HETEROSCEDASTICITY IN THE ANALYSIS OF REGIONAL ECONOMIC CONVERGENCE

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Abstract

The hypothesis of homoscedasticity of errors is convenient for the simplification of the estimation procedures. Unfortunately, this assumption is rather restrictive in the case of the analysis of spatial distributed data. Spatial units, in fact, can be very different in size, and in other economic characteristics. This circumstance suggests the presence of heteroscedasticity in this typology of data set. In this paper we study the effects of heteroscedasticity in regional economic convergence. We use two different estimators of the coefficient of variance, and covariance matrix recently introduced in spatial econometrics literature that take into account the heteroscedasticity highlighted by the error terms. This methodology can be considered a suitable alternative to the identification of convergence clubs that represents a very popular approach for the analysis of structural economic differences between regions. The empirical analysis concerns the estimate of conditional economic convergence on EU NUTS 2 regions for the period 1981-2004.

Keywords: Spatial econometrics, β – convergence, heteroscedasticity.

1. Introduction

Spatial models are very supportive in statistics, economics, regional science and are used for the analysis of an extensive collection of empirical issues. Traditional spatial statistical techniques are focused on spatial interactions due, for example, to competition among cross sectional units, spillover effects, externalities, and regional policies. Basically, spatial models are defined by taking into account for dependence and structural heterogeneities; the ignoring of these hypotheses can lead to serious misspecification problems. To take into account this propensity for nearby locations to influence each other, a general class of well-known models has been introduced in the statistical literature (Anselin, 1988, Besag 1974, Cressie 1993).

Heteroscedasticity is a further feature of cross sectional data (e.g. White (1980)). The assumption of homoscedasticity of the errors is a useful hypothesis, and generally facilitates the estimation procedures. Unfortunately, this assumption is very restrictive in the case of the analysis of spatially distributed data (Kelejian and Prucha, 2010). The spatial units can often differ in size and other structural features, a fact, which suggests that the error terms can not homoscedastic. Consider, for instance, NUTS2 European Union regions that differ in size, GDP levels, population, climatic conditions, and many other important variables in economic analysis. Therefore, robust inference in presence of heteroscedasticity, and spatial dependence is an important problem in spatial data analysis that should be tackled.

The first discussion of spatial heteroscedasticity and autocorrelation consistent (hereafter, SHAC) estimation can be found in Conley (1999). He proposed a SHAC estimator based on the assumption that each observation is a realization of a random process, which is stationary and mixing, at a point in a two-dimensional Euclidean space. Conley and Molinari (2007) examined the performance of this estimator using Monte Carlo simulation.

In this paper our aim is to analyze the problems arising from the presence of heteroscedasticity of errors in the regional economic convergence. According to the Neoclassical growth model, the economic convergence concerns the empirical observation that per capita GDP of the poorest regions grow faster than that of the richest regions, in other words the poorer areas tend over time to catch-up those most economically wealthy (Barro and Sala-i-Martin, 1995). The structural differences between different economies represent a serious problem in the analysis of economic convergence; as a consequence many scholars have decided to work on the identification of convergence clubs (for example, see Postiglione et al, 2010). A convergence club is a group of economies whose initial conditions are quite similar and that converge to the same steady state (Galor 1996). The issue of convergence clubs can be seen as a form of spatial non-stationarity in the estimated parameters or as the existence of groups of regions that share a common growth path in terms of per capita GDP. In recent years the literature on convergence clubs has been very extensive: the contributions were full of originality in terms of the methodology used, and very informative from the empirical point of view; unfortunately, the identification of these clusters is sometimes questionable and arbitrary.

For this reason, in this paper we use a heteroscedastic approach that can be considered as an alternative to identification of convergence clubs. Inferential statistical analysis of regional economic convergence will be based on two estimators of the coefficients of variance and covariance matrix recently introduced in literature by Kelejian and Prucha (2007, 2010). The estimators take into account both the presence of heteroscedasticity of the disturbances and the autocorrelation, a common situation in economic and regional studies. The first estimator used for the analysis of regional economic convergence has been defined by Kelejian and Prucha (2007). They suggest a non-parametric estimator of the variance and covariance matrix in a spatial context (i.e. spatial HAC estimator) that is consistent for both autocorrelation and heteroscedasticity. The same authors introduced the second estimator a few years later (Kelejian and Prucha, 2010). The estimation process is based on a procedure of type GMM/IV (Generalized Method of Moments/Instrumental Variables). Empirical analysis on EU NUTS2 regions will be carried out using the R package sphet (Piras, 2010).

The layout of the paper is the following. Section 2 is devoted to briefly review the model of conditional economic convergence. In Section 3 we describe the spatial econometrics estimation that takes into account the possible heteroscedasticity of the errors. Section 4 presents an empirical study of the long-run conditional convergence of per worker GDP in EU regions (1981-2004). Finally, in Section 5 we draw some concluding remarks and we outline a future research agenda.

2. The economic model

The most popular approach in the quantitative measurement of economic convergence is based on the concept of β-convergence (Barro and Sala-i-Martin, 1995). The β-convergence approach has been considered the more appealing since it leads to a quantification of the speed of convergence in time. The β-convergence approach moves from the Neoclassical growth theory (Solow, 1956) assuming exogenous saving rates, and a production function characterized by decreasing productivity of capital and constant returns.

The starting point of our analysis is the augmented Neoclassical growth model assumed by Mankiw et al. (1992), hereafter MRW. In their paper the authors included accumulation of human capital as well as physical capital, to provide a more complete explanation of why some countries are rich and other poor. This model is used for the analysis of conditional β-convergence. Conditional convergence is estimated on the basis of a multivariate regression analysis, with initial per worker GDP as dependent variable, and a set of conditioning covariates that are supposed to determine the long-run income level as explanatory variables. Conditional convergence exists if the coefficient on initial per worker GDP is negative. Following MRW framework, in order to measure the conditional β-convergence it is possible to define for each economies i the following statistical model:

$$g_i = \alpha + \beta q_i + \pi_1 s_i + \pi_2 v_i + \pi_3 b_i + \varepsilon_i \quad (1)$$

where, for each region i=1,…,n, $g_i = \ln(y_{iT} / y_{i0}) / T)$ is the average growth rate of per worker GDP between time 0 and T, $q_i = \ln(y_{i0})$ is the natural logarithm of the initial level of per worker GDP, $\beta = -(1 - e^{-\lambda T}) / T$, λ[1] is the speed of convergence which measures how fast economies will converge towards the steady state, s_i is the natural logarithm of saving rate, $v_i = \ln(n_i + l_i + d_i)$ with n_i is the population growth rate, l_i is the level of technology growth rate, and d_i is the depreciation rate of capital, b_i is the natural logarithm of a measure of human capital (see section 4 for the definition of this indicator), and ε_i is the error term which is assumed to be normally distributed $(0, \sigma_\varepsilon^2 \mathbf{I})$. In this framework l_i and d_i are supposed to be constant across regions according to Mankiw et al. (1992), with l_i+d_i=0.05 for each region i=1,…,n.

In first applications of Barro and Sala-i-Martin framework, it is assumed that the error terms are independent; however, the sampling model of independence seems inadequate to the case here considered because regional observations are likely to display positive spatial dependence (Postiglione et al. 2010). Among others, Rey and Montouri (1999) highlighted the presence of spatial association for the distribution of per worker income in the United

[1] $\lambda = -\ln(T\beta + 1) / T$

States over the period 1929-1994. This spatial association is quite stable along the time. Lopez- Bazo et al., (2004) derived a neoclassical model with spatial externalities introducing spatial autocorrelation in convergence modeling. Ertur and Koch (2007) derived a spatially augmented Solow model that yielded a conditional convergence equation, which is characterized by parameter heterogeneity. They emphasized the important role played by spillover effects in international growth and convergence processes. Finally, Ramajo et al (2008) assessed the importance of spatial heterogeneity and dependence in the analysis of the β-convergence process among the European regions in testing about the effects of EU regional policies on the regional convergence process.

So bearing in minds these evidences, we decide to move a step ahead by including spatial effects in the convergence model. In fact we are aware that spatial externalities include technological interdependence among countries, therefore models of economic growth need to include spatial proximity (contiguity) effects, associated, for example, with localized knowledge spillovers and inter-firm demand-supply networks. So, a more appropriate statistical model that takes spatial autocorrelation into account is spatial lag model (Anselin and Bera, 1998) in which spatial dependence is accounted for by including an autoregressive term of the dependent variable. Model (1) can be re-formulated as:

$$g_i = \alpha + \beta q_i + \rho_1 \sum_{j=1}^{n} w_{ij} g_j + \pi_1 s_i + \pi_2 v_i + \pi_3 b_i + \varepsilon_i \qquad (2)$$

where ρ_1 is the scalar spatial autoregressive coefficient, w_{ij} is an element of the spatial weight matrix, i=1,.., n are the regions under study, and the other variables are the same as above. In this model the errors are again considered independent observations of the probability model in the hypothesis that all spatial dependence effects are captured by the lagged term. This formulation is a way of assessing the degree of spatial dependence, while controlling for the effect of the other variables (Anselin and Bera, 1998). Hence, the main interest is in the spatial effect. Alternatively, if the purpose is to assess the significance of the other (non-spatial) variables, after the spatial dependence is controlled for, we should implement a spatial filtering (Getis, 1990).

Model (2) has been estimated through some spatial econometrics methods, introduced in literature very recently by Kelejian and Prucha (2007, 2010) that control for potential heteroscedasticity in the growth equation. These methods will be discussed in the next section.

3. The spatial econometrics approach

Conditional economic convergence model described by Equation (2) is a spatial lag model (Anselin, 1988). In matrix notation, this model can be re-defined as:

$$\mathbf{g} = \mathbf{X}\boldsymbol{\beta} + \rho_1 \mathbf{W}\mathbf{g} + \boldsymbol{\varepsilon} \tag{3}$$

where $\mathbf{W}$ is the spatial weight matrix, $\mathbf{g}$ is the response variable vector, $\mathbf{X}$ is covariates matrix, $\boldsymbol{\beta}^t = (\alpha, \beta, \pi_1, \pi_2, \pi_3)$ is parameters vector, and $\boldsymbol{\varepsilon}$ is the error term vector, where the subscript *t* denotes vector transpose. More compactly model (3) is re-written as:

$$\mathbf{g} = \mathbf{Z}\boldsymbol{\delta} + \boldsymbol{\varepsilon} \tag{4}$$

with $\mathbf{Z} = (\mathbf{X}, \mathbf{Wg})$ and $\boldsymbol{\delta} = (\boldsymbol{\beta}^t, \rho_1)^t$. As it is evident the model (3) suffers for the problem of endogeneity because of the presence of the spatially lagged variable $\mathbf{Wg}$. Typically $\mathbf{Wg}$ will be correlated with the error term $\boldsymbol{\varepsilon}$, which give reasons for the use of an instrumental variable approach.

Endogeneity is a widespread problem in econometrics, and also in spatial econometrics (Fingleton and Le Gallo, 2010). The case of endogenous variables and a spatial error process has been considered by Kelejian and Prucha (2004) in the case of a simultaneous system of spatially interrelated cross sectional equations. This paper generalizes the results given by Kelejian and Prucha (1998) in a single equation framework. However it is known that the issue of consistent estimation of spatial lag models with additional endogenous variables can be faced through the two-stage least squares procedure (see Anselin and Lozano-Gracia 2008).

The spatial two-stage least squares (S2SLS) estimator is a simple extension of the classic two-stage least squares technique. In the spatial case the suitable instruments for the spatially lagged dependent variable are represented by:

$$\mathbf{H} = (\mathbf{X}, \mathbf{WX}, \ldots, \mathbf{W}^q\mathbf{X}) \tag{5}$$

where usually $q \leq 2$. The choice of appropriate instruments has been extensively discussed in the literature see, among others, Anselin (1988), Kelejian and Prucha (1998, 1999), Lee (2003). The S2SLS estimator for $\boldsymbol{\delta}$ is defined as:

$$\hat{\boldsymbol{\delta}}_{S2SLS} = (\hat{\mathbf{Z}}^t\mathbf{Z})^{-1}\hat{\mathbf{Z}}^t\mathbf{g} \tag{6}$$

with, $\mathbf{Z} = \mathbf{PZ} = (\mathbf{X}, \widehat{\mathbf{WG}})$, $\widehat{\mathbf{WG}} = \mathbf{PWg}$, and $\mathbf{P} = \mathbf{H}(\mathbf{H}'\mathbf{H})^{-1}\mathbf{H}'$. Statistical inference is based on the asymptotic variance covariance matrix:

$$Var(\hat{\boldsymbol{\delta}}_{S2SLS}) = \hat{\sigma}^2(\hat{\mathbf{Z}}'\mathbf{Z})^{-1} \tag{7}$$

where $\hat{\sigma}^2 = (\hat{\mathbf{e}}'\hat{\mathbf{e}})/n$ and $\hat{\mathbf{e}} = \mathbf{g} - \mathbf{Z}\hat{\boldsymbol{\delta}}_{S2SLS}$.

Since spatial units as EU NUTS 2 regions differ in important structural characteristics (size, economic mass, climate conditions), the assumption on error terms $\boldsymbol{\varepsilon}$, that are generally supposed homoscedastic, seems to be rather restrictive. So following this consideration, we base the statistical inference on two recently developed estimators of coefficients' variance and covariance matrix that are consistent to the presence of heteroscedasticity and have been introduced by Kelejian and Prucha (2007, 2010). The approach described here can be seen as a proper alternative to the identification of convergence clubs.

Kelejian and Prucha (2007) described a general spatial regression model that allows for endogenous regressors, their spatially lagged values, and other exogenous covariates. Besides they supposed the subsequent form for the disturbances:

$$\boldsymbol{\varepsilon} = \mathbf{R}\boldsymbol{\xi} \tag{8}$$

where $\boldsymbol{\xi}$ is a vector defined as innovations and $\mathbf{R}$ is a non – stochastic matrix whose elements are not known. Furthermore, $\mathbf{R}$ is non-singular and the row and column sums of $\mathbf{R}$ and $\mathbf{R}^{-1}$ are bounded uniformly in absolute value by some constant (for great details see Kelejian and Prucha, 1998, 1999 and 2004).

The asymptotic distribution of corresponding IV estimators requires the variance covariance matrix defined as:

$$\mathbf{\Psi} = n^{-1}\mathbf{H}^{t}\mathbf{\Sigma}\mathbf{H} \tag{9}$$

with $\mathbf{\Sigma} = \mathbf{R}^{t}\mathbf{R}$ is the variance covariance matrix of $\boldsymbol{\xi}$. The estimate of the elements (r,s) of $\mathbf{\Psi}$ is represented by (Kelejian and Prucha, 2007):

$$\hat{\psi}_{rs} = n^{-1}\sum_{i=1}^{n}\sum_{j=1}^{n} h_{ir}h_{js}\hat{\varepsilon}_i\hat{\varepsilon}_j K(d_{ij}^{*}/d) \tag{10}$$

where h is an element of instruments matrix $\mathbf{H}$, $\hat{\boldsymbol{\varepsilon}}$ is the vector of estimated residuals, $K(d_{ij}^{*}/d)$ is the kernel function defined in terms of d_{ij}^{*} that is the distance between observation i and j, and d is the bandwidth. Note that in the definition of estimator (10) the choice of kernel functions represents a crucial issue.

The kernel function is a real, continuous and symmetric function that is bounded and integrates to one, similar to a probability density function. The bandwidth is described so that if $d_{ij}^{*} \geq d$ the kernel is $K(d_{ij}^{*}/d) = 0$. The bandwidth, that can be assumed fixed or variable, and the kernel function restrict the number of sample covariances. In our application, we used a variable bandwidth based on the distance to the 10 nearest neighbors[2], and we assess the robustness of our results with four different specifications of kernel function: the triangular $K(z) = 1 - z$, the Epanechnikov $K(z) = 1 - z^2$, the bisquare kernel $K(z) = \left(1 - z^2\right)^2$,

[2] See the next Section for the motivation about ths choice.

the Parzen kernel $K(z)=1-6z^2+6|z|^3$ if $z \le 0.5$ and $K(z)=2(1-|z|^3)$ if $0.5 < z \le 1$, where $z = d_{ij}^* / d$. See Andrews (1991) for further details about the choice of the kernel function.

Based on the SHAC estimator, the asymptotic variance covariance matrix of the S2SLS estimates of the parameters vectors is:

$$\hat{\mathbf{\Phi}} = n^2(\hat{\mathbf{Z}}^t\hat{\mathbf{Z}})^{-1}\mathbf{Z}^t\mathbf{H}(\mathbf{H}^t\mathbf{H})^{-1}\hat{\mathbf{\Psi}}(\mathbf{H}^t\mathbf{H})^{-1}\mathbf{H}^t\mathbf{Z}(\hat{\mathbf{Z}}^t\hat{\mathbf{Z}})^{-1} \tag{11}$$

Therefore, small sample inferences concerning $\hat{\boldsymbol{\delta}}$ can be based on the approximation $\hat{\boldsymbol{\delta}} \propto N(\boldsymbol{\delta}, n^{-1}\hat{\mathbf{\Phi}})$.

Kelejian and Prucha (2010) specified a possible alternative to SHAC estimator by assuming the following first order autoregressive process for the disturb $\boldsymbol{\varepsilon}$:

$$\boldsymbol{\varepsilon} = \rho_2 \mathbf{W}\boldsymbol{\varepsilon} + \boldsymbol{\xi} \tag{12}$$

where the innovations ($\xi_1, \xi_2, \ldots, \xi_n$) are assumed to be independent with zero mean and non-constant variance. Kelejian and Prucha (2010) defined a GM estimator for ρ_2, and verified both consistency and asymptotic normality for this estimator. The estimation procedure consists of two steps. Each of the two steps includes sub-steps involving the estimation of the model parameters by GM and IV methods. In the first step, $\boldsymbol{\delta}$ is estimated by S2SLS by using the matrix of instruments **H** previously defined. An efficient GMM estimator for ρ_2 is derived. The consistent and efficient estimator for ρ_2 is used to transform the model through spatial Cochrane-Orcutt methodology. In the second step of the estimation procedure the transformed model is again estimated by 2SLS: this procedure is known in the literature as generalized spatial two-stage least square (GS2SLS). The GS2SLS estimator for the parameter vector $\boldsymbol{\delta}$ is defined as:

$$\hat{\boldsymbol{\delta}}_{GS2SLS} = \left[\hat{\mathbf{Z}}_*^t \mathbf{Z}_*\right]^{-1} \hat{\mathbf{Z}}_*^t \mathbf{g}_* \tag{13}$$

with $\mathbf{g}_* = \mathbf{g} - \hat{\rho}_2 \mathbf{W}\mathbf{g}$, $\mathbf{Z}_* = \mathbf{Z} - \hat{\rho}_2 \mathbf{W}\mathbf{Z}$, $\hat{\mathbf{Z}}_* = \mathbf{P}\mathbf{Z}_*$, $\mathbf{P} = \mathbf{H}(\mathbf{H}^t\mathbf{H})^{-1}\mathbf{H}^t$.

Finally, the efficient GMM estimator for ρ_2 based on GS2SLS residuals is obtained from:

$$\tilde{\rho}_2 = \underset{\rho_2}{\operatorname{argmin}} \left[m\left(\rho_2, \hat{\boldsymbol{\delta}}\right)^t \hat{\Gamma}^{-1} m\left(\rho_2, \hat{\boldsymbol{\delta}}\right) \right] \tag{14}$$

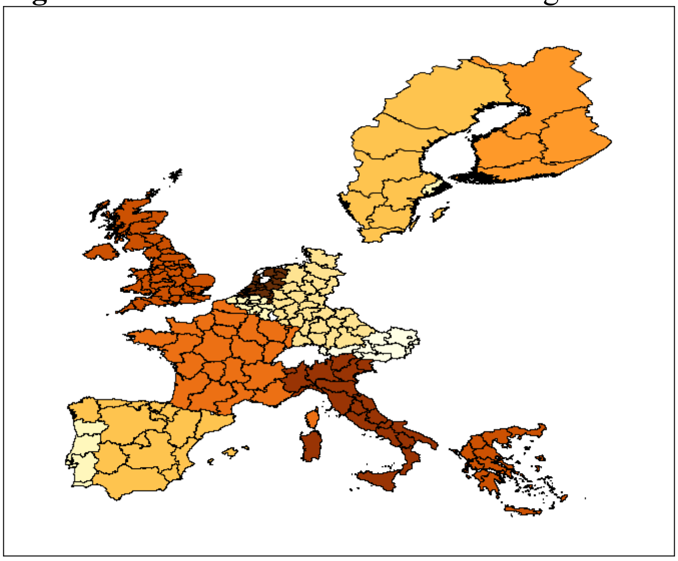
where $\hat{\Gamma}^{-1}$ is an estimator of the VC matrix of the limiting distribution of the sample moments.

Note that the goodness of fit of the spatial models described in this section will be based on a pseudo-R^2. It has been widely recognized that the R^2 calculated over the residuals of a spatial model should be interpreted with caution. See Piras et al (2011) and Anselin and Lozano-Gracia (2008) for a discussion about this topic.

4. The empirical exercise

The purpose of the empirical application is to estimate conditional economic convergence by using two spatial econometric methods recently developed that control for potential heteroscedasticity (Kelejian and Prucha 2007, 2010). In their recent paper, Rey and Le Gallo (2009) identify heteroscedasticity, and autocorrelation consistent estimators of the variance covariance matrix as one of the most interesting methodological developments in spatial econometrics growth studies. We perform analysis using cross-sectional data for the period 1981–2004 over a set of 187 EU NUTS-2 regions belonging to 12 countries of European Union (Austria, Belgium, Finland, France, Germany, Greece, Italy, Portugal, Spain, Sweden, the Netherlands, and the United Kingdom) at NUTS 2 level. Data derives from two different sources: the Eurostat REGIO database (for human capital variable), and the Cambridge Econometrics data set (for the other variables). There are several reasons why the NUTS 2 classification is the most appropriate for regional convergence studies[3] (see Canova 2004, Le Gallo and dall'Erba 2006, among others). In the following Figure 4.1 we give some details about the sample at NUTS 2 level used in the analysis.

Figure 4.1: Subdivision of EU states in regions at NUTS 2 level



We use a MRW framework, where the dependent variable is the natural logarithm of per worker GDP growth rate, and the conditioning variables are: the saving rate (s), the population growth (n), the level of technology growth rate (g), the depreciation rate of capital

[3] NUTS 2 level of European territorial subdivision has been recognized as the appropriate partition to model spatial effects. Furthermore, many EU policies are operationalized at regional level (i.e. for the determination of eligibility in the Objective 1 of EU).

(δ), and a measure of human capital (*school*). In particular, the saving rate (s) is measured in terms of average (over the period 1981 to 2004) of investment as a share of GDP and the human capital (*school*) is evaluated in terms of average (over the period 1998 to 2004) of population aged between 25-64 years by highest level attained ISCED level 3-4[4] as a share of total population aged between 25-64 years.

Table 4.1 reports empirical evidence for MRW model: the column displays OLS results for non-spatial specification (i.e. equation (1)). Standard errors are described in parentheses and significance levels are also highlighted. Finally, some statistical tests for the analysis of spatial dependence and heteroscedasticity are reported.

Table 4. 1 - Parameters estimation of non-spatial MRW model

Variable	
(Intercept)	0.04016***
	(0.00533)
Per-worker GDP	-0.00709***
	(0.00156)
Saving rate	-0.01304**
	(0.00590)
$v_i = \ln(n_i + l_i + d_i)$	-0.00189***
	(0.00064)
School	-0.00252
	(0.00440)
λ (convergence rate)	0.77718%
Moran's I	0.15110***
Breusch-Pagan	56.7475***
Studentized Breusch-Pagan	13.7594***
R^2	0.18309

Significance levels: *** 1%, ** 5%, * 10%.

[4] The International Standard Classification of Education (ISCED 1997) is the classification for organizing information on education and training maintained by the United Nations Educational, Scientific and Cultural Organization (UNESCO), and was implemented in European Union countries for collecting data starting with the 1997/98 school year. ISCED level 3-4 concerns (upper) secondary education and post-secondary non-tertiary education. Level 3 typically begins at the end of full-time compulsory education for those countries that have a system of compulsory education.

The result highlights economic convergence: the estimate of β is negative and highly significant. The implied speed of convergence (λ, see Section 2) is 0.77718%. This value is lower than that obtained by Sala-i-Martin (1996) that, analyzing separately European, North American and Japanese regions, observed that the speed of convergence are so surprisingly similar (about 2%) across different regions.

The other coefficients are mainly significant (only the coefficient of human capital is not significant), but the values show smaller magnitudes. The goodness of fit measured in terms of R^2 (equal to 0.18309) is not satisfactory, showing that the estimated model is inappropriate for our data set.

In order to evaluate the spatial dependence in the MRW regression model it is required to define a spatial weight matrix **W**. In this paper **W** is defined in terms of a row-standardized binary matrix, based on the k-nearest neighboring regions, where each single region has the same number (k) of neighbors. When we are dealing with European regions, the existence of islands does not allow defining weight matrix considering only simple binary contiguity; otherwise the islands were not connected to the continent. We choose k=10, in this way Greek regions are connected to South Italy, UK regions are linked with Ireland and continental Europe and so on (see also Le Gallo and Dall'erba, 2006).

The Moran's I test is highly significant: this evidence confirms the presence of spatial dependence. Finally, the Breusch - Pagan (BP) test reveals the presence of heteroscedasticity both in classical version, and in Koenker's studentized version. This result corroborates our idea that an approach that considers the heteroscedasticity seems to be more appropriate for the modelization of our data set. For this reason we move a step ahead to improve modeling by estimating a spatial augmented version of conditional economic convergence model through a heteroscedastic approach.

Table 4.2 presents the results for the spatial specification of MRW model. The first column highlights results of S2SLS estimation (column 1) with the different standard errors (in parentheses) obtained with the different kernel functions; while the second column contains evidence of GS2SLS-HET procedure (column 2). Significance levels of the coefficients are also emphasized.

Also in spatial augmented models the estimates of the coefficients is mainly significant (as for OLS, only the coefficient of human capital is not significant), and present the same sign of the non- spatial model.

Table 4.2 - Estimate from alternative models and standard errors for spatial MRW model

Variable		S2SLS (1)	GS2SLS-HET (2)
(Intercept)		0.02729***	0.00287***
	Classic	(0.00823)	
	HAC-GS2SLS		(0.00823)
	HAC-Ep	(0.00809)	
	HAC-Tr	(0.00804)	
	HAC-Bi	(0.00814)	
	HAC-Par	(0.00809)	
Per-worker GDP		-0.00538**	-0.00560**
	Classic	(0.00173)	
	HAC-GS2SLS		(0.00231)
	HAC-Ep	(0.00222)	
	HAC-Tr	(0.00222)	
	HAC-Bi	(0.00223)	
	HAC-Par	(0.00222)	
Saving rate		-0.00781*	-0.00832*
	Classic	(0.00624)	
	HAC-GS2SLS		(0.00574)
	HAC-Ep	(0.00456)	
	HAC-Tr	(0.00453)	
	HAC-Bi	(0.00456)	
	HAC-Par	(0.00455)	
$v_i = \ln(n_i + l_i + d_i)$		-0.00133*	-0.00132**
	Classic	(0.00067)	
	HAC-GS2SLS		(0.00067)
	HAC-Ep	(0.00074)	
	HAC-Tr	(0.00072)	
	HAC-Bi	(0.00074)	
	HAC-Par	(0.00071)	

Table 4.2 –continued

School		-0.00191	-0.00231
	Classic	(0.00423)	
	HAC-GS2SLS		(0.00574)
	HAC-Ep	(0.00541)	
	HAC-Tr	(0.00546)	
	HAC-Bi	(0.00551)	
	HAC-Par	(0.00553)	
ρ_1		0.44778**	0.05084
	Classic	(0.22451)	
	HAC-GS2SLS		(0.28398)
	HAC-Ep	(0.20769)	
	HAC-Tr	(0.21098)	
	HAC-Bi	(0.21493)	
	HAC-Par	(0.21866)	
ρ_2			0.42091**
	Classic		
	HAC-GS2SLS		(0.21842)
	HAC-Ep		
	HAC-Tr		
	HAC-Bi		
λ (convergence rate)		0.57605	0.60138
R^2		0.25159	0.24961

Significance levels: *** 1%, ** 5%, * 10%.

The magnitude of the coefficients in the spatial models is lower compared to that of the non-spatial model (see Table 4.1 and Table 4.2). In particular the results show conditional convergence (i.e. β negative and significant), but the speed of convergence is minor in the two spatial models (λ equal, respectively, to 0.57605 % and 0.60138 %).

The significance of the spatial autocorrelation coefficient (ρ_2) confirms the idea that spatial units differ in important characteristics, and this justifies the use of HAC estimators. On the other side, the coefficient (ρ_1) is significant only in the first specification of the model (see column (1) of Table 4.3); in the second case the spatial effects are entirely captured by coefficient ρ_2.

Accounting for heteroscedasticity has an important effect on the precision of the estimates for economic convergence model. Standard errors are higher for the HAC and GS2SLS-HET than for the OLS, which is consistent with previous evidence (Anselin and Lozano-Gracia 2008, Piras et al. 2011). The standard errors are essentially the same across the different choices of kernel function, which provides some evidence of the robustness of our findings.

The fit of the model improves when moving from OLS to the spatial augmented specifications of MRW model. However, the general fit of spatial models is not satisfactory good with an R^2 ranging from 0.24961 to 0.25159. A possible explanation for this inadequate result could be find in the idea of some scholars (see, among others, Dall'erba et al 2008, Postiglione et al 2010) that, though the heteroscedasticity approach improves the results, economic convergence should be analyzed not considering the entire data set as one sample, but taking explicitly into account spatial heterogeneity highlighted by data (i.e. convergence clubs or spatial regimes).

5. Concluding remarks

In this paper we analyzed economic convergence patterns for a sample of 187 EU regions from 1981 to 2004. In particular, our aim was the analysis of the influence of heteroscedasticity on the EU regional growth process. To pursue this objective, we made use of recently developed spatial econometrics techniques (Kelejian and Prucha, 2007, 2010). Independently on the econometric specification, the β coefficients are always negative and significant, revealing that the hypothesis of conditional economic convergence is satisfied. The speed of convergence is lower for the spatial specifications than OLS. The standard errors are higher by using SHAC approach compared to OLS estimation. However, the precisions are robust across the different definition of kernel functions.

Accounting heteroscedasticity and spatial effects in the modelization, the fit is always improved. Unfortunately, the R^2 is not completely satisfactory.

Future research should be devoted to the analysis of economic convergence patterns of EU regions through methods that facilitate the simultaneous treatment of the features of dependence and heterogeneity together with heteroscedasticity, and to verify robustness of the methods to different choices of bandwidth in the kernel functions.

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