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DETERMINANTS AND SPATIAL PATTERNS OF INCOME DISPARITIES IN HUNGARY

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1. BACKGROUND AND OBJECTIVES OF THE WORK

1.1. The Importance and Relevance of the Topic

Income, as a measure of development, provides an important means of comparing the welfare of the population across different geographical areas. Even the representatives of classical economics (Ricardo, Smith) were concerned with the so-called functional distribution of income; they regarded the distribution of income among the social classes – workers, capitalists and landowners – as one of the most important issues in the economy. Thus, initially, researchers were concerned not with regional income disparities, but with the distribution of income within society. Per capita income indicators reflect the economic viability of regions, whilst also signalling potential differences in living standards. The unequal distribution of income perpetuates social division and also hinders overall economic growth (Marchand et al., 2020).

In the international literature, the topic of income distribution and inequality is closely linked to that of economic development. The analysis of regional income distribution plays a key role in terms of both social justice and economic competitiveness. Such analyses provide information on the situation of marginalised regions, the efficiency of resource allocation and growth opportunities, thereby promoting the emergence of more balanced regions and sustainable development. Regional income disparities must be understood as a complex and multifaceted phenomenon that reflects deeper inequalities. Addressing these inequalities is essential for promoting equitable economic growth and ensuring more equal access to resources for all members of society (Marchand et al., 2020; Hao et al., 2016). Income levels determine macroeconomic processes such as growth and sustainability (Dabla-Norris et al., 2015), and can also influence people's everyday lives, health and social conditions (Rowlingson, 2011; Egri, 2017).

Following the transition, regional income disparities in Hungary have intensified. The lagging behind of less advantaged areas (e.g. peripheral regions, villages) is associated with persistent unemployment, lower wage levels and modest investment. The regional disparities that emerged at that time can still be observed today, and these processes have a direct impact on social mobility, as opportunities for upward mobility are limited in economically underdeveloped regions. Higher incomes generally result in better-funded education, healthcare and social services, which in turn affect life expectancy, the willingness to have children, and so on. Regional disparities can also pose a threat from a social policy perspective, as persistent income inequalities heighten the risk of social conflict and political discontent. A regional-level analysis of the factors affecting incomes is essential for accurately mapping the situation, as effective economic and rural development policies can only be formulated on the basis of sound data. Modern data collection and analysis technologies (GIS, econometric models, etc.) enable a much more detailed examination of regional characteristics than was previously possible. The importance of spatial analysis is further underscored by its ability to identify patterns of economic activity that are not necessarily apparent through traditional statistical analysis.

1.2. Objective

In this thesis, I undertake the following:

1. ***In a territorial breakdown, I identify the factors that influence the amount of total domestic income per capita in Hungary***. It is justified to examine this issue because exploring the income situation and the factors affecting income provides important and necessary information for policy-makers (Sarel, 1997) and gives a picture of the welfare situation within a given geographical area (Ékes, 1998). Identifying the determinants of income can

contribute to the success of development programmes, the catching-up of rural areas, and the development of the local economy. The development of geographically defined problem areas and underdeveloped regions is an important area of intervention for spatial policy (Rechnitzer–Smahó, 2011).

2. However, studies conducted at different levels of aggregation may yield differing results, which can influence the allocation of regional development or other forms of support. I therefore also aim to examine ***what differences exist in the results of analyses conducted at different levels of aggregation when investigating the factors affecting per capita income***. Based on findings in the literature, a more detailed spatial breakdown provides more information, as some information is lost during spatial aggregation; therefore, it is advisable to conduct analyses at the smallest possible spatial unit (e.g. Tagashira-Okabe, 2002; Dusek, 2003; Wang-Di, 2020). The smallest available territorial unit in Hungary is the settlement level, as indicators are not available at a lower level of disaggregation (e.g. individual income data). The district level can also be used for the analysis, as the sample size here does not yet have as great a distorting effect on the results of the econometric models as in county- or region-level analyses.

3. My objective is also to determine whether ***the determinants of per capita income are spatially homogeneous across the country or exhibit significant regional variations.*** By examining this question, I aim to contribute to a more nuanced understanding of income distribution in Hungary, highlighting the importance of local contexts in economic analyses. My preliminary assumption is that the determinants of per capita income are not spatially homogeneous. Should this hypothesis be confirmed, it could help ensure that specific policy measures are designed to align with the particular needs and strengths of individual territorial units and regions.

2. MATERIAL AND METHOD

2.1. Variables Included in the Research

The variables included in my analysis are listed in full in *Table 1*. The outcome variable of my research is total domestic income per working-age resident (aged 15–64) for the year 2019, which I calculated based on data from the TEIR (NAV).

$$y_i = \frac{total\ domestic\ income}{permanent\ population\ aged\ 15-64_i}$$

The ‘total domestic income’ income category in the TEIR is the aggregate of income subject to personal income tax (declared income), which does not include social benefits and several other income components not included in the tax base.

The explanatory variables consist of key economic and social variables; their selection was guided not only by recommendations in the literature and previous experience but also by the need for them to be available at various levels of aggregation. Variables expressed in monetary terms, including the outcome variable, refer to an annual period. Variables not expressed in monetary terms are stock data (generally as at 31 December) and do not contain annual averages or interim totals.

I conducted my analysis at the settlement and district levels, then compared the results of the econometric models run at the two levels of aggregation.

Table 1: Variables included in the study

Abbreviation	Variable	Description	Unit
Dependent variable (in the form of a natural logarithm in the models)			
jöved	Total domestic income per resident of working age	Total domestic income / number of working-age (15–64 years) permanent residents	HUF/capita/year
Independent variable (in the form of a natural logarithm in the models)			
nép	Permanent working-age population	Number of working-age (15–64 years) permanent residents	capita
egyv	number of individual entrepreneurs	(number of registered individual entrepreneurs / working-age population) * 1000	persons/1000 persons
társv	joint ventures	(number of registered partnerships / working-age population) *1000	units/1000 persons
mérlf	total assets	(total assets of businesses / working-age population) *1000	HUF/1000 persons/year
állásk	number of jobseekers	(number of jobseekers / working-age population) *1000	persons/1000 persons
eutám	European Union funding (2015–2019)	(EU funding (2015–2019) / working-age population) *1000	HUF/1000 persons/year
önkber	local government investment (2019)	(local government investment (2019) / working-age population) *1000	HUF/1000 persons/year
távbp	distance from the capital	In the case of time-based optimisation, the length of the fastest route to Budapest in kilometres (km)	km
távmsz	distance from the county seat	In the case of time-based optimisation, the length of the fastest route to the county town in kilometres (km)	km
szakm	number of people with vocational qualifications	(number of people with secondary education, without a high school graduation exam, holding a vocational qualification / residents aged 7–X) *1000	persons/1000 persons
érett	high school graduation certificate	(number of people with a high school graduation exam / residents aged 7–X) *1000	persons/1000 persons
dipl	degree	(number of people with a university, college, etc. degree / residents aged 7–X) *1000	persons/1000 persons
FEOR-08-0	Employees in FEOR-08-0	(employees in armed forces occupations / total employees) *1000	persons/1000 persons
FEOR-08-1	Employees in FEOR-08-1	(economic, administrative and representative leaders, legislators / total employees) *1000	persons/1000 persons
FEOR-08-2	Employees in FEOR-08-2	(employees in occupations requiring independent application of higher education qualifications / total employees) *1000	persons/1000 persons
FEOR-08-3	Employees in FEOR-08-3	(employees in occupations requiring other higher or secondary education / total employees) *1000	persons/1000 persons
FEOR-08-4	Employees in FEOR-08-4	(employees in office and administrative (customer service) occupations / total employees) *1000	persons/1000 persons
FEOR-08-5	Employees in FEOR-08-5	(employees in trade and service occupations / total employees) *1000	persons/1000 persons
FEOR-08-6	Employees in FEOR-08-6	(employees in agricultural and forestry occupations / total employees) *1000	persons/1000 persons
FEOR-08-7	Employees in FEOR-08-7	(employees in industrial and construction occupations / total employees) * 1000	persons/1000 persons
FEOR-08-8	Employees in FEOR-08-8	(Machine operators, assemblers, drivers / total employees) *1000	persons/1000 persons
FEOR-08-9	Employees in FEOR-08-9	(employees in occupations not requiring qualifications (unskilled) / total employees) *1000	persons/1000 persons

Source: own editing

2.2. Introduction to Spatial Regression Models

Spatial regression models allow us to explicitly examine the spatial relationships that play a role in the development of regional income levels. In traditional OLS regression, we assume that observations are independent of one another; however, the spatial pattern of income distribution often exhibits clustering: the income levels of neighbouring regions tend to be similar, which suggests spatial autocorrelation. Thus, studies analysing the determinants of development, income levels or other social phenomena have widely used econometric models that take spatial correlations and neighbourhood relationships into account (e.g. case studies show that these models exhibit better fit at all levels of aggregation compared to the standard OLS method (e.g. Chasco et al., 2008; Saib et al., 2014; Lee et al., 2015; Szendi, 2017). Among the global autocorrelation tests, I used the Moran's I test, whilst for identifying spatial autocorrelation trends and spatial clustering, I used the local Moran's test.

Moran's I statistic is used to measure global spatial autocorrelation: its value ranges from –1 to +1. A positive value of the Moran index (I>0) indicates positive spatial autocorrelation (similar values in neighbouring areas are more common than would be expected by chance); a value close to zero indicates no detectable autocorrelation, whilst a negative value (I<0) indicates negative autocorrelation (values in close proximity tend to differ). The global Moran's I is a single summary measure for the entire area, and therefore assumes a continuous, homogeneous spatial pattern.

Local Moran's I (or LISA = Local Indicators of Spatial Association) is an index introduced by Anselin in 1995, whereby a single value is assigned to each individual spatial unit under investigation. This is effectively a 'local breakdown' of the global Moran's I, thus showing the extent to which the values of individual spatial units correlate with those of their surroundings. (Moran, 1948; Cliff- Ord, 1981; Anselin, 1995, cited in Varga, 2002; Tóth, 2003). Anselin's Local Moran I index can thus be calculated for a given observation i as follows:

$$I_i = \frac{(x_i - \bar{x})}{S^2} \sum_{j=1}^{N} w_{ij}(x_j - \bar{x}), \text{ where} \tag{1}$$

x_i is the value of the variable under study for the i-th area,

$\bar{x}$ is the mean value of the variable,

S^2 the square of the standard deviation of the variable,

w_{ij} elements of the neighbourhood weighting factors in a weighting matrix, which expresses how 'close' areas i and j are to each other in space.

The resulting I_i values can be used to describe the nature of the spatial pattern. Four typical patterns can thus be identified in the areas under investigation: HH (high–high) clusters, where high values are grouped with high-value neighbours; LL (low–low) clusters, where low values are grouped with low-value neighbours; and HL (high–low) and LH (low–high) outliers, where the value of an area is of the opposite sign to its surroundings.

In spatial regression models, the value of a variable measured at a given point is correlated with the values of the same variable measured at other points in the space using weight matrices. In my analysis, I used four spatial econometric models: spatial lag (SLM), spatial error (SEM), spatial Durbin (SDM) models and geographically weighted regression (GWR). The aim of running these models is to examine how the explanatory variables affect the outcome variable at the settlement and district levels. I compare the results obtained with those of the traditional OLS method.

SLM – spatial lag model

The SLM model is a regression procedure in which the dependent variable (e.g. the income level of a region) depends not only on its own explanatory variables, but also on the values of the dependent variables of neighbouring units. The SLM model is appropriate when we wish to model the spatial patterns of the dependent variable, and there is strong suspicion or evidence that neighbouring units mutually influence each other's performance. (LeSage-Pace, 2009). The model uses the weighted average of the values measured in the observation units belonging to a given degree of neighbourhood (Varga, 2002). The general form of the SLM model is:

$$y_{(n*1)} = \rho w_{(n*n)} y_{(n*1)} + X_{(n*k)} \beta_{(k*1)} + \varepsilon_{(n*1)}, \text{ where} \quad (2)$$

y is the vector of values of the outcome variable,

w is the standardised weight matrix,

x is the matrix of explanatory variables,

ρ is the spatial autoregressive parameter,

β is the parameter vector of the explanatory variables,

ε is the vector of error terms that are independent of one another and have the same probability distribution.

The SLM is capable of capturing spillover effects that may arise between neighbouring localities through, for example, labour flows, commuting, market linkages or consumer demand. The SLM model directly addresses spatial dependence by 'linking' the values of the dependent variable with those of its neighbours.

SEM – spatial error model

The SEM model does not model spatial interaction via the dependent variable, but rather the spatial autocorrelation of the regression error term. The SEM (spatial error) model also filters out the spatial autocorrelation effects of the explanatory variables and the outcome variable , and serves to correct for spatial autocorrelation between error terms (Varga, 2002). The general form of the model is:

$$y_{(n*1)} = x\beta_{(k*1)} + \varepsilon, \text{ and} \tag{3}$$

$$\varepsilon_{(n*1)} = \lambda w\varepsilon + \xi, \text{ where} \tag{4}$$

y is the vector of values of the response variable,

x is the matrix of explanatory variables,

β is the parameter vector of the explanatory variables,

ε is the vector of autoregressive error terms,

w is the row-standardised weight matrix,

λ is the parameter of the spatially delayed values of the autoregressive error terms,

ξ is the vector of error terms that are independent of one another and have the same probability distribution.

In the SLM model, ρ (rho) is a scalar parameter that indicates the effect of the dependent variable in neighbouring areas on the value of the dependent variable in the area under investigation (Drukker et al., 2013). In SEM, λ (lambda) indicates the spatial correlation between error terms. If ρ and/or λ are not 0, models incorporating spatial autocorrelation may provide more accurate estimates than the OLS method (Tsionas, 2019). Of the two models, the more appropriate one can be selected using Lagrange multiplier (LM) diagnostics, i.e. by running LM error and LM lag tests (Anselin 2005, cited in Szendi, 2017).

SDM – Spatial Durbin Model

If the Lagrange multiplier tests indicate the presence of both types of dependence, then testing both the SLM and SEM models is warranted, and in some cases a more general model (e.g. SDM) may provide a better fit. The SDM (spatial Durbin model) is an extension of the SLM model, combining elements of both the SLM and the SEM. The SDM incorporates the effect of spatial lags for both independent and dependent variables (unlike the SLM model, which only takes into account the effect of spatial lags on the independent variables). The results of the model directly reveal the direct effect (impact on a given area) and indirect effect (impact via neighbouring areas) of each explanatory variable, which provides valuable information from a policy perspective. (Anselin, 1988; LeSage-Pace, 2009). The general form of the model is as follows:

$$y_{(n*1)} = \rho w_{(n*n)} y_{(n*n)} + X_{(n*k)} \beta_{(k*1)} + W_{(n*n)} X_{(n*k)} \theta + \varepsilon_{(n*1)}, \quad (5)$$

where

y is the vector of values of the outcome variable,

w is the row-standardised weight matrix,

x is the matrix of explanatory variables,

ρ is the spatial autoregressive parameter,

β is the parameter vector of the explanatory variables,

θ is the vector of parameters describing the effects of spatially neighbouring variables,

ε is the vector of error terms that are independent of one another and have the same probability distribution.

GWR – Geographically Weighted Regression

Geographically Weighted Regression (GWR) is a statistical method that allows for the exploration of spatial heterogeneity, in contrast to traditional global models. This model allows for spatial variation in regression coefficients (Fotheringham et al., 2002).

GWR fits a separate regression model to each observation point, in which the parameters may vary from place to place. Due to spatial heterogeneity, different parameters must be estimated at different points for the same explanatory variable. To achieve this, GWR employs a weighting function that weights individual observations based on geographical distance. During regression, closer observations are given greater weight, whilst more distant ones are given less. GWR is used to examine spatial heterogeneity (non-stationarity), whereas traditional spatial regressions (SLM, SEM) model the phenomenon of spatial autocorrelation within a global framework (Raza et al., 2019; Zhao et al., 2022). The general formula for the GWR model is as follows:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i) x_{ik} + \varepsilon_i, \text{ where} \quad (6)$$

u_i ,v_i denote the geographical coordinates of the i-th data point,

β_k (u_i ,v_i) is the calculated value of the continuous function β_k (u,v) at the i-th point,

ε_i is an independent and identically distributed error term (Fábián, 2012).

The interpretation of local coefficients is one of the most exciting aspects of GWR, as it reveals in which regions a given relationship is stronger or weaker. By mapping the coefficients, it is easy to identify regions where, for example, a positive effect is amplified, or where the effect is negligible or negative. Thus, local coefficients may differ spatially not only in the strength of the effect but also in its sign.

Technically, GWR implements the location-dependent estimation of coefficients by performing a regression in the vicinity of a data point associated with a given location – within a neighbourhood of a specified radius or by including a given number of nearest neighbours. The weighting function is typically a Gaussian or bisquare kernel, which ensures that closer observations have a stronger influence on the estimate of the given point, whilst the weight of points that are too far away may even be zero. A key parameter is the bandwidth, which determines the extent of the 'local' range.

To determine the optimal bandwidth, I tested various numbers of nearest neighbours (N = 20, 30, 50, 75). Of these models, $N = 30$ provided the best fit at the settlement level and $N = 25$ at the district level. To evaluate the fit of the models, I used traditional goodness-of-fit statistics (t-test, R^2) and the corrected Akaike information criterion (AICc).

The main advantages of GWR over global models are:

(1) Handling of spatial heterogeneity – it allows the model to take account of regional differences in the effects of variables;

(2) More detailed local information – it provides separate results (coefficients, fit) for each location, which allows for a richer analysis;

(3) Uncovering hidden patterns – it can reveal local effects or relationships that global models fail to show due to 'averaging';

(4) Location-specific results – local results enable more targeted, spatially differentiated policy recommendations, as opposed to 'one-size-fits-all' solutions.

3. RESULTS

3.1. Spatial Autocorrelation of Income Data

Spatial autocorrelation among income indicators has been widely documented in the literature (e.g. Rey-Montouri, 1999; Kalogirou-Hatzichristos, 2007). The effect of aggregation (scaling) on spatial autocorrelation can be verified through empirical studies. In this study, I examined the presence of spatial autocorrelation in income data at the settlement and district levels using the Moran I statistic. (Further levels of aggregation, such as county and region, contain too few spatial units for an unbiased estimate.) I also applied several weighting matrices (queen, rook and nearest neighbours). According to the results, the degree of autocorrelation is moderately strong at both the settlement and district levels.

The global Moran's I value decreases in four out of the six cases examined using different weighting matrices, and increases minimally in two cases when I aggregated the income data at the district level compared to the settlement level. This phenomenon is consistent with the finding found in most of the literature that the value of spatial autocorrelation generally decreases at higher levels of aggregation. The reason for this is that a higher level of aggregation masks differences within spatial units; due to the scale effect, smaller spatial units merge into larger ones, and previously smaller heterogeneous units appear as larger homogeneous units (Brunsdon et al., 2002, cited in Dusek, 2004; Jelinski-Wu, 1996).

When using the queen's neighbourhood weight matrix, the local Moran's I index shows a very similar pattern of clustering at both the settlement and district levels. At the settlement level, we can see that settlements in the Budapest agglomeration area, as well as in the northern and western Transdanubian regions, are those where the high income of the settlement's population has a positive effect on the income of the population in neighbouring settlements. This is indicated by the colour red on the maps. It is clear that these are the regions of Hungary where the population's income has been high since the change of regime. Of the 3,155 settlements and 175 districts, the statistics classify 944 settlements and 48 districts into the high-high cluster, whilst 1,057 settlements and 50 districts fall into the low-low category. A clustering of poorer settlements can be observed in South Transdanubia, as well as along the country's eastern and northern borders.

It can be said that aggregation reduces the size of both the high-high and low-low clusters. Only those areas within these clusters at district level remain marked on the map where autocorrelation between neighbouring settlements is indeed strong. At the district level, it is primarily the clusters along the western border and in the central parts of the country that disappear compared to the settlement maps. Based on the above, it can be observed that data on total domestic income per capita show spatial autocorrelation across a significant part of Hungary's territory. Thus, it is justified to use models that take spatial effects into account, rather than traditional global regression models, when examining factors affecting income.

3.2. Results of OLS, SLM, SEM and SDM Regressions

I have demonstrated the presence of spatial autocorrelation in the case of the outcome variable above. The autocorrelation effect between variables justifies the inclusion of neighbourhood effects in the regression analysis. I use four different regression models (OLS, SLM, SEM, SDM) to conduct the analyses at two different levels of aggregation: settlement and district levels.
(Due to space constraints, the thesis booklet contains only the results at the settlement level.)

Results of the OLS method

In the case of the settlement-level OLS method (*Table 2*), the *number* of *individual entrepreneurs (egyv), total assets (mérlf), local government investment (önkber), and educational attainment indicators (szakm, érett, dipl)* have a significantly positive influence on the population's income. *The number of joint ventures (társv), the number of jobseekers (állásk), and the distance from Budapest and the county seat (távbp, távmsz)* have a demonstrably negative impact on income. *The population* of the settlement (*nép*) and the *level of European Union funding (eutám)* did not prove to be significant factors in the model.

When the main employment groups are incorporated into the OLS-based models, the magnitude of the coefficients of the above significant variables decreases; in this model, *population* size (*nép*) has a negative effect on income, whilst *total assets (mérlf)*, in contrast to the previous model, are not a significant factor. Income is positively influenced if a settlement has a higher number of *employees in the armed forces (FEOR-08-0)*, *those employed in occupations requiring independent application of higher education qualifications (FEOR-08-2)*, *those employed in office and administrative (customer service) occupations (FEOR-08-4)*, *workers employed in industrial and construction occupations (FEOR-08-7)*, and *machine operators, assemblers and drivers (FEOR-08-8)*. Income trends are negatively affected if there are more *economic, administrative, and advocacy leaders, legislators (FEOR-08-1)*, *those employed in trade and service occupations (FEOR-08-5)* and *those in occupations not requiring professional qualifications (unskilled) (FEOR-08-9)*. According to the OLS method, no correlation can be demonstrated between income and the number of *employees in occupations requiring other higher or secondary education (FEOR-08-3)*, or *in agricultural and forestry occupations (FEOR-08-6)*.

Table 2: OLS method – The effect of variables on total domestic income per working-age resident

Y = income	Settlement	Settlement	District	District
Constant	12,969*** (0.096)	15.096*** (0.133)	11.331*** (0.655)	12.389*** (0.561)
nép	0.000 (0.003)	-0.006** (0.003)	-0.018 (0.015)	-0.023* (0.012)
egyv	0.040*** (0.007)	0.020* (0.006)	0.030 (0.061)	0.166*** (0.053)
társv	-0.025*** (0.005)	-0.018*** (0.005)	-0.025 (0.040)	0.012 (0.038)
mérlf	0.003** (0.001)	0.002 (0.001)	0.035*** (0.011)	0.013 (0.010)
állásk	-0.079*** (0.004)	-0.042*** (0.004)	-0.068*** (0.020)	-0.062*** (0.017)
eutám	-0.001 (0.000)	0.000 (0.000)	-0.006 (0.010)	-0.004 (0.009)
önkber	0.003** (0.001)	0.003*** (0.001)	-0.006 (0.014)	0.009 (0.012)
távbp	-0.150*** (0.007)	-0.124*** (0.006)	-0.080*** (0.016)	-0.068*** (0.013)
távmsz	-0.059*** (0.005)	-0.038*** (0.004)	-0.042*** (0.015)	-0.017 (0.013)
szakm	0.182*** (0.013)	0.078*** (0.014)	0.159** (0.074)	-0.060* (0.085)
érett	0.254*** (0.012)	0.126*** (0.012)	0.501*** (0.076)	0.386*** (0.091)
dipl	0.054*** (0.006)	0.034*** (0.006)	-	-
FEOR-08-0	-	0.014*** (0.003)	-	0.039*** (0.013)
FEOR-08-1	-	-0.013*** (0.004)	-	-
FEOR-08-2	-	0.009** (0.004)	-	-
FEOR-08-3	-	0.007 (0.006)	-	0.049 (0.082)
FEOR-08-4	-	0.021*** (0.004)	-	0.119* (0.071)
FEOR-08-5	-	-0.028*** (0.006)	-	-0.316*** (0.057)
FEOR-08-6	-	0.002 (0.002)	-	0.000 (0.014)
FEOR-08-7	-	0.031*** (0.005)	-	0.029 (0.043)
FEOR-08-8	-	0.077*** (0.006)	-	0.138*** (0.029)
FEOR-08-9	-	-0.279*** (0.014)	-	-
FEOR variables combined	X	✓***	X	✓***
R^2	*0.6904*	*0.7673*	*0.7886*	*0.8732*
Adjusted R^2	*0.6892*	*0.7656*	*0.7743*	*0.8585*
Log-likelihood	*1076.670*	*1526.96*	*171.205*	*215.904*
Number of observations	*3155*	*3155*	*175*	*175*

Source: own compilation (*** p<0.01; ** p < 0.05; * p < 0.1) (White's standard error in brackets)

Results of the SLM

One important feature of the SLM is that it takes into account both the dependent variable's own values and those of neighbouring areas. This model assumes that a settlement's income level depends partly on its own explanatory variables and partly on the income levels of neighbouring settlements. Consequently, the effect of the explanatory variables can be broken down into two components (direct and indirect/spillover effects). Thus, positive coefficients estimated in the SLM may also indicate that these factors improve income prospects not only locally but also indirectly in neighbouring areas. For example, based on the results at the settlement level, the disappearance of the effect of local government investment (*önkber*) in the SLM may suggest that local investment activity operates through different mechanisms within an embedded spatial context.

The variations observed at district level are consistent with the MAUP hypothesis: in larger territorial units, local phenomena may be averaged out. In the SLM results, the positive impact of sole traders (*egyv*) and those with a high school graduation exam (*érett*) suggests that economic activity and educational attainment remain significant even when regionalised, but EU subsidies (*eutám*) and local government investments (*önkber*) show no direct correlation in any of the district SLM models. The SLM (*Table 3*) shows a high degree of agreement with the results of the OLS method at the settlement level, with the exception that in the model excluding employment variables, *the level of local government investment (önkber)* is not a significant variable. If we also incorporate the FEOR main groups into the SLM, the only difference compared to the OLS method is that *the number of employees in occupations requiring higher education qualifications (FEOR-08-2)* is not significant.

Table 3: Spatial lag model (SLM) – The effect of variables on total domestic income per working-age resident

Y = income	Settlement	Settlement	District	District
Constant	12,970*** (0.191)	15.090*** (0.210)	11.674*** (0.759)	12.516*** (0.618)
nép	-0.005 (0.004)	-0.010*** (0.004)	-0.039** (0.017)	-0.032** (0.014)
egyv	0.040*** (0.010)	0.019** (0.008)	-0.021 (0.050)	0.141*** (0.046)
társv	-0.026*** (0.007)	-0.019*** (0.006)	-0.028 (0.036)	0.005 (0.035)
mérlf	0.003** (0.001)	0.002 (0.001)	0.033*** (0.012)	0.013 (0.009)
állásk	-0.079*** (0.006)	-0.043*** (0.007)	-0.081*** (0.020)	-0.068*** (0.018)
eutám	0.000 (0.001)	-0.000 (0.000)	-0.001 (0.012)	-0.006 (0.009)
önkber	0.003 (0.002)	0.004** (0.001)	-0.008 (0.012)	0.007 (0.011)
távbp	-0.152*** (0.008)	-0.126*** (0.007)	-0.070*** (0.025)	-0.063*** (0.018)
távmsz	-0.057*** (0.005)	-0.032*** (0.005)	-0.042** (0.020)	-0.018 (0.015)
szakm	0.180*** (0.031)	0.076** (0.031)	0.119 (0.083)	-0.054 (0.079)
érett	0.256*** (0.019)	0.127*** (0.018)	0.571*** (0.082)	0.415*** (0.086)
dipl	0.053*** (0.010)	0.033*** (0.010)	-	-
FEOR-08-0	-	0.014*** (0.003)	-	0.036*** (0.010)
FEOR-08-1	-	-0.014** (0.006)	-	-
FEOR-08-2	-	0.010 (0.007)	-	-
FEOR-08-3	-	0.009 (0.010)	-	0.054 (0.081)
FEOR-08-4	-	0.021*** (0.008)	-	0.115 (0.076)
FEOR-08-5	-	-0.028** (0.016)	-	-0.308*** (0.050)
FEOR-08-6	-	0.002 (0.003)	-	-0.002 (0.012)
FEOR-08-7	-	0.031*** (0.011)	-	0.011 (0.044)
FEOR-08-8	-	0.077*** (0.009)	-	0.134*** (0.029)
FEOR-08-9	-	-0.277*** (0.021)	-	-
ρ (rho)	0.000*** (0.000)	0.000*** (0.000)	0.001*** (0.000)	0.001* (0.000)
σ (sigma)	0.172*** (0.004)	0.149*** (0.004)	0.088*** (0.005)	0.070*** (0.005)
FEOR variables combined	X	✓***	X	✓***
R^2	*0.5829*	*0.7230*	*0.7810*	*0.9021*
Adjusted R^2	*0.5813*	*0.7211*	*0.7662*	*0.8908*
Log-likelihood	*1083.416*	*1,533,334*	*176,968*	*217,427*
Number of observations	*3155*	*3155*	*175*	*175*

Source: own compilation (*** p<0.01; ** p<0.05; * p<0.1) (robust standard error in brackets)

SEM results

The essence of SEM is that it assumes spatial correlation among the regression residuals. In other words, using SEM, we incorporate into the model the latent spatial effects that omitted variables may induce. SEM models the error terms such that they are composed of the weighted sum of the errors of neighbouring units, using a weight matrix. Since the tests indicated that SEM provided the best fit, we can assume that spatial dependence manifests itself primarily in the omitted variables or in hidden spatial processes. An example of this might be a specific regional infrastructure provision, which the model does not specify as an independent variable, but whose effect spreads across neighbouring areas. Accordingly, the SEM models at the settlement level also show similar main relationships to those of OLS and SLM, but the effects of skilled labour and entrepreneurial activity remain consistently positive, whilst the negative effects (distance, unemployment) also remain unchanged. An interesting difference is that, for the FEOR-08-2 variable, the SEM reproduces the positive relationship, which may indicate that, among the spatial models, the income advantages of higher-skilled occupations are more clearly reflected when dealing with the error component.

Based on Lagrange multiplier diagnostics, SEM (*Table 4*) provides the most accurate results at both the settlement and district aggregation levels. With two exceptions (*nép, eutám*), all explanatory variables are significant in the model. *A higher number of individual entrepreneurs (egyv), a* higher *total assets (mérlf),* a greater volume of *local government investment (önkber)*, and *educational attainment (szakm, érett, dipl)* increase incomes. A higher number *of joint ventures (társv)*, a higher *unemployment rate (állásk),* and *distance from the capital and county seat (távbp, távmsz)* have a negative impact on wage levels.

Table 4: Spatial Error Model (SEM) – The effect of variables on total domestic income per working-age resident

Y = income	Settlement	Settlement	District	District
Constant	12,977*** (0.096)	15.100*** (0.133)	11.682*** (0.622)	12.523*** (0.531
nép	-0.005 (0.004)	-0.010*** (0.003)	-0.039** (0.016)	-0.032** (0.013)
egyv	0.040*** (0.007)	0.019*** (0.006)	-0.020 (0.060)	0.141*** (0.052)
társv	-0.026*** (0.005)	-0.019*** (0.005)	-0.028 (0.037)	0.006 (0.036)
mérlf	0.003** (0.001)	0.002* (0.001)	0.033*** (0.011)	0.013 (0.009)
állásk	-0.079*** (0.004)	-0.043*** (0.004)	-0.081*** (0.019)	-0.069*** (0.016)
eutám	-0.000 (0.000)	-0.000 (0.000)	-0.010 (0.010)	-0.006 (0.008)
önkber	0.003** (0.001)	0.004** (0.001)	-0.008 (0.014)	0.008 (0.011)
távbp	-0.152*** (0.007)	-0.126*** (0.006)	-0.071*** (0.015)	-0.064*** (0.013)
távmsz	-0.057*** (0.005)	-0.032*** (0.005)	-0.042*** (0.014)	-0.018 (0.012)
szakm	0.180*** (0.013)	0.077** (0.014)	0.121* (0.070)	-0.053 (0.080)
érett	0.256*** (0.012)	0.128*** (0.012)	0.572*** (0.074)	0.416*** (0.087)
dipl	0.053*** (0.006)	0.033*** (0.006)	-	-
FEOR-08-0	-	0.014*** (0.003)	-	0.036*** (0.012)
FEOR-08-1	-	-0.014*** (0.004)	-	-
FEOR-08-2	-	0.010* (0.004)	-	-
FEOR-08-3	-	0.009 (0.006)	-	0.054 (0.077)
FEOR-08-4	-	0.021*** (0.004)	-	0.114* (0.066)
FEOR-08-5	-	-0.028** (0.006)	-	-0.308*** (0.053)
FEOR-08-6	-	0.002 (0.002)	-	-0.002 (0.013)
FEOR-08-7	-	0.031*** (0.05)	-	0.011 (0.042)
FEOR-08-8	-	0.077*** (0.006)	-	0.134*** (0.027)
FEOR-08-9	-	-0.277*** (0.014)	-	-
λ (lambda)	0.000*** (0.000)	0.000*** (0.000)	0.002*** (0.000)	0.001* (0.000)
σ (sigma)	0.172*** (0.002)	0.149*** (0.002)	0.088*** (0.005)	0.070*** (0.004)
FEOR variables combined	X	✓***	X	✓***
R^2	*0.6801*	*0.7602*	*0.6219*	*0.8423*
Adjusted R^2	*0.6789*	*0.7585*	*0.5964*	*0.8241*
Log-likelihood	*1083.497*	*1533.053*	*176.950*	*217.396*
Number of observations	*3155*	*3155*	*175*	*175*

Source: own compilation (*** p<0.01; ** p<0.05; * p<0.1) (standard error in brackets)

After incorporating the main employment groups into the model, the variable relating to the working-age population becomes significantly negative in the model, whilst the significance and direction of effect of the other variables remain unchanged. (Only the significance level changes for some variables). The effects of the individual main employment groups correspond to the directions described in the SLM results, except in the case of *employees in occupations requiring independent application of higher education qualifications (FEOR-08-2)*. This variable has a positive effect on income in the SEM, as in the model based on the OLS method, in contrast to the non-significant result shown in the SLM.

The results of the SDM

The SDM combines the spatial lag model with the simultaneous treatment of the spatial components of the explanatory variables. In practice, the SDM posits that the value of the dependent variable depends not only on the explanatory variables of its own region, but also on the weighted average of the same characteristics in neighbouring regions. As a result, SDM incorporates direct and indirect effects in a simpler manner, and according to simulation results, it is often a preferable choice in terms of bias. In my results, SDM also provides consistent confirmation of previous findings (*Table 5*): it shows a positive effect of educational attainment and entrepreneurial activity, and a negative effect of unemployment and distances. The now positive effect of local government investment indicates that the influence of local central capital extends across the entire region.

At the settlement level, the *working-age population (pop)* and *the number of individual entrepreneurs (egyv)*, as well as higher *educational attainment indicators (szakm, érett, dipl),* drive up the population's income. The number of *joint ventures (társv)* and *jobseekers (állásk)*, as well as *greater distance from major cities (távbp, távmsz)*, reduces the population's wage level. After incorporating the employment variables, the sign of *the population* variable *(nép)* changes in the model, whilst *the extent of local government investment (önkber)* becomes positively significant. 6 of the 10 FEOR variables are significant in the SDM: *employees in* the *armed forces (FEOR-08-0)*, *employees in occupations requiring independent application of higher education qualifications (FEOR-08-2)*, *employees in office and administrative (customer relations) occupations (FEOR-08-4)*, *employees in industrial and construction occupations (FEOR-08-7)*, *machine operators, assemblers and drivers (FEOR-08-8)* in a positive sense, whilst *those employed in occupations not requiring qualifications (unskilled) (FEOR-08-9)* with a negative sign.

Overall, it can be concluded that the results obtained using different spatial aggregation levels and estimation methods are consistent with one another. In all models, the spatial effect parameters (ρ and λ) are significant, suggesting that both direct spatial effects and the spatial correlation inherent in the residuals play an important role in shaping income levels.

Table 5: Spatial Durbin Model (SDM) – The effect of variables on total domestic income per working-age resident

Y = income	Settlement	Settlement	District	District
Constant	12,428*** (0.214)	14.558*** (0.227)	11.573*** (0.715)	12.407*** (0.634)
nép	0.009* (0.005)	-0.003*** (0.005)	-0.041*** (0.052)	-0.032** (0.015)
egyv	0.039*** (0.010)	0.022*** (0.008)	0.012 (0.050)	0.044 (0.049)
társv	-0.015** (0.007)	-0.013** (0.006)	0.003 (0.033)	0.028 (0.037)
mérlf	0.002 (0.001)	0.001 (0.001)	0.029*** (0.009)	0.013 (0.008)
állásk	-0.060*** (0.008)	-0.043*** (0.008)	-0.042* (0.025)	-0.059*** (0.023)
eutám	-0.001 (0.001)	-0.001 (0.000)	-0.002 (0.010)	0.002 (0.008)
önkber	0.003 (0.002)	0.004** (0.001)	-0.013 (0.011)	-0.001 (0.009)
távbp	-0.126*** (0.022)	-0.131*** (0.018)	-0.039 (0.039)	-0.050** (0.024)
távmsz	-0.022* (0.012)	-0.032*** (0.010)	-0.050*** (0.019)	-0.025 (0.017)
szakm	0.195*** (0.033)	0.099*** (0.032)	0.124* (0.075)	-0.064 (0.089)
érett	0.261*** (0.020)	0.135*** (0.017)	0.502*** (0.076)	0.381*** (0.099)
dipl	0.059*** (0.010)	0.038*** (0.009)	-	-
FEOR-08-0	-	0.014*** (0.003)	-	0.036*** (0.013)
FEOR-08-1	-	-0.005 (0.006)	-	-
FEOR-08-2	-	0.012* (0.007)	-	-
FEOR-08-3	-	0.014 (0.010)	-	0.123 (0.085)
FEOR-08-4	-	0.023*** (0.008)	-	0.101 (0.074)
FEOR-08-5	-	-0.008 (0.015)	-	-0.229*** (0.051)
FEOR-08-6	-	0.003 (0.003)	-	0.011 (0.013)
FEOR-08-7	-	0.030*** (0.011)	-	0.017 (0.041)
FEOR-08-8	-	0.047*** (0.008)	-	0.109*** (0.031)
FEOR-08-9	-	-0.221*** (0.023)	-	-
FEOR variables combined	X	✓***	X	✓***
R2	0.6560	0.7788	0.8879	0.9471
Adjusted R2	0.6534	0.7757	0.8717	0.9332
Log-likelihood	1202.050	1716.342	204.375	235.628
Number of observations	3155	3155	175	175

Source: own compilation (*** p<0.01; ** p<0.05; * p<0.1) (robust standard error in brackets)

3.3. Interpretation of the Results of the Regression Models

The more precise results of the spatial models are confirmed by the fact that the spatial autoregressive coefficients (ρ and λ) are both positive and significant at both the settlement and district levels (*Tables 2–5*). We can draw conclusions in two directions from the results presented in the previous chapter. On the one hand, we gain an understanding of which explanatory variables, according to the various econometric models, actually influence the total domestic income per working-age resident. On the other hand, it becomes clear how the results of the individual models change with aggregation.

The *working-age population (nép)* appears in the individual models (OLS, SLM, SEM, SDM) either as an insignificant factor or with a negative sign at both the settlement and district levels. This may be explained by the fact that income is high primarily due to the spatial environment, i.e. neighbouring wealthy regions, rather than simply because of the large population of the settlement or district in question. In itself, a larger local population (if we disregard the income benefits of proximity) can even be a disadvantage, for example in the form of an oversupply in the labour market. To put it another way, we can explain it as follows: the high population of neighbouring areas has a positive 'spillover' effect on local incomes (for example, the labour market of a nearby town drives up incomes in surrounding settlements), whilst the direct effect of the local population is negative, because the additional labour force does not in itself increase local wages.

The number of registered individual entrepreneurs (egyv) has a positive effect on per capita income at the settlement level, whilst at the district level the effect is the opposite in models that do not include employment variables (FEOR-08). If FEOR variables are incorporated into the district-level models, the effect of the variable becomes significant again. This phenomenon is likely partly due to the MAUP effect. The true relationship between the number of sole traders and income levels at district level can only be demonstrated if we control for the occupational structure. It is then that the true relationship becomes apparent: given a particular occupational distribution, per capita income is higher in those districts where there are more sole traders. Without controlling for this, the occupational structure is often more homogeneous at the settlement level, so the beneficial effect of entrepreneurs is more clearly evident, whereas at the district level the more heterogeneous occupational structure may mask this, unless we specifically include it in the model.

Contrary to my initial expectations, the number *of registered joint ventures (társv)* has a significantly negative impact on the income situation of the population at the settlement level, whereas at the district level the variable is not significant. One explanation for this phenomenon may be the issue of spatial heterogeneity, i.e. that the relationship between business density and income does not follow the same pattern everywhere. For example: in certain more developed regions, a higher number of businesses is associated with higher per capita income, whilst in some underdeveloped peripheral areas the opposite is true, with a high number of (mainly small) businesses tending to be associated with poverty.

Another possible explanation is that the negative estimate for social enterprises is due to a bias caused by an omitted variable. If this omitted factor has a positive effect on income, but is negatively correlated with the number of social enterprises per capita (i.e., the more alternative employment opportunities there are, the less one 'needs' to work in a social enterprise), then omitting this variable from the model may bias the coefficient for social enterprises downwards. In other words, the estimated negative effect of partnerships may partly stem from the fact that this variable (*társv*) reflects the impact of an uncontrolled labour market factor that is negatively correlated with the number of partners variable.

The size of total assets per working-age resident (mérlf) generally has a positive effect in models without FEOR variables (except in the SDM model at the settlement level), whilst in models adjusted for FEOR variables, the variable's effect on income disappears (except in the SEM model at the settlement level). In theory, total assets indicate a region's capital base and economic weight (the value of companies and investments). Such a variable is generally positively correlated with income, as a larger capital stock increases productivity, wages and profits. However, the fact that, after incorporating variables indicating the employment structure, the role of total assets ceases in most models suggests that regional income disparities are primarily driven by the qualifications of the workforce and the sectoral structure.

The proportion of jobseekers (állásk) has a negative impact on incomes; that is, higher unemployment leads to lower incomes. This is not surprising, as fewer working-age residents receive regular earned income, which reduces total domestic income per capita. Unemployment was a problem in Hungary primarily in the 1990s and early 2000s. The regions struggling with economic depression (the north-eastern and south-western peripheral areas of the country, as well as small-village, peripheral rural areas) were clearly identifiable, having fallen steadily behind since the change of regime. In these areas, the collapse of traditional industries (mining, heavy industry, large-scale agriculture) often led to the loss of a large number of jobs, and insufficient new investment came in to replace them.

EU funds paid out between 2015 and 2019 per resident of working age (eutám) (adjusted for inflation and allocated to the beneficiary municipality) did not show a significant impact on total domestic income at either the municipal or district level in any of the spatial regression models (nor in the case of the OLS method). This may come as a surprise, given that EU funds have financed significant investments across the country. There may be several reasons behind the lack of the expected significant effect.

Many EU-funded projects do not directly increase the population's income, but rather improve the economic environment indirectly by channelling a significant portion of the funding into infrastructure development or public services (such as the renovation of roads, utilities, schools and healthcare facilities). These investments do not immediately generate higher wages for local residents, but they can create the conditions for long-term development. Furthermore, the multiplier effect of the funding may also come into play indirectly. When an investment project is implemented, the wages paid to contractors and the demand for purchased materials trigger a ripple effect in the economy. However, these secondary effects may not necessarily occur in the locality where the project is taking place. For example, on a construction site, some of the workers or suppliers may not be local, so part of the wages paid and revenue generated will appear in other localities. Spatial models attempt to account for these effects, but it may be the case that the economic benefits of the grants are spatially dispersed and do not concentrate in the income of the beneficiary locality.

Furthermore, it is also possible that the impact of EU grants received between 2015 and 2019 on wages will only become apparent in the longer term, with a delay. It is conceivable that the positive economic effects (e.g. the arrival of new investors, job creation, reduced commuting times, etc.), which will subsequently influence wage trends, cannot yet be measured in 2019.

The value of local government investment per working-age resident (önkber) significantly increases income at district level in the SLM, SEM and SDM models. At settlement level, however, this variable has a significant (has a positive effect). Higher local government investment can increase average income through several mechanisms: it improves infrastructure and services (which can have an immediate impact on business operations), creates jobs, stimulates economic activity, and lays the foundations for sustainable growth in the longer term.

In most models, *distance from Budapest and the county seat (távbp and távmsz)* has a negative impact on income at both the settlement and district levels. This means that if a settlement or district is located further away from the capital or the county town, there is a good chance that the total domestic income per working-age resident will be lower there. The reason behind this is that the catchment areas of urban centres extend far beyond their administrative boundaries: the closer a settlement or district is to a major urban centre, the more it can benefit from the economic advantages generated by that centre. Peripheral regions, by contrast, are excluded from these benefits, leading to lower income levels. Settlements close to centres enjoy agglomeration benefits: they are close to suppliers and markets (connectivity advantage); they have access to a larger concentrated labour supply and labour pool (labour market advantage); the flow of information and the dissemination of knowledge are faster (information externalities) (Fujita et al., 1999).

Three variables relating to educational attainment were included in the models: the *proportion of those with vocational qualifications (high school graduation exam) (szakm)*, the proportion *of those with a high school graduation certificate (érett)*, and the *proportion of those with a university or college degree (dipl)*. (For methodological reasons, those with a university degree (*dipl*) are not included in the district-level model.) All three variables are significantly positive in the models in almost all cases. At district level, the variable indicating the proportion of those with vocational qualifications is not significant in all cases.

The significant positive effect of all three variables is due to the fact that the baseline against which the models compare income levels is the proportion of those without secondary education. This explains the positive effect even of the group with vocational school or trade certificates but without a school-leaving certificate. This group also represents significantly higher human capital than the primary-educated or uneducated workforce. Workers with vocational qualifications possess specialised skills, and their work can be far more productive and valuable than that of the unskilled workforce. Higher levels of human capital in all three qualification categories contribute to an increase in per capita income, as all three groups represent a more valuable workforce compared to those with the lowest qualifications. Well-educated workers are better able to utilise modern technologies, learn new processes more quickly, and adapt more easily to innovations. As a result, in regions where the proportion of those with secondary and tertiary education is high, business productivity is also higher, as the overall performance of the workforce is better.

The main occupational groups incorporated into models based on *the Standard Classification System of Occupations (FEOR–08)* have varying effects on income trends.

The data show that *employees in the armed forces (FEOR-08-0), those employed in office and administrative (customer service) occupations (FEOR-08-4), and machine operators, assemblers,* and *drivers (FEOR-08-8)* have a positive impact on the population’s income in almost all of the models. This means that, according to the models, these occupational categories offer the best prospects for achieving a high wage.

According to a report by the Hungarian Central Statistical Office (KSH, 2024), those working in occupations within the armed forces requiring higher education qualifications (FEOR-08-0110, FEOR-08-0210) earned well above the average wage in 2019, but the average wage of those employed in roles requiring secondary education within the same sector was also higher than the national average.

If the proportion of *employees in office and administrative occupations (FEOR-08-4)* is high in a settlement, this may indicate that there are more companies and administrative units operating there. This may signify higher productivity and a modern economic environment, which generally goes hand in hand with higher average incomes. So, it is probably not the case that office and administrative staff have high incomes, but rather that the proportion of people working in these roles is high in those settlements/districts where the population's income is higher due to the economic environment.

In Hungary, the employment rate *of machine operators, assemblers and drivers (FEOR-08-8)* is generally characteristic of regions with a strong industrial base. Developed clusters in the automotive and engineering industries (e.g. the areas around Győr, Kecskemét and Székesfehérvár) have significant international investment and supplier networks. These centres often concentrate machine operator and assembly worker roles, which also has a positive impact on the average income of the town and its surrounding area. Machine operators, assembly workers and drivers typically work in high-productivity sectors (mechanical engineering, automotive manufacturing, logistics). According to European statistics, average wages in these sectors are generally higher than in the rest of the economy.

Surprisingly, in the local authority-level models, *the proportion of economic, administrative and advocacy leaders and legislators (FEOR-08-1)* has a negative impact on earnings. (This variable was not included in the district-level models for methodological reasons.) There are essentially two possible explanations for this unexpected effect. On the one hand, for example, if the proportion of managers is higher in a region but the rate of self-employment is low and unemployment is high, then the *FEOR-08-1* coefficient may shift in a negative direction. In this case, therefore, the indicator reflects differences in the employment structure rather than the higher proportion of managers causing the decline in income. Another possible explanation is that smaller rural towns or county seats are often important centres for public services and administration, where social services, elderly care and childcare centres, etc., are located. These public service institutions create administrative and managerial positions, but, for example, the salaries of managers at the institutions listed were not particularly high in 2019, according to data from the Hungarian Central Statistical Office (KSH, 2024).

If more people work *in occupations requiring the independent application of higher education qualifications (FEOR-08-2)* and *in industrial and construction occupations (FEOR-08-7)*, then the average income increases at the local authority level. The result for the *FEOR-08-2* variable is not surprising, as this likely reflects the effect that a higher education qualification leads to higher income. The effect of *FEOR-08-7* is likely positive because the wages of those employed in this sector are higher than those of workers in certain other sectors. The average gross monthly wage for those working in industrial and construction occupations was approximately 310,000 forints in 2019. This figure is higher than the average wage for most office, service or unskilled jobs.

Two variables have a clearly negative impact on total domestic income per capita. These are *the proportion of employees in trade and service occupations (FEOR-08-5)* and *the proportion of employees in unskilled (simple) occupations (FEOR-08-9)*.
The negative impact of *FEOR-08-5* may be due to the fact that main group 5 includes, for example, shop assistants, hospitality workers, personal service providers (hairdressers, beauticians, etc.), who, according to KSH (2024) statistics, did indeed have lower wages in 2019 across several occupational categories. As these roles generally require secondary or lower-level qualifications, the average wage of those working in these roles is also lower than in professions requiring higher qualifications. Furthermore, commercial activities are often volatile and seasonal in nature, leading to fluctuations in income and, overall, a lower average.
The FEOR-08-9 occupational group comprises jobs that do not require any formal qualifications (simple cleaner, loader, porter, shelf-stacker, kitchen assistant, etc.). From the employees' perspective, these positions generally represent the lowest qualification and income categories; wages for those working in these occupations are low on average because the work performed requires few specialised skills. The high proportion of unskilled occupations often points to marginalisation in the labour market: these workers frequently have fewer opportunities for promotion, are typically employed on a part-time or casual basis, and are also more likely to end up in the informal economy.

In none of the models is the effect of the proportion of *employees in occupations requiring other higher or secondary education (FEOR-08-3)* and *in agricultural and forestry occupations (FEOR-08-6)* significant.

3.4. The Effect of Aggregation on the Results of the Models

The results of the econometric models can also be compared in terms of how the number of significant explanatory variables and the signs of their coefficients change at different levels of aggregation.

Table 6 shows that, in all models, the number of significant explanatory variables at the district level decreases compared to the settlement level as the level of aggregation increases. This is explained by the fact that aggregating the data has a smoothing effect, which obscures the differences observed in smaller territorial units and thus influences the results of the regression models. At higher levels of aggregation, the standard error of the models is also higher. Higher standard errors introduce uncertainty into the models, which is one reason why the number of significant variables decreases. These results suggest that spatial analyses should be conducted at the smallest possible spatial scale to obtain the most accurate model estimates. If we compare, on a model-by-model basis, the explanatory variables that are significant at both the settlement and district levels, we can also see that the sign of the variables changes as a result of aggregation in only one case (the variable *'number of working-age population'* in the SDM model). We can therefore conclude that the sign of the coefficients is not affected by aggregation.

The results are consistent with the phenomena described in the literature. Aggregating the data increases the accuracy of the fit of multivariate models, as well as the coefficients of determination and correlation coefficients, due to the so-called smoothing effect, which is attributable to a reduction in the variance within individual variables (Fotheringham-Wong, 1991; Arbia, 2012, cited in Zhou et al., 2022). If we aggregate socio-demographic characteristics at a larger scale, a significant portion of the variance within the area may be lost (Zhou et al., 2022). The standard error of the regression parameters also increases in the models as a result of the aggregation, so the number of significant explanatory variables decreases at higher levels of aggregation (Pietrzak, 2014). This is because the standard error depends in part on the number of observations used in the models (Fotheringham–Wong, 1991).

Table 6: Number of significant explanatory variables

Model	Level of aggregation	Significant / total explanatory variables	Percentage of significant variables
OLS	Settlement	10/12	83.33%
	Settlement with FEOR	18/22	81.82%
	District	6/11	54.55%
	District with FEOR	10/18	55.56%
Spatial lag (SLM)	Settlement	9/12	75.00%
	Settlement with FEOR	17/22	77.27%
	District	6/11	54.55%
	District with FEOR	8/18	44.44%
Spatial error (SEM)	Settlement	10/12	83.33%
	Settlement with FEOR	19/22	86.36%
	District	7/11	63.64%
	District with FEOR	9/18	50.00%
Spatial Durbin (SDM)	Settlement	9/12	77.8%
	Settlement with FEOR	16/22	52.6%
	District	6/11	54.55%
	District with FEOR	7/18	38.89%

Source: own compilation

3.5. Results of the GWR Model

The greatest advantage of geographically weighted regression (GWR) is that it provides local estimates, whereas most other spatial regression methods, such as the classical SLM/SEM/SDM models, only estimate global parameters (valid for the entire study area). Consequently, the spatial variability (non-stationarity) of the effects of explanatory variables can be revealed. GWR fits a separate regression equation to each observation point, thereby revealing where an effect is stronger or weaker. Thus, through local parameters ( ),

'location-specific' decision support can be provided, as opposed to recommendations based on global average effects. Local parameters, local R^2 or local residuals can be plotted directly onto a map. These 'sensitivity maps' immediately show where intervention is warranted (e.g. targeted economic development support). In my case, by revealing local variations in the determinants of income, the GWR model can help to eliminate, through targeted policy interventions tailored to local conditions, those disadvantages that negatively affect total domestic income per working-age resident. Furthermore, the results of GWR models can highlight the factors that increase per capita income in a specific location. For example, identifying areas where educational attainment has a more significant positive impact on income than elsewhere can provide guidance on the allocation of resources for education and training programmes.
To determine the optimal bandwidth of the models, I tested procedures taking into account different numbers of nearest neighbours (NN = 20, 30, 50, 75). Based on the corrected Akaike information criterion (AICc), the model considering 30 nearest neighbours at the settlement level and 25 at the district level shows the best fit. (Due to space constraints, the thesis booklet contains only the settlement-level results.)

The working-age population (nép) has a significant effect in the model incorporating FEOR variables for 466 settlements. In 296 settlements, a higher population size has a positive impact on residents' income. These settlements are located in Transdanubia and the eastern part of the Great Plain, but Budapest is also included among them. In certain settlements in the counties of Nógrád, Heves, Borsod-Abaúj-Zemplén, Szabolcs-Szatmár-Bereg and Győr-Moson-Sopron, however, a higher population results in lower income. In the model without FEOR variables, this variable has a significant effect on income trends in 1003 settlements. In the majority of these settlements, the effect is positive; these are located in Transdanubia and near the Romanian border. In the northern parts of Jász-Nagykun-Szolnok, Borsod-Abaúj-Zemplén, Heves and Győr-Moson-Sopron counties, there are settlements where, according to the model, a larger population leads to a lower income level.

A higher number *of individual entrepreneurs (egyv)* tends to push incomes upwards, particularly in the eastern half of the country. In the southern part of the central region, however – in the strip stretching from Lake Balaton to Szeged – a negative effect can be observed, contrary to our expectations. However, in the case of 1182 settlements where the variable's effect is significant, the relationship is predominantly positive (784 settlements). The model without FEOR variables thus shows a high degree of agreement.

The number of *joint ventures (társv)* per resident of working age proved to be a variable with a significant effect in only a quarter or a third of the settlements. As already described for other spatial models, this variable has a negative effect on income levels according to the GWR model as well. The map results of models including and excluding FEOR variables show a high degree of agreement, with the exception that, in the former, there are fewer settlements in each district of the country where the variable has a negative effect, whilst in the model containing FEOR variables, there are more settlements where the impact of social enterprises is favourable. The latter settlements are located in Veszprém and Vas counties, as well as in the northern part of Zala county; furthermore, similar settlements can be found at the junction of Hajdú-Bihar, Borsod-Abaúj-Zemplén and Jász-Nagykun-Szolnok counties.

The *total assets per working-age resident (mérlf)* shows a positive effect in the middle range of the country for both settlement-level models. The number of settlements is roughly the same, but their distribution varies between models that include FEOR variables and those that do not. In the latter case, a distinct, broad band stretching from the Slovak border to the Serbian border can be observed, whilst in the former, Budapest and its surroundings are no longer visible on the map, replaced instead by settlements in Baranya County. In addition to these, there are scattered settlements in the north-eastern and western Transdanubian parts of the country where total assets have a positive effect on income trends.

A higher number of *jobseekers (állásk)* naturally has a negative impact on income, as indicated by the GWR models. In the case of the model not including FEOR variables, this negative effect is stronger in the Danube-Tisza region and in East of the Tisza than in Transdanubia. After incorporating the FEOR variables, the significant effect is observed in fewer settlements, and the extent of the negative effect is levelled out; no marked difference can be observed between Transdanubia and the rest of the country.

At the settlement level, the effect of *per capita European Union funding (eutám)* is significant in only about one-quarter to one-fifth of settlements, and even within this group, the sign of the variable's effect varies, though it is mostly negative. This is an effect contrary to our initial expectations. (See Chapter 4.3 for a possible explanation!) Maps showing and not showing employment classes exhibit a high degree of similarity; groups of settlements where the impact of EU funding is detectable are scattered across the country.

In the area around Lake Balaton, and in settlements close to one another in Tolna, Baranya and Bács-Kiskun counties, *local government investments* *(önkber)* have a positive impact on per capita income. Like EU funding, this variable also shows a significant effect only in a smaller proportion of settlements, approximately one-fifth of them.

According to GWR models, the effect of *distance from the capital (távbp)* on income is detectable in about two-thirds of settlements. In the majority of cases, of course, the relationship holds that greater distance from Budapest has a negative impact on income levels. This negative effect is most pronounced in Szabolcs-Szatmár County. In Southern Transdanubia and the northern part of Borsod-Abaúj-Zemplén County, however, the effect of this variable is the opposite in the GWR models.

The negative effect *of distance from the county seat (távmsz)* is most pronounced in Transdanubia and the central part of the Great Plain. North-east of Budapest, as well as in certain settlements in Borsod-Abaúj-Zemplén and Szabolcs-Szatmár-Bereg counties, the effect of this variable is, however, the opposite: that is, in settlements further from the county seat, the total domestic income per working-age resident is higher.

A higher proportion of *the population with vocational qualifications (szakm)* leads to higher income figures across almost the entire country, with the exception of the immediate vicinity of Budapest. The extent to which this positive effect is higher or lower varies considerably across different areas. After incorporating the FEOR variables into the model, this variable loses its significance in a significant proportion of settlements in Transdanubia, whilst the effect of the proportion of the population with vocational qualifications remains unchanged in the rest of the country.

The effect of the proportion of *those with a school-leaving certificate (érett)* on income levels shows a very similar spatial distribution to that of the proportion of the population with vocational qualifications. This is the variable that has a significant effect in most settlements in the model without FEOR variables, accounting for 88.6 per cent of settlements. With the exception of Budapest and its surroundings, as well as a strip along the Romanian border, the effect of the variable is positive almost everywhere, contributing most significantly to the rise in income levels in the Great Plain. The inclusion of FEOR variables reduces both the number of settlements where, according to the model, passing the school-leaving examination leads to higher income, and the magnitude of the variable's positive effect. (This is likely due to the fact that certain FEOR variables 'take over' the 'explanatory role' of the school-leaving certificate.)

In the model including employment classes, a higher proportion *of those with a degree (dipl)* has an impact on income in significantly fewer settlements than in the model without FEOR variables. In the former case, the proportion of graduates has a demonstrable influence mainly in Transdanubia and the Szeged area, as well as in certain settlements in northern and north-eastern Hungary. (In the case of other settlements, certain FEOR variables likely take on the role of this explanatory variable.) In Győr-Moson-Sopron County (and partly in Vas County), the model suggests that a university degree has an income-reducing effect in settlements bordering Austria. This is likely due to the fact that, because of the high level of employment in Austria and the region's level of development, the income advantages for graduates—which in the rest of the country go hand in hand with college or university qualifications—are lost. In the model without FEOR variables, the positive impact on the population's income situation is most pronounced in Budapest and the central part of the country. In Transdanubia and the north-eastern regions, the effect is also positive; however, in the eastern part of the country, the proportion of graduates has no significant impact on income levels. Budapest and the western regions are more economically developed, with more high value-added sectors (e.g. technology, finance, services). In these regions, there is greater demand for a more highly skilled workforce, which results in higher wages. There are fewer jobs requiring higher education qualifications in the eastern regions. Consequently, those with higher education qualifications find it harder to find suitable work, which reduces the income benefits associated with a degree. Highly qualified workers often move to more developed regions or abroad due to better job opportunities. This process weakens the positive impact of higher education on the local economy in less developed areas. The benefits of secondary and vocational education may be stronger in less developed regions, where the economy is more dependent on industries, agriculture or services that require such qualifications. Skilled workers and those with secondary qualifications find it easier to find work locally, which increases their income and has a positive impact on the local economy.

The positive impact of the proportion of *employees in the armed forces (FEOR-08-0)* is limited to a north-south strip of the Transdanubia region, Szeged and its surroundings, and Borsod-Abaúj-Zemplén County.

As discussed above, *economic, administrative and advocacy leaders, and legislators (FEOR-08-1)* have, for the most part, a negative impact on income levels, which is a surprising result compared to initial expectations. This negative impact is most evident in the southern part of Pest County, as well as in certain settlements in Bács-Kiskun, Hajdú-Bihar, Szabolcs-Szatmár-Bereg and Borsod-Abaúj-Zemplén. In the case of Transdanubia, the impact of the variable is positive in more than 130 settlements.

The higher proportion *of employees in occupations requiring independent application of higher education qualifications (FEOR-08-2)* results in higher wages mainly in Budapest, the eastern half of Szabolcs-Szatmár-Bereg, and Győr-Moson-Sopron. This map can therefore serve as a kind of supplement to the map illustrating the effects of the proportion of graduates, since in that map the effect of higher education was not evident in these areas of the country (with the exception of Budapest), whereas here higher education is clearly included in this variable.

The proportion of *employees in occupations requiring other higher or secondary education (FEOR-08-3)* has the greatest positive impact on household income in the southern and south-western parts of Transdanubia, as well as in the areas of Békés and Hajdú-Bihar counties close to the Romanian border. There are groups of settlements (e.g. in Nógrád and Szabolcs-Szatmár-Bereg counties) where the effect of this variable is negative.

The proportion of employees in office and administrative (customer relations) occupations (FEOR-08-4) has the greatest positive impact on household income in settlements in Transdanubia; however, in approximately two-thirds of the country's settlements, this variable is not significant.

The results for the variable *'employees in trade and service occupations' (FEOR-08-5)* as shown by GWR models confirm the findings of the OLS and spatial models, namely that the effect of this variable on income is negative in a significant proportion of the country's settlements, with settlements where a higher proportion of workers in FEOR-08-5 leads to higher wages found mainly in Vas County.

Employment in agricultural and forestry occupations (FEOR-08-6) has a positive effect in certain settlements in Transdanubia and Borsod-Abaúj-Zemplén, however, in most of the country the effect is not significant, and in a smaller group of settlements, a higher proportion of people working in agriculture and forestry has a negative impact on the population's income.

According to the results of the GWR model, it is worthwhile to work *in industry and construction (FEOR-08-7)* in the southern and western parts of Transdanubia, as well as in Budapest and the settlements lying south of it along the banks of the Danube. Furthermore, at the junction of Jász-Nagykun-Szolnok, Heves, Borsod-Abaúj-Zemplén and Hajdú-Bihar counties, there are still settlements where income is higher if more people work in the FEOR-08-7 main group. Not far from here (in parts of Szabolcs-Szatmár-Bereg and Hajdú-Bihar counties), however, this variable has the opposite effect.

A higher proportion of employees in *the machine operators, assemblers, and drivers (FEOR-08-8)* has the greatest positive impact on income in the north-western part of Transdanubia, but in the southern part of Transdanubia and the eastern part of the Great Plain, higher wages result when more people work in these occupations.

The variable *for those employed in (unskilled) occupations not requiring qualifications (FEOR-08-9)* is significant almost everywhere except in the north-western part of Transdanubia. With few exceptions, the effect of the variable is negative everywhere; this is not surprising, as the nature of this employment category means that these jobs require the lowest level of educational attainment, which is also reflected in the trends in income and wage levels. Only in settlements along the Austrian border— —does the FEOR-08-9 indicator have a positive effect on income. This is likely due to the fact that the higher wage levels observed in this region also drive up the wages of those employed in occupations not requiring specialist qualifications.

The GWR method can also be used to statistically examine the geographical variability of explanatory variables. If the value of the difference in criteria (AICc) is greater than two, this indicates that the variable does not exhibit geographical variability, meaning that, in the case of my analysis, its effect on the dependent variable is homogeneous across the entire country. Coefficients that do not indicate geographical variability should be interpreted as global rather than local variables. If, however, the aforementioned value is negative, then the variable has a different effect on the dependent variable in each geographical unit. We can see that in the settlement-level model without FEOR variables, 7 out of the 12 variables are statistically those whose effect on income is not uniform across the country's various settlements. After incorporating the FEOR variables, 9 out of 22 variables show geographical variability. *The proportion of individual entrepreneurs* (*egyv*), *distance from the capital* (*távbp*), *distance from the county seat* (*távmsz*), *the proportion of those with vocational qualifications (szakm*), and *the proportion of those with a high school graduation* (*érett*) are variables in both models whose effects are not geographically uniform. In addition to these, the *proportion of jobseekers (állásk), the proportion of graduates (dipl),* and the proportion of those employed in the *FEOR-08-5, FEOR-08-7, FEOR-08-8 and FEOR-08-9* occupational groups are the variables that exhibit spatial heterogeneity in one of the models. The greatest geographical variability is shown by the *distance from Budapest* (*távbp*) and the *proportion of the population with a high school graduation (érett)*.

4. CONCLUSIONS AND RECOMMENDATIONS

My research sets out three interrelated research objectives: (1) to identify, at a spatial resolution, the factors influencing total domestic income per working-age resident; (2) to examine the extent to which analyses conducted at different levels of aggregation (settlement and district) lead to differing conclusions (MAUP); (3) to investigate whether the factors shaping income are spatially homogeneous or exhibit locally varying patterns (spatial heterogeneity).

1) In my dissertation, I demonstrated, using spatial regression models, that income patterns in Hungary exhibit marked spatial autocorrelation. The results of the global spatial models provide a generally consistent picture of the main factors shaping income. At the settlement level, entrepreneurial activity (particularly the proportion of sole traders) and more favourable educational indicators (vocational qualifications, school-leaving certificates, degrees) typically increase income levels, whilst labour market disadvantages (a higher proportion of jobseekers) and greater distance from centres (measured from Budapest or the county seat) have a downward effect. Spatial models also provide additional insight by highlighting the role of neighbourhood (indirect) effects alongside direct effects.
The inclusion of occupational structure (FEOR-08 main groups) also provides significant explanatory power; and, based on the models, several occupational groups show a significant and divergent relationship with income (e.g. certain office/administrative and machine operator-driver groups often have a positive effect, whilst trade and service occupations and those requiring no formal qualifications generally have a negative effect).

2) The results of this study confirm that different conclusions can be drawn from the analyses conducted at the municipal and district levels. At the district level, fewer explanatory variables are significant in models constructed with the same specifications. I have thus empirically demonstrated that the choice of the spatial unit of analysis significantly influences the outcome of income analyses in the case of Hungary as well.

3) The results of my dissertation confirm that in Hungary, the factors influencing per capita income among the working-age population do not have the same spatial impact; that is, these variables influence income patterns in a spatially heterogeneous manner. This finding is consistent with my preliminary hypothesis, which states that a uniform relationship between the explanatory variables and income levels cannot be assumed everywhere. The results of the geographically weighted regression (GWR) indicated that, for certain variables, the strength and even the sign of the relationship may vary from region to region. For example, the proportion of people with vocational qualifications contributes to income growth in many regions, but there are areas where the effect of this factor is much weaker or insignificant. Similarly, greater distance from Budapest is generally associated with a decline in income levels, but the extent of this negative effect may vary across different parts of the country. My findings therefore emphasise the need for a spatial perspective and more refined spatial analysis to accurately understand income dynamics, as aggregated national or regional averages may mask local characteristics; the application of spatial models is essential for uncovering spatial variability.

My research also provides important lessons from a practical perspective. The finding that different factors prove decisive in shaping the income situation of the population across different regions conveys the message that policy measures should be planned and implemented at a regional level in a tailored manner. A 'one-size-fits-all' general economic development or welfare measure is likely to be less effective if it does not take into account the specific characteristics of the region in question. The development of human capital (raising educational standards) is particularly justified in those districts and settlements where low educational attainment limits income growth. In areas, however, where high unemployment is the main problem, job creation, expanding employment and labour market programmes can contribute to income growth. Infrastructure development and transport programmes, as well as the expansion of remote working and digitalisation, may offer a solution to mitigating the disadvantages faced by peripheral settlements located far from Budapest and county seats, as these can reduce the labour market and access disadvantages arising from distance. Another important practical finding is that the quality of local economic activity matters: according to my findings, a high number of sole traders contributes to the prosperity of settlements, whilst the number of limited companies does not in itself guarantee a higher income level. This suggests that supporting the small business sector and self-employment may be a more effective means of raising incomes in rural areas than simply encouraging business start-ups on a larger scale. Another interesting finding is that the positive impact of local authority investments on incomes is evident at the settlement level, which highlights the importance of local development; however, this effect diminishes at a higher level of aggregation. This suggests that local development programmes and investments exert their effects directly on the ground, but are less detectable at the regional aggregate level; in other words, local investments are most effective when they are directly tailored to the needs of the local population.

In my research, the parallel examination of global and local models ensured that the analysis provided a more reliable and comprehensive picture of the causes of regional income disparities within the income situation of Hungary's population. A comparison of the different models highlighted that spatial regression models (SLM, SEM, SDM) and GWR provide a better fit and a deeper understanding of income dynamics than ordinary least squares (OLS). The presence of spatial autocorrelation justified the use of these models: the results indicate that the income levels of neighbouring settlements influence one another in a statistically significant manner. The use of spatial models revealed spillover effects, whereby, for example, the economic success of a given settlement also has a positive impact on the incomes of neighbouring settlements. The GWR model clearly demonstrated that, alongside the generalised results of global models, there are significant local variations: local regressions highlighted the regions where the effects of individual variables deviate markedly from the national average. However, with the help of the GWR, we can also see which regions are most similar or most different from one another in terms of the income impact mechanism.

The results of this paper also suggest a number of further research directions. On the one hand, it may be worthwhile to supplement the analysis with time-series analysis to reveal how these spatial patterns and effects have changed over time (for example, as a result of the economic difficulties caused by the Covid-19 pandemic or the Russia-Ukraine war). A further step in the research would be if additional variables became available and the results could be refined by incorporating them into models. It is also conceivable to examine correlations between territorial levels, such as analysing the impact of urban–rural relationships on incomes.

International comparative studies also offer significant opportunities. It may be worthwhile to examine the extent to which the correlations and trends identified in Hungary hold true in other countries. Within the framework of regional comparisons, for example in the Central European region, it could be explored whether the factors affecting incomes follow a similar pattern in neighbouring countries, or whether, given different historical and economic backgrounds, other factors are more significant. From a broader international perspective, the study could even be conducted using EU or global data.

5. NEW RESEARCH RESULTS

1. I have empirically demonstrated that the factors determining per capita income have a spatially heterogeneous impact. The settlement-level analysis showed that the impact of individual explanatory variables (e.g. educational indicators, labour market conditions, geographical location) varies significantly across different parts of the country.

2. I demonstrated that in Hungary, the choice of the spatial unit of analysis has a substantial impact on the results; in other words, there is a distortionary effect of the level of aggregation (MAUP) in income analyses.

3. I have highlighted the correlations at the settlement and district levels regarding the impact of local economic and social factors on incomes in Hungary. According to my findings, a higher proportion of people with higher educational attainment and greater small business activity (number of individual entrepreneurs) contribute to higher income levels, whilst labour market disadvantages and peripheral location have a demonstrably adverse effect on the income situation of the population.

6. PUBLICATIONS RELATED TO THE SUBJECT OF THE DISSERTATION

- BAREITH, T., CSIZMADIA, A. (2025): Are the Determinants of per Capita Incomes Spatially Homogeneous? *Post-Communist Economies*, 37 (6) pp. 517–532. DOI: http://doi.org/10.1080/14631377.2025.2487237
- BAREITH, T., CSIZMADIA, A. (2024). Település, járás vagy vármegye? Mi alapján hozzunk szakpolitikai döntéseket? *Portfolio.hu* (March 28, 2024) https://www.portfolio.hu/krtk/20240328/telepules-jaras-vagy-varmegye-mi-alapjan-hozzunk-szakpolitikai-donteseket-677057
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- CSIZMADIA, A. (2023): A lakossági jövedelmek modellezése földrajzilag súlyozott regresszióval. 113–118. p. In BENE, SZ. (szerk.): *XXIX. Ifjúsági Tudományos Fórum: Konferenciakötet*. Keszthely: MATE Georgikon Campus. 316 p. https://press.mater.uni-mate.hu/165/
- CSIZMADIA, A., BAREITH, T. (2023). The Importance of Aggregation in Regional Household Income Estimates. *Regional Statistics*, 13 (6) pp. 1059–1097. DOI: http://doi.org/10.15196/RS130603
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