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An Empirical Study Of Productivity Growth In EU28 - Spatial Panel Analysis[1]

Abstract

This paper investigates the spatial process of productivity growth in the European Union on the foundations of the theory of New Economic Geography. The proposed model is based on the study of NUTS 2 regions and takes into consideration a spatial weights matrix in order to better describe the structure of spatial dependence between EU regions. Furthermore, our paper attempts to investigate the applicability of some new approaches to spatial modelling including parameterization of the spatial weights matrix. Our study presents an application of the spatial panel model with fixed effects to Fingleton's theoretical framework. We suggest that the applied approach constitutes an innovation to spatial econometric studies providing additional information hence, a deeper analysis of the investigated problem.

Keywords*: spatial panel model, spatial econometrics, productivity growth*

1. Introduction

New Economic Geography (NEG) presented mainly in Fujita, Krugman and Venables (1999) has significantly influenced the regional analysis of the concentration of economic activity, and in particular placed increasing returns

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processes in the mainstream of economics. However, the NEG theory is more a theoretical description of the real world than a ready formula for application. Nevertheless, recently the number of papers which take the new theory as a point of departure for their analysis is increasing (cf. Combes and Lafourcade 2001 and 2004, Combes and Overman 2003, Redding and Venables 2004, Fingleton 2005a, 2005b, 2006).

The aim of this paper is to analyse the spatial process of productivity growth in the European Union (EU) on the foundations of the theory of New Economic Geography. The presented model is based on the study of NUTS 2 regions and applies Fingleton's model of productivity growth which, in turn, is essentially founded on the NEG theory. Our work also takes into consideration a spatial weights matrix in order to better describe the spatial structure of the dependencies among the EU regions. Additionally, we attempt to investigate the applicability ,in the context of our study, of a new approach for describing the spatial structure, namely the parameterization of the spatial weights matrix.

This paper is structured as follows. Section 2 introduces the general idea of the spatial models and, in particular, inverse distance parameterized spatial weights matrix. In Section 3 we present the theoretical background for our study. Section 4 describes data used in the empirical analysis. Empirical results and discussion are presented in Section 5. Finally, Section 6 provides a summary and some concluding remarks.

2. Inverse distance parameterized spatial weights matrix

Spatial data usually violates the assumption made by ordinary regression methods that observations are independent of each other. This has strong methodological implications for the quality of estimates and therefore, for the conclusions drawn from such models. Alternative methods for dealing with relationships involving spatial data are the econometric tools delivered by spatial econometrics.

A classic spatial autoregressive SAR model for cross-sectional observations with normal disturbances takes the following form:

$$\mathbf{y} = \rho\mathbf{W}\mathbf{y} + \mathbf{X}\boldsymbol{\beta} + \mathbf{u}, \quad \mathbf{u} \sim \mathrm{N}(\mathbf{0}, \sigma^2\mathbf{I}), \tag{1}$$

where $\mathbf{y}$ (N×1) represents an N×1 vector consisting of one observation of the dependent variable for every unit in the spatial sample i=1,… , N. Matrix $\mathbf{X}$ (N×K) denotes observations on K exogenous variables. Typically, matrix $\mathbf{W}$ is a given *a priori* spatial weights matrix which represents the neighbourhood structure of the spatial locations. Typically, the elements of **W** ($N \times N$) are ones if locations *i* and *j* are close to each other and all others (in particular the diagonal elements) are zeroes.

One of the most often criticized aspects of using spatial econometric models is that the spatial weights matrix **W** is specified in advance instead of being estimated along with all the parameters in the model.

Researchers dealing with geographical units often adopt a *binary contiguity matrix* with elements equal to one if two regions share a common border and zero otherwise. The other popular spatial weights matrices based on the distance metrics are: *k-nearest neighbours matrix* with fixed number (*k*) of neighbours and the *inverse distance matrix*.

The common practice is to adopt one of the above spatial weights matrices. However, according to Vega and Elhorst (2013) even if there are theoretical reasons indicating that distance matters, it is usually not clear from the theory the degree to which the spatial dependence between units diminishes as distance increases. It seems to be reasonable to assume that theory should be the driving force that determines the specification of **W** (see e.g. Corrado and Fingleton (2012)). However, if there is no theoretical background, a good solution could be to compare the results using alternative functional forms of **W**.

Vega and Elhorst (2013) suggest that a remedy to that problem might be to estimate the *distance decay parameter*. Fischer et al. (2006) and Fischer et al. (2009) estimate the distance decay parameter using an exponential function in empirical applications investigating knowledge spillover. There have also been other studies that employ parameterized **W** (cf. Burridge and Gordon 1981, Kakamu 2005).

One of the most popular forms of the *inverse distance matrix* is that described by the *inverse distance power function* of the form:

$$w_{ij} = 1 / d_{ij}{}^{\gamma},$$

where w_{ij} are the elements of **W** matrix, d_{ij} denotes the distance between locations *i* and *j*, and γ is the *distance decay parameter*.

Let us consider the classic SLX model containing spatially lagged explanatory variables:

$$\mathbf{y} = \mathbf{X\beta} + \mathbf{WX\beta} + \mathbf{u}, \quad \mathbf{u} \sim \mathrm{N}(\mathbf{0}, \sigma^2\mathbf{I}). \tag{2}$$

If we adopt an inverse distance power matrix with γ as the distance decay parameter to the model (2), a Nonlinear Least Squares estimation method can be used for obtaining γ. That parameter along with the W matrix (defined above) can be used in any spatial econometric model such as the SAR model (eq. 1).

According to Vega and Elhorst (2013) the above specification of W provides more information about the nature of the interdependencies of the observations in the sample than conventional W. For instance, a low estimate of γ indicates that global rather than local spillover effect is present. Therefore, in such a case, the commonly used binary contiguity matrix would not accurately represent the spatial dependence structure.

3. The theoretical background

The theoretical background for the study is Bernard Fingleton's model (2001, 2004b) based on the New Economic Geography theory. By employing some simplifications he developed a spatial econometric model based on Verdoorn's Law (see Verdoorn 1949, Kaldor 1957) which ties up increase in productivity with increase in production. Verdoorn's law seems to be important in regional growth analysis as it embodies scale effects.

In Fingleton's model the rate of technical progress is assumed to be an indication of the presence of technological externalities. The technical progress rate is modelled by the means of a function of socio-economic conditions characteristic for a specific region. It is also assumed that the technical progress influences and is influenced by technical progress in neighbouring regions

As a result, the technical progress rate varies by region instead of being an unmodelled constant. It is assumed that the technical progress rate (λ) depends on the terms: Human capital (*H*), the Initial Level of Technology (*G*), the Spillover of Knowledge (*S*) and an autonomous rate which reflects 'learning by doing' which proceeds regardless of the other factors.

Another assumption is that fast/slow technical progress in neighbouring regions affects given region, which as a result, also experiences faster/slower technical progress. Furthermore, the rate of technical progress in distant regions will have less impact, so that the set of neighbouring regions is important due to the spatially impeded knowledge flows.

On the basis of the above assumptions Fingleton introduced the following specification:

$$\lambda = b_0 + \rho S + b_1 H + b_2 G + \varepsilon, \tag{3}$$

Let us notice that spillover of knowledge S is a spatially weighted rate of technical progress $S = \mathbf{W}\lambda$, where $\mathbf{W}$ is a spatial weights matrix defined in the previous section. Combining (3) and the above formula for S as determinants of the rate of growth of productivity, we obtain:

$$p = \lambda + b_3 q, \quad p = b_0 + \rho\mathbf{W}\lambda + b_1 H + b_2 G + b_3 q + \varepsilon. \tag{4}$$

Further, applying some basic algebra we get:

$$\lambda = p - b_3 q, \quad \rho\mathbf{W}\lambda = \rho\mathbf{W}p - \rho\mathbf{W}b_3 q. \tag{5}$$

Thus:

$$p = b_0 + \rho\mathbf{W}p + b_1 H + b_2 G + b_3 q - b_4 \mathbf{W}q + \varepsilon. \tag{6}$$

This specification stipulates that $b_4 = \rho b_3$. This restriction makes the estimation somewhat problematic therefore, Fingleton (2004) suggest taking $b_4 = 0$. Alternatively, we can assume that the rate of technical progress depends not only on weighted average of technical progress in neighbouring regions but also on the weighted average of the rate of productivity growth:

$$\lambda = b_0 + \rho\mathbf{W}p + b_1 H + b_2 G + \varepsilon. \tag{7}$$

Then, the rate of productivity growth can be described by the formula:

$$p = b_0 + \rho\mathbf{W}p + b_1 H + b_2 G + b_3 q + \varepsilon. \tag{8}$$

In the above equation the parameter $b_3 = (\gamma - 1)/\gamma$ is called *Verdoorn's coefficient*. According to the assumptions of Verdoorn's law this coefficient should be around 0.5 (*cf*. Bernat 1996, Fingleton and McCombie 1998, Fingleton 2004b, Fingleton and López-Bazo 2006). Other empirical studies based on the framework given in (8) were carried out in Fingleton (2001, 2004b) and Olejnik (2012).

4. Data

The EU comprises 28 member states and 273 NUTS 2 regions. This study covers 261 regions of those excluding some French, Portuguese and Spanish regions due to their isolated position and Croatia because of the lack of comparable data. The eliminated regions are: Réunion (FR), Guadeloupe (FR), Martinique (FR), Guyane (FR), Região Autónoma dos Açores (PT), Região Autónoma da Madeira (PT), Ciudad Autónoma de Ceuta (ES), Ciudad Autónoma de Melilla (ES), Canarias (ES), Jadranska Hrvatska (HR) and Kontinentalna Hrvatska (HR).

All data used in the empirical part of this study are published by Eurostat[2] and refer to the years 2000-2011. Some missing information was interpolated from the past trends. Table 1 reports the essential description of the variables used in the study.

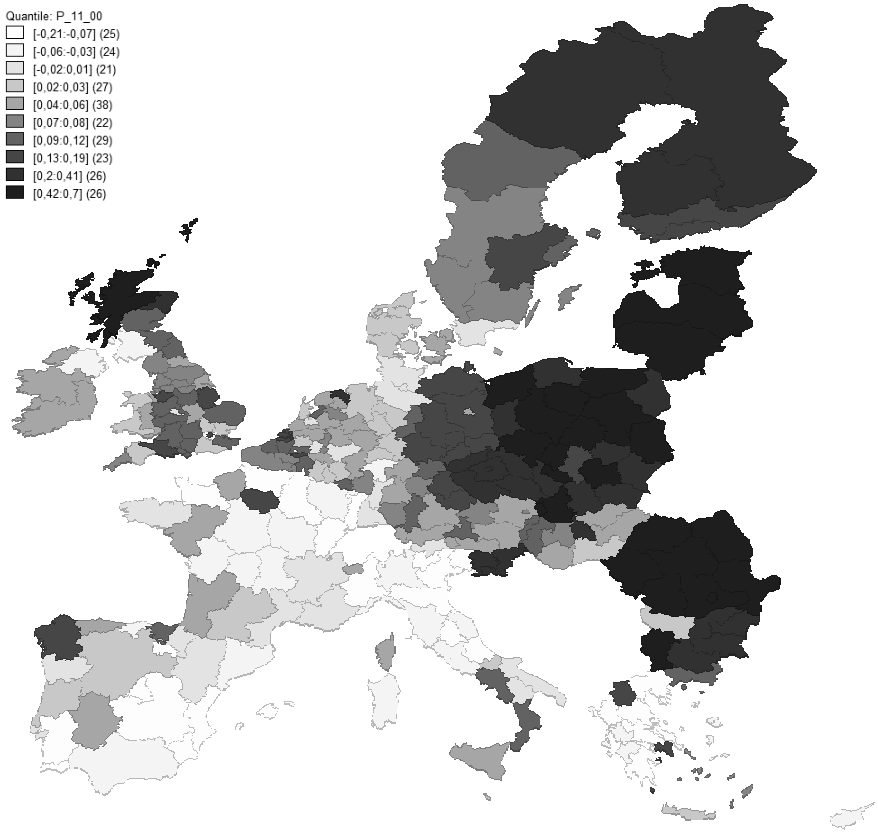
The regional productivity is explained by the quotient of regional GDP and the number of Economically Active Population (L). The productivity growth (p) for the years 2001-2011 is approximated by the exponential change of regional productivity in these years to regional productivity in the year 2000:

$$p = \ln\left[(GDP/L)_t^i / (GDP/L)_{2000}^i \right]. \tag{9}$$

The regional GDP is expressed in millions of Euro in constant prices (year 2000), where Economically Active Population is in thousands of people at the age of 15 or over. The map shown in Figure 1 visualizes the distribution of the productivity growth in the European regions in the year 2011 compared to 2000.

[2] http://epp.eurostat.ec.europa.eu/portal/page/portal/statistics/search_database

Figure 1. Exponential change of productivity growth in EU NUTS 2 (year 2011/2000)

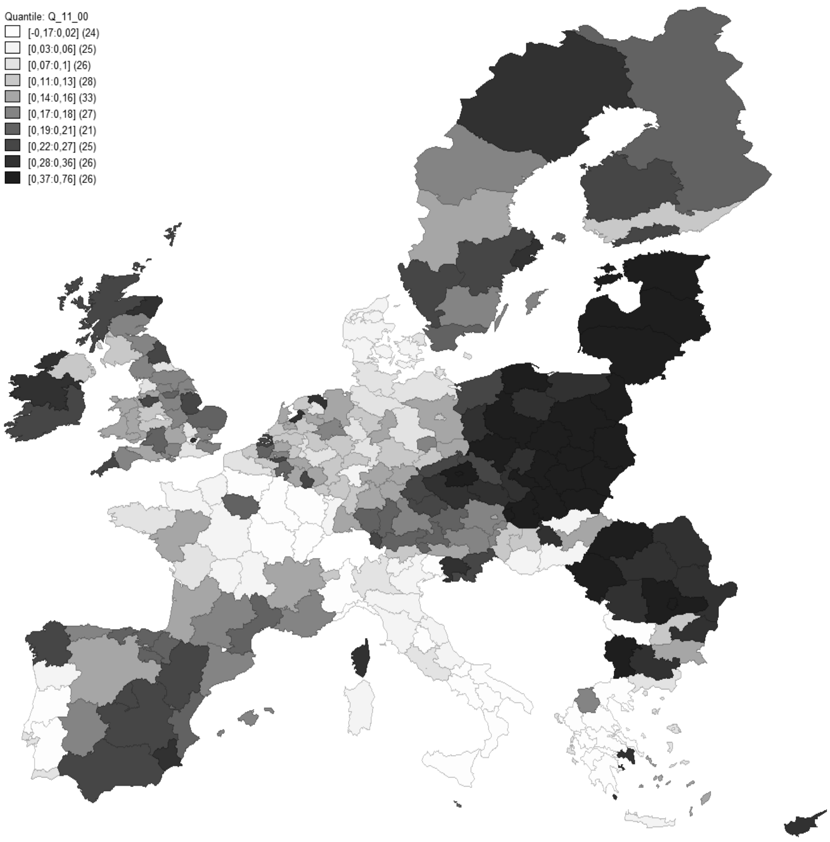


Source: author's own.

It can be seen in the figure that there is a clear tendency towards clustering regions with similar productivity growth (positive spatial autocorrelation).[3] The highest growth can be observed for regions of New European Union countries with the exception of some regions of Hungary and Bulgaria. Let us notice that Sud-Muntenia in Romania is the region with the highest productivity growth rate for years 2011/2000. Additionally within the old EU countries the highest productivity growth is observed for the Highlands and Islands region in UK. See Figures 2-4 for the visualization of the other variables.

[3] Regions in light colours are close to region in dark colours.

Figure 2. The exponential change of regional production in EU NUTS 2 (year 2011/2000)



Source: author's own.

The exponential change of regional production in years 2001-2011 to regional production in the year 2000 is approximated by:

$$q = \ln\left[(GDP_t^i / GDP_{2000}^i) \right]. \tag{10}$$

The Human capital (H) is defined by the Employment in Technology and Knowledge-intensive Sectors (T) as a percentage of Economically Active Population (L):

$$H = \ln\left[(\mathrm{T}/L)_t^i \right]. \tag{11}$$

The Initial Level of Technology (G_0) represents the technological gap between the i-th region and the technology leader of the whole economy of EU.

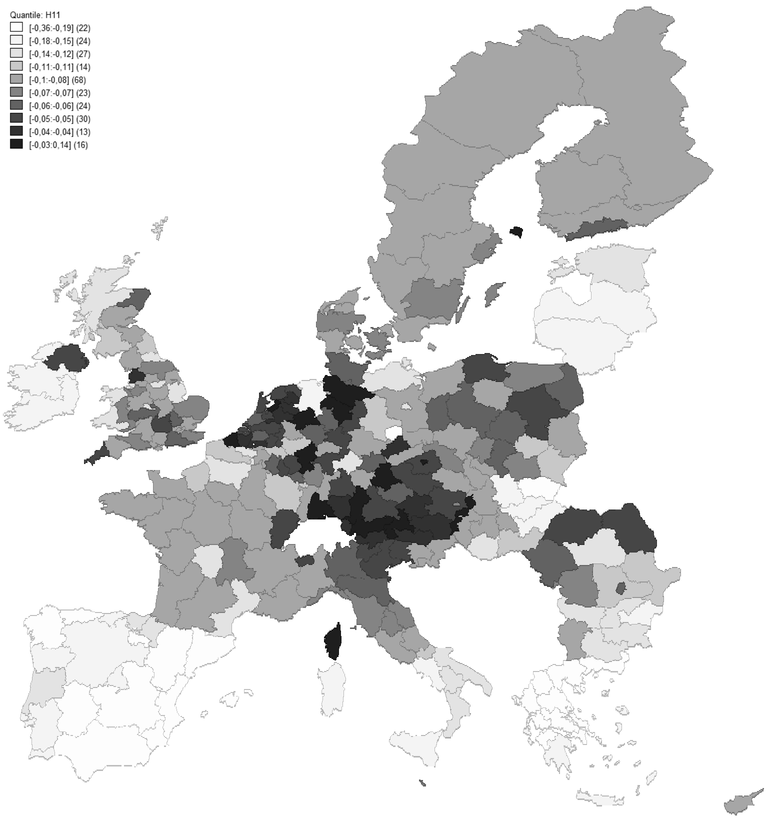
Therefore, the term G_0 is approximated by the economic distance from the technology leader at the beginning of the study which is year 2000:

$$G_0 = \ln[(GDP_{2000}^{\max} - GDP_{2000}^{i}) / GDP_{2000}^{\max}], \tag{12}$$

In this study the leading NUTS 2 region in terms of the highest *GDP per capita* level is Inner London.

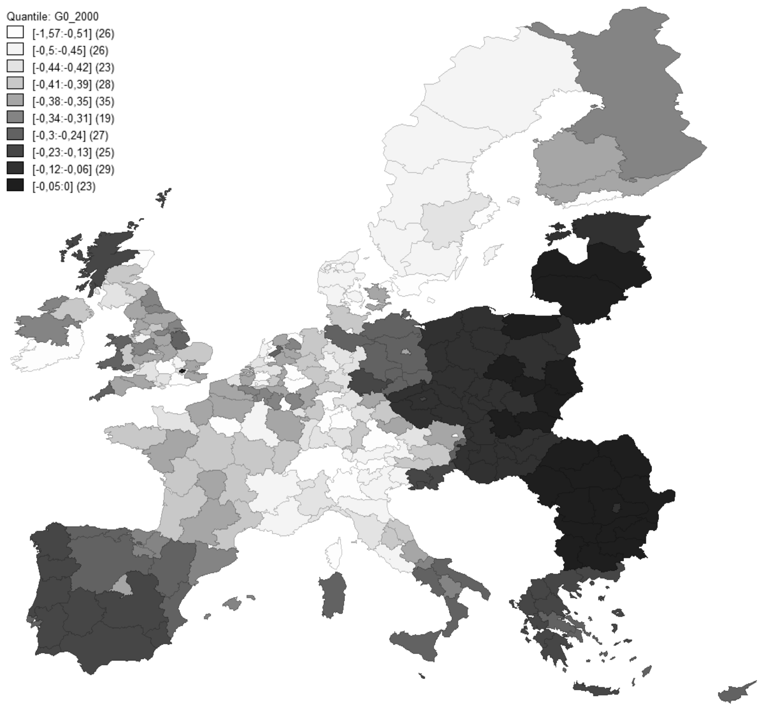
For the specification of the structure of the spatial effects we apply in turn: a row standardised spatial weights matrix **W** (261×261) of the three nearest neighbours (3nn), the contiguity and the inverse distance parameterized spatial weights matrix, described in Section 2.

Figure 3. Human Capital in EU NUTS 2 (year 2011)



Source: author’s own.

Figure 4. Initial Level of Technology in EU NUTS 2 (year 2000)



Source: author's own.

Table 1. Variables description

Variable	***Mean***	***σ***	***Min***	***Max***
p	0.0825	0.1328	-0.2297	0.7043
q	0.1242	0.1121	-0.1678	0.7580
G_0	-0.3067	0.1929	-1.7906	-0.0163
H	-0.0891	0.0646	-1.0039	0.4760

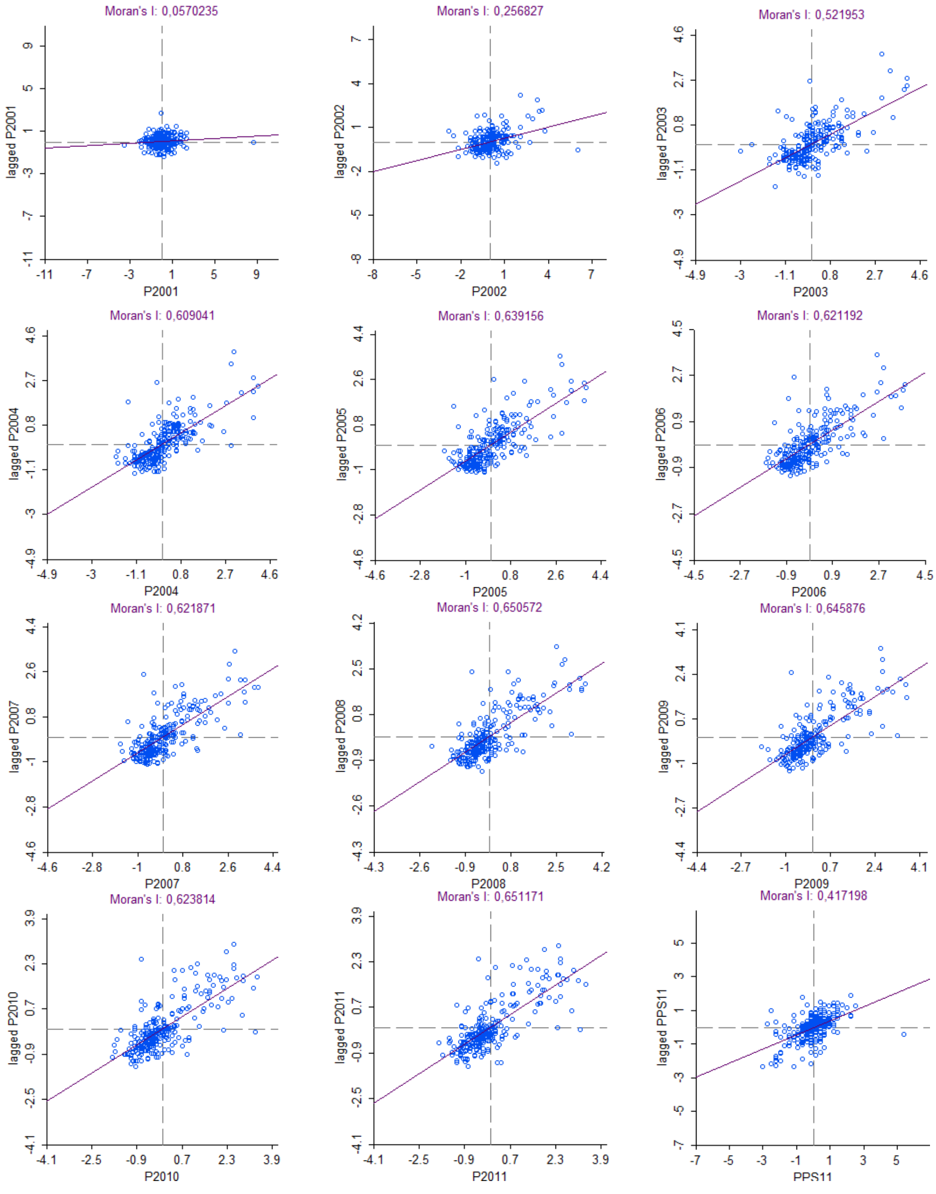
Source: Own calculations.

5. Empirical results and discussion

The starting point of the empirical part of the study was the analysis of spatial autocorrelation of the productivity growth. Figure 5 shows very strong spatial autocorrelation (Moran's I=0.6) over the time period of analysis. However, for 2001/2000 the spatial autocorrelation is weak yet significant at the 10% level.

The reported results are for 3nn spatial weights matrix, however, for contiguity spatial weights matrix the results were very similar. For comparison, spatial correlation for the year 2011 has also been added into the Figure 5.

Figure 5. Moran scatterplot for productivity growth for year 2001-2011(3nn matrix)



Source: Own calculations in GeoDa program.

The point of departure of our econometric analysis was the following spatial lag model:

$$\mathbf{p}=\alpha_0 + \rho_1\mathbf{Wp} + \alpha_1\mathbf{H} + \alpha_2\mathbf{G_0} + \alpha_3\mathbf{q} + \boldsymbol{\varepsilon}, \tag{13}$$

where **p** represents the productivity growth for 2011/2000, **H** – Human Capital in 2011, $\mathbf{G}_0$ – Technology Gap in 2000 and **q** – growth of production in 2011 to 2000. The empirical results of the estimation are presented in Table 2. It can be seen that all the variables are highly significant at 1% level. The spatially lagged variable is also significant which suggests existence of the spatial spillover effect on the productivity growth.

Table 2. SAR results

Variable	*Coefficients*	*Std.*	*T-stat*
α_0	0.03	0.02	1.53
Wp	0.39	0.04	9.54
H	0.33	0.08	3.10
$\mathbf{G}_0$	0.16	0.03	5.87
q	0.70	0.04	15.69
R^2	0.83		

Source: Own calculations in GeoDa program.

The next step of the analysis was the estimation of the spatial panel model with fixed effects:

$$\mathbf{p}=b_0 + \rho\mathbf{Wp} + b_1\mathbf{H} + b_2\mathbf{G_0} + b_3\mathbf{q} + \boldsymbol{\varepsilon}, \tag{14}$$

where **p** represents the productivity growth over the years 2000 to 2011, **H** – Human Capital and **q** – the growth of production for these years and $\mathbf{G}_0$ – Technology Gap in the year 2000.[4] The empirical results of the estimation of spatial panel model for three spatial weights matrices are presented in Table 3.

4 The model was estimated with the sar_panel_FE (spatial lag model estimates for spatial panels with spatial fixed effects and/or time period fixed effects) MATLAB procedure available at: http://www.regroningen.nl/elhorst/software.shtml.

Table 3. Panel SAR with fixed effects results

Coefficient	W - *(3nn) matrix*		W - *contiguity matrix*		(γ=0.091)	
Wp	0.30	***	0.38	***	0.82	***
q	0.63	***	0.66	***	0.82	***
H	0.08	***	0.07	***	0.16	***
$\mathbf{G}_0$	-0.55	***	-0.51	***	-0.60	***
spatial fixed effects	Yes		Yes		Yes	***
time fixed effects	No		No		Yes	***
$\mathbf{R^2}$	0.95		0.95		0.94	

Source: Own calculations.

Firstly, let us consider the estimation results for 3nn and contiguity spatial weights matrix reported in 2nd and 3rd column. All the variables are highly significant (at 1% level), thus have statistically significant impact on the productivity growth in EU NUTS 2 regions. Verdoorn's coefficient is close to 0.6 which is similar to that reported in the literature - 0.5. Therefore, we conclude that increasing returns to scale exist, where faster output growth induces faster productivity growth. In addition, employment in technology and science intensive sectors also stimulate faster productivity growth. Furthermore, we conclude from the model that the larger initial gap to the technology leader a region experiences, the lower productivity growth it is likely to achieve. In fact, this negative relationship between G_0 and the part of **p** unexplained by the remaining variables might imply existence of regional divergence. Spatial-specific time-invariant effects turned out to be significant for all the applied spatial weights matrices. In contrast, time period-specific spatial-invariant effects are not significant in any of those models.

Finally, the last step of the empirical work was the estimation of distance decay parameter in the inverse distance power spatial weights matrix. According to the procedure presented in Section 2 initially we estimated the SLX model:

$$\mathbf{p}=\alpha_0 + \alpha_1\mathbf{H} + \alpha_2\mathbf{G_0} + \alpha_3\mathbf{q} + \beta_1\mathbf{WH} + \beta_2\mathbf{W}\,\mathbf{G_0} + \beta_3\mathbf{Wq} + \boldsymbol{\varepsilon}, \quad (15)$$

using the NLS pooled estimation, where $\mathbf{W}=[1/d_{ij}^{\gamma}]_{i,j}$. From the above model we obtained γ parameter which turned out to be 0.091, which is unexpectedly small. This could suggest that the global spatial effect is present and as a result almost all NUTS 2 regions of EU interact with each other, which does not seem to be correct, especially in the context of the theoretical framework. Furthermore, incorporation of the spatial weights matrix based on the inverse distance (Table 3, column 4) in the main model (eq. 14) has not improved the estimation results in comparison to those based on 3nn and contiguity matrices.

6. Conclusions

This paper is fundamentally based on Fingleton's model which analyses the spatial process of productivity growth in regions of EU for the period 2000-2011 on the foundations of the theory of New Economic Geography. We have investigated the spatial productivity growth within the spatial setting provided by the spatial fixed effects panel model. Moreover, a new approach to defining the spatial structure, namely the parameterization of the spatial weights matrix has been presented and tested.

Concluding, the model presented provides evidence of the importance of increasing returns to scale for regional economic growth, which lead to divergence effects for EU regions. Similar implications can be observed in the case of regionally differentiated human capital. The significance of cross regional spillover implies that the impact of policy instruments on the productivity growth in one region may effect productivity growth in neighbouring regions.

The implemented method of parameterizing **W** did not improve the model, unlike in Vega and Elhorst (2013). This might be due to the fact that Vega and Elhorst in their work presented an example for 46 US states over the period 1963 to 1992. It appears that larger and more homogenous regions like the US states, observed for a longer period might give better results. Further work needs to be done as there is still a need to add more flexibility into the spatial weights matrix as the theory should determine the specification of **W**. In particular, there are other functional forms that can be specified not only with one but two or even three parameters.

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Streszczenie

BADANIE EMPIRYCZNE WZROSTU PRODUKTYWNOŚCI W UE 28 – PRZESTRZENNA ANALIZA PANELOWA

W pracy zaprezentowano przestrzenną analizę procesu wzrostu produktywności w Unii Europejskiej w oparciu o elementy teorii Nowej Ekonomii Geograficznej. Do analizy na poziomie regionów NUTS 2, zastosowano macierze wag przestrzennych w celu lepszego opisu interakcji przestrzennych pomiędzy regionami UE. Ponadto przedmiotem referatu jest próba zbadania pewnych nowych metod konstrukcji macierzy wag, w tym jej parametryzacji. W badaniu wykorzystano przestrzenny model panelowy z efektami stałymi. Zatem całość rozważań stanowi nowy element ekonometrii przestrzennej, a poprzez włączenie dodatkowej informacji na temat badanego zjawiska umożliwia wnikliwszą jego analizę.

Słowa kluczowe*: przestrzenny model panelowy, ekonometria przestrzenna, wzrost produktywności*