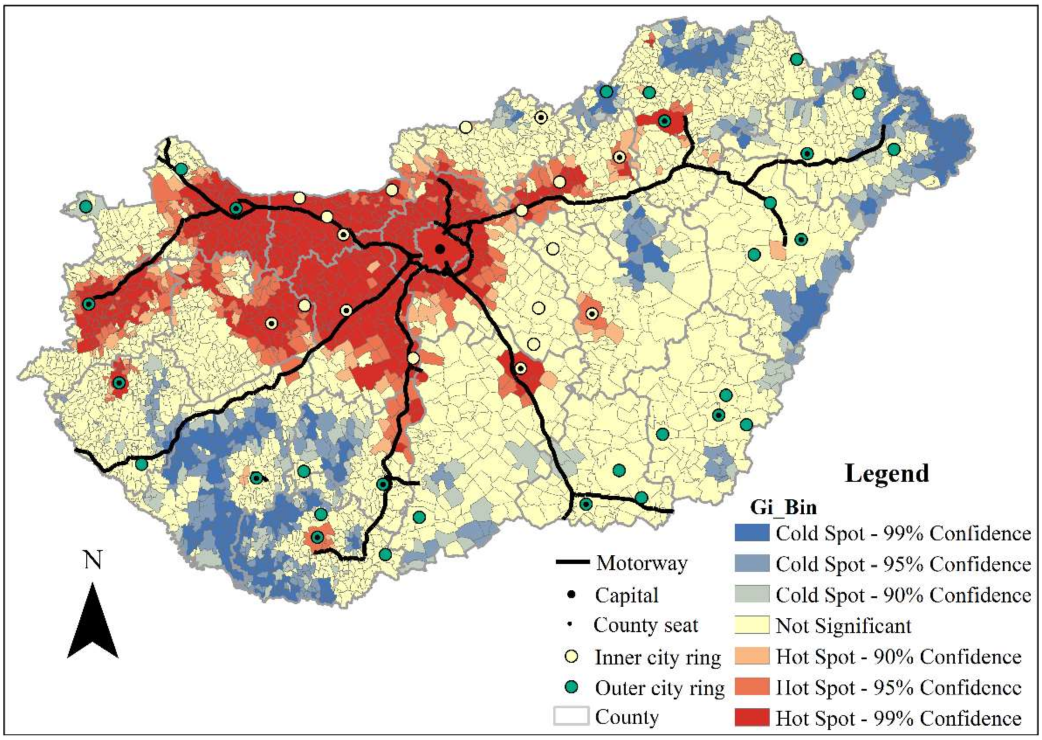
The spatial structure of incomes based on geographical proximity was analysed using the High/Low Clustering (Getis-Ord General G) method and Hot spot analysis. Based on the results of the former method, the p-value for the period 2012-2019 shows a low value (0.000) and a high significance level in all cases, i.e. spatial clustering of incomes is observed. The z-scores show a positive value in each year (ranging from 24.27 to 28.38), i.e. high-income settlements are clustered in Hungary in the period under study.

The income spatial structure in the examined period is very stable, indicating a clearly spatially separated meso (larger scale) centre-periphery pattern (income convergence clubs). The results shown on the map confirm the spatial correlations reported in sources on spatial income autocorrelation in the 2010s (Tóth & Nagy, 2013; Pénzes et al., 2014), with no significant visual differences between the two dates. (Fig. 2)

Figure 2 Local spatial patterns of income per capita (2012, 2019)



Source: Authors' own construction



Source: Authors' own construction

During the period under study, a very significant part of the settlements in North-West Hungary merged with the agglomeration of Budapest, thus forming a coherently stable developed hot spot. In addition, the metropolitan agglomerations (Miskolc, Eger, Pécs, Zalaegerszeg, Szombathely, etc.) located along the main expressway axes (M3, M6, M7, M86) represent the hot spot cluster members. The cold spot settlements also form extensive stable peripheral clusters in the north-east, south-west and in the eastern parts of the country along the border and Lake Tisza.

The spatial autocorrelation results show the local clubs behind the meso-level (NUTS2) convergence clubs (European Commission 2017), which overall have a very significant spatial extent. The local results partly indicate the imprints of Hungarian urbanization and, on the other hand, the higher-order transport network.

Stability/mobility of clubs based on neighbourhood relations

The third research question related to this chapter is: to what extent do spatial income clubs exhibit temporal variability? To what extent can Hungary's spatial income centre-periphery pattern be considered stable/mobile? Can the spatial transition be modelled?

For the research tasks, the income dynamics of the period following the economic crisis are analysed using the LISA Markov chain method. The method describes the dynamics of the spatial dependence of per capita income, modelling the probabilities of movements between the categories of the Getis-Ord local Gi* statistic with the addition of non-significant categories.

Table 5 LISA Markov chain results (2012-2019)

	0	-3	-2	-1	1	2	3	no. of observations
0	***0.956***	0.000	0.002	0.022	0.017	0.002	0.001	12643
-3	0.003	***0.897***	0.098	0.002	0.000	0.000	0.000	1502
-2	0.010	0.109	***0.762***	0.119	0.000	0.000	0.000	1813
-1	0.201	0.002	0.182	***0.615***	0.000	0.000	0.000	1293
1	0.234	0.000	0.000	0.000	***0.530***	0.235	0.001	813
2	0.023	0.000	0.000	0.000	0.134	***0.717***	0.126	1186
3	0.002	0.000	0.000	0.000	0.001	0.045	***0.953***	2828
initial	0.573	0.068	0.088	0.057	0.034	0.056	0.125	
ergodic	0.503	0.086	0.080	0.054	0.037	0.062	0.177	

Legend: 0 – not significant, -3 – Cold spot 99 percent confidence, -2 – Cold spot 95 percent confidence, -1 – Cold spot 90 percent confidence, 1 – Hot spot 90 percent confidence, 2 – Hot spot 95 percent confidence, 1 – Hot spot 99 percent confidence.
Source: Authors' own construction

Over the growth period 2012-2019, real income growth has been outstanding, with taxable income rising by 70.6 percent in real terms and per capita income by 73.1 percent[6]. In the initial and final years of the analysis, the composition of spatial clubs did not change significantly, with the share of cold spots increasing from 21.3 to 21.8 percent and the share

[6] The growth results are based on our own calculations, which are also confirmed by the statistics of the Hungarian Central Statistical Office. (https://www.ksh.hu/stadat_files/mun/hu/mun0070.html)

of hot spots from 21.4 to 22.7 percent. These preliminary results may suggest that there are no really significant spatial changes in the spatial structure based on geographic proximity during periods of income growth.

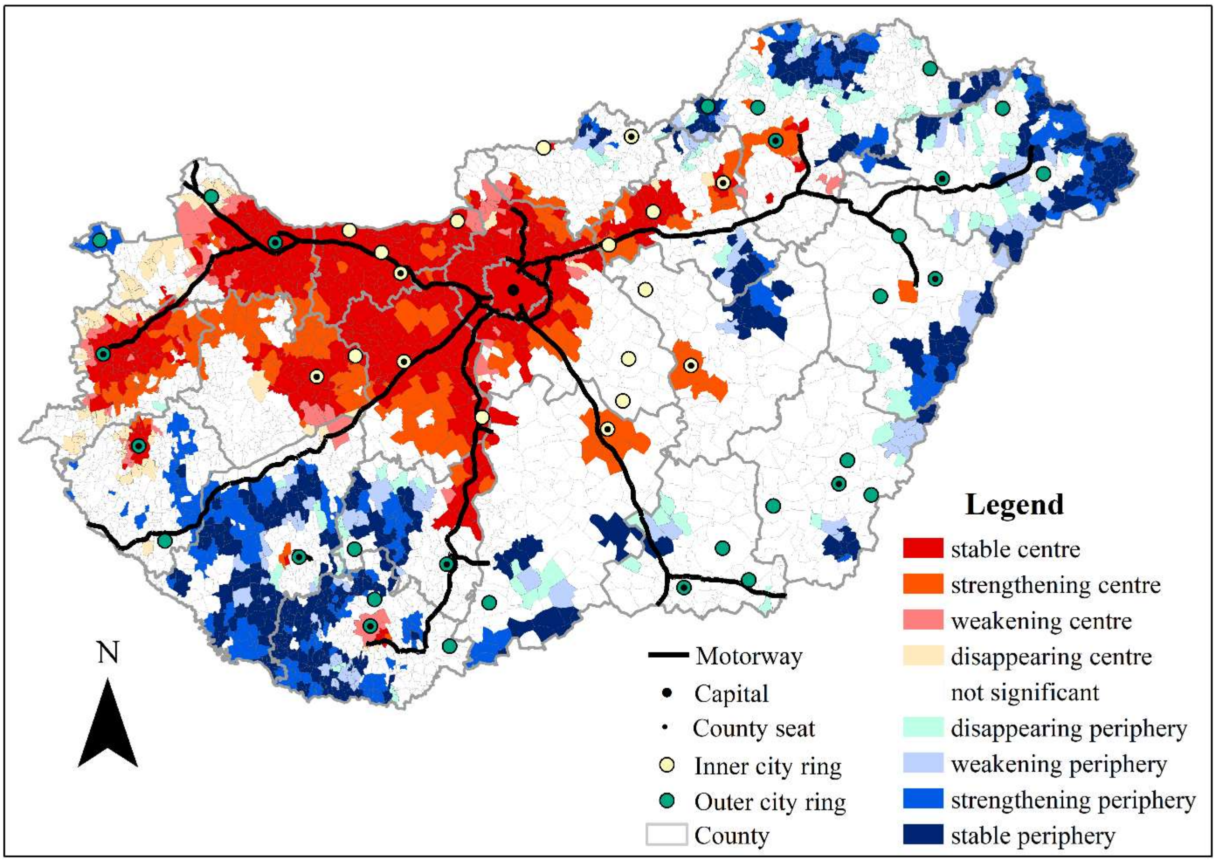
However, according to the LISA Markov chain based on the panel approach, the above statement is in any case modified, and a detectable movement dynamic between the two time points can be detected. (Tab. 5.) Most of the most stable 'extreme' categories (cold and hot spots in the 99 percent confidence interval) have very high persistence. Thus, the consistent presence of income convergence clubs is very clear, and the domestic income spatial structure is characterised by stable centre-periphery relations, clearly separated in time and space, even during the growth period. There is also a slight decline in peripherals, with the rate of movement from the most stable cold spot to -2 (Cold spot 95 percent confidence) at 9.8%. On the other hand, the movements of -1 and -2 cold spots are not so clear-cut, with dynamic exchanges between the settlement of the groups. Among the hot spots, the cluster with the weakest significance level (1, Hot spot 90 percent confidence) shows a larger scale improvement or strengthening (23.5% upward movement), while category 2 shows a dynamic movement in the relation between clusters 1 and 3. So, overall, there is no linearity between average income growth and spatial convergence, peripheries are being regenerated, as are centres. This is also suggested by the ergodic distributions defined on the basis of current movements, which indicate a more significant increase in the centres and a slight increase in the peripheries, with a future strengthening of regionalisation. The stability of the centre and peripheral areas of the LISA Markov chain confirm Myrdal's (1957) cumulative causality theory, (spatial) backwardness is caused by backwardness itself, while the same is true for development.

The LISA Markov method has been used to model the relationship between local movements, but these analyses by their very nature do not answer the question ‘where are these processes taking place?’, i.e. which settlements and which contiguous (and non-contiguous) clubs are affected by these spatial movements. In order to avoid redundancy, hot and cold spot settlements that do not change category are labelled as stable, category changers are labelled as weakening or strengthening, and settlements that become member of non significant cluster are labelled as disappearing. These settlement stability and mobility (increase, decrease) are illustrated in the Fig. 3. The spatial income inequality processes of the 2010s indicate a close relationship with Richardson's (1980) theory of polarization reversal.

In the income conjuncture period, the expansion of the contiguous hot spot cluster (the ‘spread’ effects) is most significant, with four-fifths of the growing centre regions located here. There is a marked spread along the high-income club. (Especially in its west-south-western part, affecting small and medium-sized urban spaces, e.g. the areas of Vasvár, Celldömölk, Pápa, Balatonalmádi-Balatonkenese and Sárbogárd.)

Thus, in the settlement space west of the Budapest agglomeration, the Richardsonian (1980) phase of economic spatial dispersion appears, with a more even, uniform income spatial structure. The income spatial structure also reflects a phase of interregional decentralization, at both small and large urban scales. For example, the agglomerations of Kecskemét, Szolnok and Miskolc (with favourable accessibility) are strengthening their position in the income space. The period of interregional decentralization is associated with a further differentiation of spatial development and expansion, with the average income conjuncture not affecting peripheral spaces in the same way. Significant and increasing spatial marginalisation characterises the South Transdanubian region (especially Somogy County), Zala County and the eastern border regions of Hajdú-Bihar, Szabolcs-Szatmár and Borsod-Abaúj-Zemplén, while the South Great Plain is characterised by a significant peripheral decline. In addition, the opposite processes of spatial interregional decentralization are also apparent, for example, the income role of Pécs in spatial processes decreases in this period.

Figure 3. Spatial changes in spatial income configuration between 2012 and 2019



Source: Authors' own construction

It can be observed that during the income growth period, income ‘spread’ and ‘backwash’ effects are observed on a neighbourhood basis in the settlement space. The effects take the form of spatially differentiated interregional decentralization and economic dispersion (suburbanization) phases, or inverse versions of these. Again, it is important to note that the relationship between growth and spatial convergence is not linear over the period under study. In other words, the Richardson processes based on neighbourhood effects also exhibit very heterogeneous characteristics in terms of spatial income processes. For example, the peripheralisation of south-western settlement clusters is further intensified along the income conjuncture, or the centre areas are slightly reduced along the west Transdanubian hotspot.

The majority of the ‘spread’ and ‘backwash’ effects appear along contiguous income blocks. This also indicates that, during the income growth phase, the major spatial ‘spread’ effects do not necessarily promote the retreat and development of income peripheries, but rather the areas of Kecskemét and Szolnok, which are relatively close to the capital (and the contiguous hot spot) and belong to Hungary’s inner urban ring.

In our opinion, the latter processes confirm the spatial organisation of the metropolitan region around Budapest described by György Enyedi (2012)[7]. It is also worth noting here that the spatial spreading processes clearly show the differential and localised economic development role of the higher road networks (M3, M35, M6), highlighting the importance of transport and (also) development axes (Pottier, 1963).

The eastern Hungarian corners of the outer ring of cities (Debrecen, Nyíregyháza, Békéscsaba, Szeged) are still missing in the income spatial structure, with neither large cities nor their local spillovers. Moreover, the former center of heavy industry Ózd (also an outer suburb) today forms a stable periphery with its catchment area in the northern part of the country.

It is also important to highlight that the economic suburbanisation of hot spot areas west of the Budapest agglomeration is more significant, while the East-Hungary axis (along the M3 motorway) also shows a growing but much lower concentration.

DISCUSSION

With regard to the first research question and hypothesis, we can state that spatial proximity clearly determines not only the static but also the dynamic evolution of income inequality in settlements (catching-up, lagging behind, stagnation). Our results agree with the results of

[7] The cornerstones are Tatabánya, Székesfehérvár, Kecskemét, Szolnok, Gyöngyös and Vác.

spatial Markov chain studies performed at a higher territorial level (NUTS2, NUTS3 level regions) (Le Gallo, 2001; Gutiérrez & Rey, 2013; Bufetova, 2016; Karahasan, 2017; Karahasan, 2020). That is, regions whose neighbours belong to high income classes are more likely to move into higher income classes, while peripheral regions associated with the poor become increasingly isolated. In our opinion, our analysis of Hungarian settlements describes the role of spatial proximity in the characteristics of income inequality between 2012-2019 in a much more nuanced way. We consider it particularly important to demonstrate the differential impact mechanisms of neighbours with different incomes. It is an important phenomenon that, in the case of taxable incomes that are much more balanced compared to the GDP indicator, dynamic polarization is experienced as a result of spatial proximity. Similar indirect results based on GDP/capita are provided by Le Gallo (2001). In addition, in our opinion, the poverty trap can be interpreted as a result of weak endogenous endowments (Hacker, 2021; Kiss, 2007; Káposzta, 2014) and also as a result of significant neighbourhood effects, the regional environment, consisting of the most deprived settlements, has a clear negative impact on development opportunities, resulting in a geographical 'lock-in club'. The existence of peripheral areas in the urban network, the lack of cooperation between settlements and the accessibility of centres and their catchment areas are among the serious problems of the spatial structure in Hungary (Tóth & Csatári, 1983; Salamin et al., 2008; Izsák et al. 2011). In Hungary, several attempts have been made to develop economic and spatial policies based on central places (National Concept for the Development of Settlement Networks, the Pole Programme, the Modern Cities Programme). However, it is also worth pointing out that the spillover effects in the metropolitan-catchment area dimension has either not been 'treated', not been reinforced (Bereczki, 1989; Izsák et al., 2011), or it is not actually evident in all cases and everywhere, the two spatial structural units do not necessarily support each other (Tóth & Nagy, 2013). For this reason, further analysis of local-level correlations is necessary in the future.

The second research question and hypothesis were also confirmed, i.e. mobilities based on local neighbourhood effects result in income convergence clubs. Evidence for the creation of convergence clubs can be found at a higher sub-national level (Le Gallo, 2001; Rey, 2001; Ayouba & Le Gallo, 2019), but here you can also find results at the local level (district, settlement) related to East-Central Europe (Stankov & Dragićević, 2015; Kozera, Głowicka & Wołoszyn, 2017; Török & Benedek, 2018; Netrdová & Nosek, 2020; Ręklewski, 2022). Similar to the results in Serbia, Poland, Romania and the Czech Republic, the presence of socio-economic interactions behind the center-periphery relations can also be clearly assumed in the case of Hungarian income clubs. (For example knowledge spillovers, commuting, economies of scale, flow of transfers, political interventions, socio-economic characteristics, see Rodríguez, Pose & Tselios 2015.) In Hungary, similarly to Romania (Török & Benedek, 2018), the east-west axis of development appears in the organization of settlement clubs, while the Polish and Serbian results (Stankov & Dragićević, 2015; Kozera, Głowicka & Wołoszyn, 2017; Ręklewski, 2022) show income center-peripheries along the city network.

The third hypothesis was partially confirmed, in the period of the income boom between 2012-2019, there was a partial change in Hungary's spatial structure. Behind the phenomenon, on the one hand, the spatial evidence of cumulative causality can be seen, and the analogy of Myrdal (1957) is correct: (spatial) backwardness is caused by backwardness itself, while the same is true for development. In addition, the picture of income mobility after the economic crisis is related to Richardson's (1980) theory of polarization reversal (phase of interregional decentralization). In connection with this hypothesis, NUTS2 level results concerning the study period are available (Ayouba-Le Gallo, 2019), but local level studies are scarce. The results of Stankov & Dragićević (2015) for the period 2000-2010 show the decline of the settlement income centers and the stability of the peripheries. In the period following the crisis, however, the strengthening of local centers can be seen in Poland (Ręklewski, 2022), similarly to Hungary. Furthermore, we note that the LISA Markov chain (based on the Getis-Ord Gi* statistics) we used for the first time describes local spatial income inequality processes in a new and nuanced way.

We emphasise that the path dependence of territorial units is also a factor to be taken into account, and several studies point to the endogeneity of the spatial structure of development, i.e. that the phenomenon (development/underdevelopment) is characterised by long-term determinants (Győri-Mikle, 2017, Pénzes, 2020).

CONCLUSION

In our paper we investigated the role of geographical proximity, which has been revalued in the period of regime change, and its impact on settlement level income inequality in Hungary.

In our research, we focused on dynamic rather than static relationships, looking for answers to the question of how geographical proximity shapes the stability and mobility of settlement incomes, whether the phenomenon of convergence clubs of incomes is detectable, and to what extent the income spatial structure in Hungary can be considered stable.

We have addressed our research questions and hypotheses using the ETSDA and ESTDA methods used in spatial econometrics.

Our analyses show that geographical proximity significantly affects the income dynamics of settlements, and it can be argued that the evolution of income inequality cannot be interpreted without including geographical proximity. In Hungary, different neighbourhood effects shape the chances of settlements with different strengths, crucially influencing the chances of catching up and lagging behind as well as stability.

The income processes of the settlement space based on geographical proximity and showing similar trajectories point to the phenomenon of multiple spatial equilibria, which are predominantly shaped by the neighbourhood microenvironment. These settlement spaces are organized into significant income clubs based on spatial proximity.

The patterns of income centre-periphery and its changes in the post-crisis period are linked to the classical theories of regional economics, Richardson's (1980) theory of spatial structure polarization reversal and Myrdal's (1957) theory of cumulative causality. Based on cumulative causality, the spatial location of centres and peripheries can be considered to be mostly constant. The settlement processes underlying the spatial persistence result in a significant and mesoscale (spatial scale) centre-periphery split in the country. In addition, spread and backwash effects are also clearly reflected in the dynamic spatial income structure between 2012 and 2019.

The results show that settlement level income inequality processes in Hungary are spatially embedded to a considerable extent. They also indicate that Hungary is still rather a transition (transforming) market economy in terms of spatial inequalities. The temporal and spatial stability and mobility of income centres and peripheries may represent an opportunity for spatial and economic policy makers to address spatial disparities. Based on the existing socio-economic (globalisation) processes, the national and international literature and the present results, the objective of dissolving the spatial centre-periphery relation can be formulated (OFTK 2014), but the results are still rather pessimistic.

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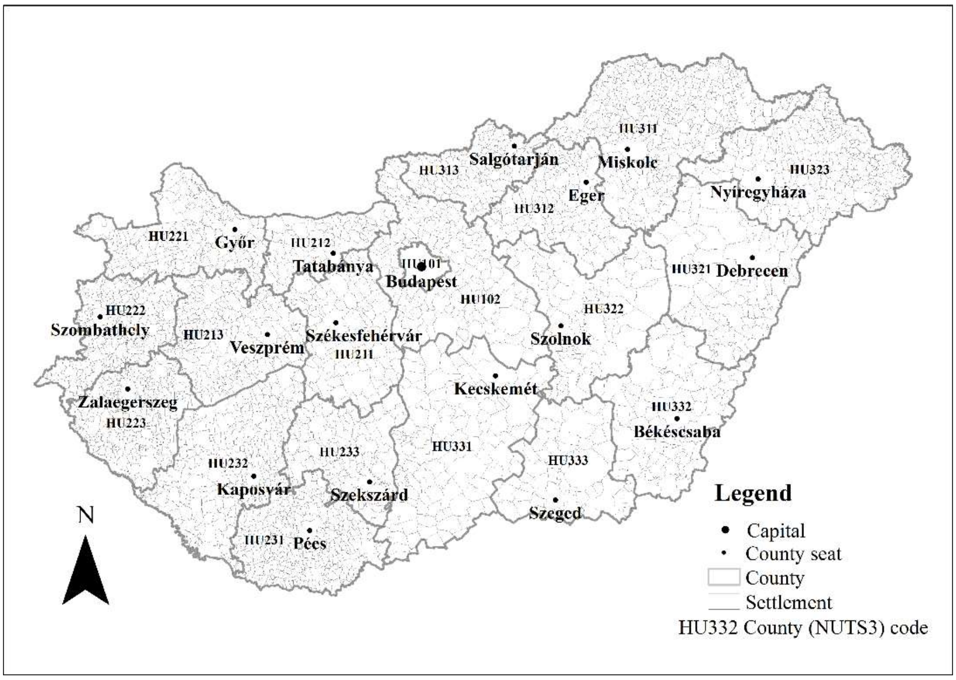
Annex 1

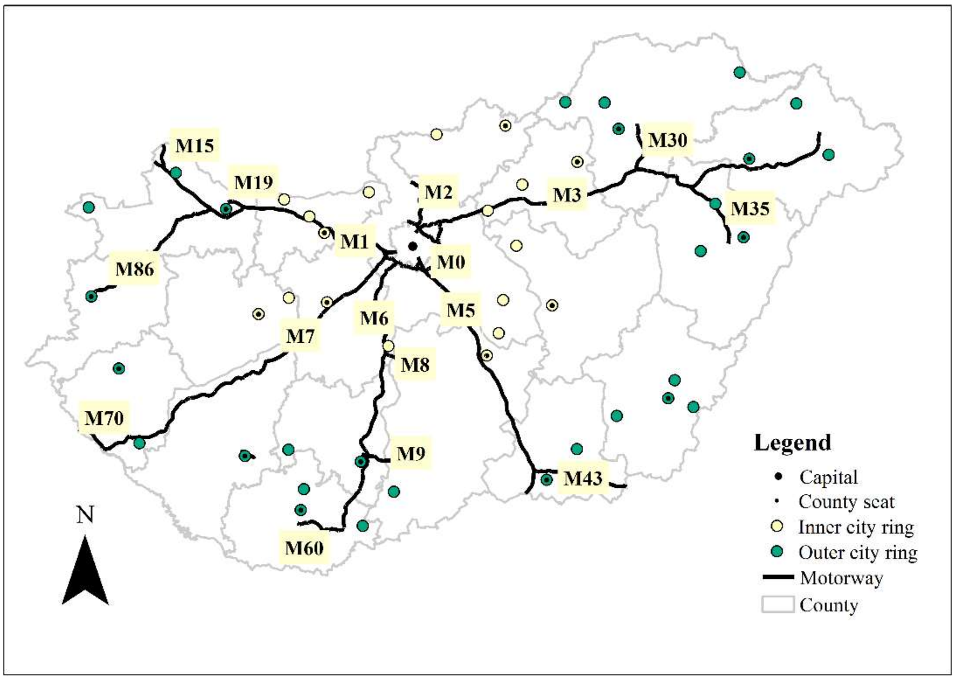
Administrative classification of Hungary



Note: County (NUTS3) codes – HU101: Budapest, HU102: Pest, HU211: Fejér, HU212: Komárom-Esztergom, HU213: Veszprém, HU221: Győr-Moson-Sopron, HU222: Vas, HU223: Zala, HU231: Baranya, HU232: Somogy, HU233: Tolna, HU311: Borsod-Abaúj-Zemplén, HU312: Heves, HU313: Nógrád, HU321: Hajdú-Bihar, HU322: Jász-Nagykun-Szolnok, HU323: Szabolcs-Szatmár-Bereg, HU331: Bács-Kiskun, HU332: Békés, HU333: Csongrád-Csanád.

Source: Authors' own construction

The main (settlement and motorway) networks in Hungary



Source: Authors' own construction

Annex 2 Initial and ergodic distributions of the model using different spatial lags (2012-2019)

initial distribution	1	2	3	4	5
Hungary	0,200	0,200	0,200	0,200	0,200
spatial lag 1.	0,535	0,283	0,118	0,047	0,016
spatial lag 2.	0,283	0,332	0,251	0,108	0,027
spatial lag 3.	0,127	0,240	0,311	0,247	0,074
spatial lag 4.	0,050	0,120	0,260	0,338	0,232
spatial lag 5.	0,005	0,025	0,059	0,259	0,652
ergodic distribution	1	2	3	4	5
Hungary	0,136	0,192	0,245	0,237	0,190
spatial lag 1.	0,412	0,323	0,173	0,069	0,023
spatial lag 2.	0,170	0,320	0,334	0,140	0,036
spatial lag 3.	0,083	0,193	0,349	0,296	0,079
spatial lag 4.	0,043	0,126	0,290	0,361	0,180
spatial lag 5.	0,009	0,038	0,088	0,298	0,567

Source: Authors' own construction