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Spatial and non spatial approaches to agricultural convergence in Europe

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Abstract

The paper starts from the critiques to the Barro-style methodology for convergence analysis with the aim of reviewing the econometric approaches for testing spatial effects in convergence process related to both cross sectional and panel data regressions, a framework that is applied to a sample of 80 regions of the EU-15 at NUTS-2 level over the time period from 1980 to 2007. The empirical analysis compares results from approaches and, at the same time, provides empirical evidence from techniques that are now widely recognised in the understanding of regional growth and the influence of space but never or rarely applied to the agricultural context. Results point out the complexity of the process of agricultural regional convergence in Europe that cannot be adequately captured by the non-spatial growth regression models that have dominated the research and policy debate in this field. Evidence for convergence and spatial dependence emerges especially when estimations refers to spatial panel models while the effects of spatial heterogeneity and the existence of convergence clubs come out from the geographically weighted regression approach. The paper represents a point of departure for further researches in this field whose most important directions are underlined.

Keywords: Convergence, Spatial approaches, Non spatial approaches

JEL classification: C21, C33, Q19.

1. INTRODUCTION

In the European Union, real convergence has a political and financial importance and, in this context, a renewed interest is deserved to agriculture for its possible contribution to the acceleration of growth and income (see, for example, Artis, Nixson, 2001) and for the recent emphasis on the role of the Common Agricultural Policy and of the Rural Development Policy in the process of reducing territorial disparities (European commission, 2010). However, only little attention is deserved by economic analysis to the agricultural issue and the number of studies that deal with the theoretical and empirical advancements are rather small. The prevailing contributions (see, for example, Sassi, 2008, 2006, Bernini Carri, Sassi 2003, Gutierrez, 2000) are referred to the one-sector economic growth model by Solow (1956) according to which, due to diminishing marginal returns of input factors in a production function with constant return to scale, economies converge towards a dynamic long-run steady state, a trend only driven by the rate of technological progress (Eckey, Türck, 2007; Paci, Pigliaru, 1997).

Since the beginning of the 1990s the empirical research on convergence has proceeded in a number of directions. One of them is the investigation of spatial effects whose interest is partly related to the development of new growth theory and new economic geography. According to this perspective, as underlined by Dell'erba and Le Gallo (2008), some forces, such as productivity (Lopez-Bazo et al., 1999), transportation infrastructures (Krugman and Venables, 1995, 1996) technology and knowledge spillovers (Martin and Ottaviano, 1999), factor mobility (Krugman 1991a, b; Puga, 1999), have a geographic component that can support different paths of regional growth and of coexistence of divergent and convergent groups of territorial units. Anselin (1988) provides an extensive review of the importance of taking into consideration the spatial issue and a wide body of the literature underlines the errors and misspecifications that can occur if spatial effects are not included in cross-section data analysis, among which there is testing regional per capita income convergence.

Two spatial effects are included in the empirical investigation of economic convergence, the spatial autocorrelation and the spatial heterogeneity.

The more appropriated approach for testing the former issue refers to the multivariate spatial data statistics among which spatial global regressions have been widely applied. These models introduce in the estimation equation an endogenous or exogenous spatial lag variable or assume that the spatial dependence works through omitted variables. First tested within cross-sectional models by Rey and Monturi (1999) in the US context and by Fingleton (1999) in the European one, they find application in the European agricultural context only in the analysis of Bivand and Brunstad (2003, 2005). This approach produces parameter estimates that represent an average type of behaviour (Fotheringam et al., 2006). However, according to the principles of the regional science not only explanatory variables might differ across space but also their marginal responses (Ali et al., 2007). The GWR techniques, developed more recently, address the issue estimating locally different parameters and find some applications in testing the European agricultural convergence process (see, for example, Sassi, 2009a, b).

A second line of research investigates regional convergence by panel data model. Due to omitted variables and heterogeneity in the steady state, the cross sectional regressions might generate bias (Islam, 2003) that can be corrected by this approach that more recently has been integrated with spatial leg and error variables. While some empirical studies apply panel approach to test agricultural convergence in Europe (see, for example, Esposti, 2010, Sassi, 2010a), there is no evidence of analysis based on spatial panels.

In the light of these observations, the paper aims at two central objectives. Fist, the Barro-style methodology for convergence analysis is presented and then extended to a spatial econometric framework for spatial effects investigation related to both cross sectional and panel data regressions.

Second, this framework is applied to a sample of 80 regions of the EU-15 at NUTS-2 level over the time period from 1980 to 2007 in order to investigate the convergence issue in the agricultural sector. Despite the analysis is not focused on the understanding of the impact of convergence policy, the time span has been split into two sub-periods in order to compare results in two programming periods of the Structural Funds.

The structure of the paper is as follows. In the following section, we present the cross-sectional models and how they can rearranged in order to introduce spatial dependence while in the third section we discuss the spatial panel dynamic models. In the fourth section, we apply the previous models to a sample of 80 European Union regions at NUTS-2 level during the full period 1980–2007 and two sub-periods 1980-1994 and 1995-2007. We find signs of convergence and spatial dependence especially when estimating spatial panel models and spatial heterogeneity with the geographically weighted regressions. Moreover, it emerges strong differences between the two sub-periods. Specifically the European regions show a higher rate of convergence during the second sub-period. Section five concludes underlining the interesting points of departure for further researches in this field.

2. CROSS-SECTIONAL MODELS AND SPATIAL DEPENDENCE

The absolute β-convergence approach finds its roots in the neoclassical model of long-run exogenous growth of Solow (1956) and Swan (1956). Assuming a set of spatial regions represented by closed economic systems with exogenous saving rates and production functions with a decreasing productivity and constant returns to scale, economies only differ by their initial conditions and tend towards the same steady state. For estimating this neoclassical hypothesis of unconditional β-convergence, the literature refers to a version of the model developed by Barro and Sala-i-Martin (1991, 1992) and Sala-i-Martin (1995) specified as follows:

$$g_{T,i} = \alpha + \left(1 - e^{-\gamma k}\right) \ln y_0 + \mu_i, \qquad \mu \approx N\left(0, \sigma^2\right) \qquad (1)$$

where the dependent variable, $g_{T,i} = \frac{1}{T} \ln\left(\frac{y_{T,i}}{y_{0,i}}\right)$, is the annual average growth rate of *y*, the per capita income, over the time period form *0*, the initial year, and *T*, the final year, of the *i* (*i=1, 2, …, n*) regions; the explanatory variable is the natural logarithm of y at time *0* while μ_i is the error term that is assumed normally distributed, independently of the $\ln y_0$ and with $\left[\mu_1, ..., \mu_n\right]$ independent observations of the probability model. γ is the coefficient of convergence expressing how fast regions converge towards the steady state and estimated through non-linear square. The empirical literature usually re-parametrises equation (1), setting $\beta = \left(1 - e^{-\gamma k}\right)$ and estimating the parameter of convergence, β, by Ordinary Last Square (OLS). If β is negative and statistically significant, the neoclassical hypothesis of convergence is verified: poor economic systems grow faster than rich ones and all converge to the same steady state, a process only driven by the rate of technological progress. From β the speed of convergence is estimated on the basis of the following equation:

$$\gamma = -\frac{\ln\left(1 + T\hat{\beta}\right)}{T}. \qquad (2)$$

The empirical literature also take into consideration the so called half life, that is the time necessary for the regions to fill half of the variation which separate them from their steady state. It is estimated as:

$$\tau = \frac{-\ln(2)}{\ln\left(1+\hat{\beta}\right)}. \qquad (3)$$

According to the neoclassical perspective to convergence, also shared by the neoclassical new growth theory, the role of technological diffusion in convergence refers to a perception of knowledge as entirely disembodied and understood as a pure public good. Knowledge spillover diffuses instantaneously across any regions that, imitating the more successful technology, catches-up immediately to the other economic systems. As a consequence, differentials of income and growth rate across economic systems cannot be explained in terms of different stocks of knowledge (Döring, Schnellenbach, 2006).

This view represents an important point of disagreement with the economic geography theory according to which knowledge is a regional public good with limited spatial range (Abreu et al., 2005). Under this assumption the regions might show different path of growth even in the opposite direction, with coexisting convergent and divergent groups of economies. Thus, geography matter for growth and convergence that might be affected by the spatial spillover effects and the agglomeration process. Since the extensive review of the importance of considering spatial effects by Anselin (1988) a growing literature has shown the relevance of the problem and the errors and misspecifications that can occur if the issue is ignored in cross-sectional data analysis involving geographic units.

The spatial effects that can be included in the analysis are the spatial autocorrelation and the spatial heterogeneity. According to Anselin (1988) spatial autocorrelation refers to the coincidence of attribute similarity and location similarity, that translated in the field of convergence analysis means that rich regions tend to be geographically clustered as well as poor regions, or, in other wards, that the value of variables sampled at nearby location are not independent from each other (Tobler, 1970). As underlined by Dell'erba and Le Gallo (2003) at least three reasons suggest the integration of spatial autocorrelation into the β-convergence model. The first is econometric and regards the assumption of independent and identical distributed residuals that if violated may bias parameter estimates and increase the type I error rates. The second has to do with the possibility to take into account variations in the dependent variable determined by latent or unobservable variables differentiating the steady state. Finally, the inclusion of spatial autocorrelation captures geographic spillover effects. The cross-sectional models that allow to investigate the role of this spatial component on the convergence process are the spatial lag models (SLM), also called spatial autoregressive models, that handle spatial dependence by introducing an endogenous spatial lag variable and the spatial error models (SEM) in which spatial dependence works through omitted variables. More precisely, the former frameworks verify whether spatial dependence is caused by the impact of spatial spillovers on growth in neighbouring regions while the latter estimate the effect of possible spatially auto-correlated explanatory variables. This effect is of specific importance when referred to the European agricultural sector growth where the common sectoral policy and legislation might have a similar impact on regions within the EU borders (Fingleton, 2003).

SLM and SEM assume spatial stationarity, that is spatial autocorrelation is constant across the regions. However, if the main cause of spatial autocorrelation is dispersal, or the regression model shows structural instability or group-wise heteroskedasticity, stationarity is likely to be violated: behaviours are not stable over space and there is the possibility of multiple, locally stable, steady state equilibria. Very few methods deal with this issue. One of them is represented by the geographically weighted regressions (GWR) that, incorporating the spatial location of data, address the issue of locally different parameters of convergence, under the hypothesis that not only explanatory variables might differ across space but also their marginal response describing spatially varying relationships (Fotheringham *et al.*, 2006).

2.1. Global and local spatial regressions

The spatial lag models introduce in equation (1) and endogenous spatial lag variable ($Wg_{T,i}$) assuming the following form:

$$g_{T,i} = \alpha + \beta y_{0,i} + \rho W g_{T,i} + \mu_i, \qquad \mu \approx N\left(0, \sigma^2 I\right) \quad (4)$$

where ρ is the spatial autoregressive parameter that indicates the extent of interaction between observations according to a spatial pattern exogenously introduced by means of the standardized weight matrix *W* (Le Gallo *et al.*, 2003). A positive and statistically significant ρ confirms the positive effect of spatial spill-over on regional convergence giving a measure of how the growth rate of per capita GDP in a region is affected by those of neighbouring regions. In this case, the estimated β informs on the nature of convergence once spatial effects are controlled for. Equation (2) is estimated by the Maximum Likelihood Method (ML) or Instrumental Variables Methods (IV). In fact, the OLS approach produces inconsistent estimators due to the presence of a stochastic regressor Wg_T, which is always correlated with μ_i; in other words, the presence of g_T as dependent and explanatory variable means that there is a correlation-between-errors-and-regressors problem and the resulting estimates will be biased and inconsistent.

In the spatial error models, spatial dependence works through omitted variables and this misspecification is handled by the error process: errors from different regions display spatial covariance. Assuming a first order spatial autoregressive process for the errors, the econometric model is specified as follows:

$$g_T = \alpha S + \beta y_0 + \varepsilon \quad \varepsilon = \lambda W \varepsilon + \mu \qquad \mu \approx N\left(0, \sigma^2 I\right) (5)$$

where λ is the scalar parameter expressing the intensity of spatial correlation between regression residuals.

The model is estimated by ML of Generalised Methods of Moments (GMM). The OLS method yields insufficient estimators and a possible misleading interference due to biased estimates of the parameter of variance. This correction captures the effect of the omitted variables, different from factor migration, trade and spillover, which might have a negative or positive effect on growth (Arabia *et al.*, 2005).

In the spatial lag and error model the *W* matrix specifies the structure and the intensity of the spatial effects between two regions (Anselin, Bera, 1998). The most frequently adopted scheme is the binary: for a set of *n* regions, *W* is a *n* by *n* matrix whose elements $w_{i,j}$ are set nonzero if *i* and *j* are neighbours and zero if not. This scheme can be designed according to several algorithms; the simplest one is the First order Neighbour Weights where *W* is based only on adjacency of spatial units (for a review of the algorithms see, for example, Cliff, A.D. and Ord, J.K.,1981 and Griffith, D.A., 1987) referred to the Queen's contiguity where neighbours are the regions that share borders and vertices (see Anselin and Bera (1998) for other contiguity weights). Further, the spatial weights are generally row-standardized, i.e. the row elements for each observation sum to 1 (for a discussion on stadardization see, for example, Manski, 1993; Lenders, 2002).

Finally, with the GWR approach global OLS regression coefficients are replaced by local parameters *i*, so that equation (1) is rewritten as:

$$g_T = \alpha_i\left(u_i, v_i\right) + \sum\nolimits_j \beta_j\left(u_i, v_i\right)\ln y_{ij,0} + \mu_i, \qquad (6)$$

where $\left(u_i, v_i\right)$ denotes the geographic coordinates of the ith region of the sample. $\beta_j\left(u_i, v_i\right)$ is a realization of the continuous function $\beta_j\left(u, v\right)$ at point *i*. In the GWR each data point is a regression point that is weighted by the distance from the regression point itself; a spatial kernel adapts to the data and a kernel bandwidth indicate the distance beyond which the neighbour regions no longer have influence on local estimates (Sassi, 2010b, 2009a). This latter can be global when constant over space or local if threshold varies spatially. The weight assigned to observations is an inverse function of the distance from the economic system *i* according to the spatial weighting scheme selected (for further details see Fotheringham *et al.*, 2006).

Algebraically, the GWR estimator is specified as follows:

$$\hat{\beta} = \left(X'W_iX\right)^{-1}X'W_iy, \qquad (7)$$

Where

$$\hat{\beta} = \begin{pmatrix} \hat{\beta}_{i0} & \hat{\beta}_{i1} & \ldots & \hat{\beta}_{ij} \end{pmatrix}$$

and the weight matrix is an *n* by *n* matrix in the form of:

$$W_i = \begin{bmatrix} w_{i1} & 0 & \dots & 0 \\ 0 & w_{i2} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & w_{in} \end{bmatrix}, \qquad (8)$$

where w_{ij} is the weight of the data at region *j* on the calibration of the model around regions *i*. A specific feature of the GWR is that these weights vary with *i*, contrary to the Weighted Least Squares where the weighting matrix is fixed. Using weighted regression it is also possible to overcome the problem of more unknown parameters than degree of freedom that characterises this approach.

The spatially weighting scheme generally selected in convergence analysis (see, for example, Sassi, 2009a; 2009b, 2010b) is an adaptive bi-square function defined as:

$$w_{ij} = \begin{cases} \left[1-\left(d_{ij}/h\right)^2\right]^2 & if \quad d_{ij} \prec h \\ 0 & otherwise \end{cases} \qquad (9)$$

where h represents the different bandwidths and d_{ij} is the distance of the observation from the regression point. The number of regions to retain within the weighting Kernel window is irrespective of the geographic distance and is selected according to statistical tests referred to the alternative fixed-Gaussian or near-Gaussian schemes and minimising the Akaike Information Criterion (AIC) (for the choice of the spatial weighting functions see, Fotheringham *et al.*, 2006).

In addition to the standard performance measure of traditional regressions, GWR produces local parameter estimates and R^2 values for each region. The possibility of mapping the local parameters estimated provides a visual inspection of a likely spatial autocorrelation, that is, the coincidence of attribute similarity and location similarity (Anselin, 1988). By this way, the hypothesis of convergence clubs is also investigated. GWR defines clubs from the data contrary to the traditional types of analysis referred to a priori hypothesis of groups of regions whose initial conditions are near enough to converge towards the same long-term equilibrium (for a survey of the model that generates clubs of convergence see, for example, Gallor, 1996).

3. PANEL MODELS AND SPATIAL DEPENDENCE

Due to omitted variables and heterogeneity in the steady state, the cross sectional regressions in the form of equation (1) might generate bias (Islam, 2003) that can be corrected by the panel approach that allows for technological differences across regions modelling the specific regional effect (for the benefits of this approach see, for example Baltagi (2001) and Islam (2003)). The technology-gap approach and the empirical literature on convergence show that technological knowledge is not a public good, as in the neoclassical theory, but it is country related and a key determinant of growth rate differentials (Fagerberg, 1994).

As underlined in the previous sections, two different approaches to addressing the issue of spatial dependence have been proposed in literature specifically the spatial error models and spatial lag models (Anselin, 2001). The design of both specifications relies on the spatial weight matrix W_n based on the euclidean distances among regions and that describes the spatial arrangement of the cross-section units and the elements of W_n are row-normalized so that each row sums to one. Spatial panel approach assumes that W_n remains constant over time.

As is well known, the panel data may feature both time dependence (dependent variable autocorrelated over time) and spatial dependence (dependent variable autocorrelated in space). As suggested by Anselin et al. (2007), several specifications can be considered by introducing spatial, time-space and/or autoregressive terms. The starting point is the following general specification:

$$y_{i,t} = \alpha y_{i,t-1} + \rho \sum_{j \neq i} w_{ij} y_{i,t} + \phi \sum_{j \neq i} w_{ij} y_{i,t-1} + \left(\eta_i + v_{i,t}\right) \qquad (10)$$
$$|\alpha| < 1, \; |\beta| < 1, \; |\phi| < 1 \qquad i = 1, ..., N; \quad t = 1, ..., T$$

where $y_{i,t}$ is the observation of the dependent variable at time t for the cross-section i. The coefficient α captures the serial dependence of the dependent variable, the coefficient ρ represents the intensity of a contemporaneous spatial effect and ϕ captures space-time autoregressive and space-time dependence.

Following Anselin et al. (2007), specification (10) nests various special cases of spatial lag models on panel data discussed in the literature. If $\alpha = \rho = 0$, a so-called "pure-space recursive model" is obtained in which dependence results from the neighborhood locations in the previous time period (i.e. it only includes the lagged spatial lag $\sum_{j \neq i} w_{ij} y_{i,t-1}$); if $\rho = 0$ the model reduces to the "time-space recursive model" in which dependence is connected to the location $y_{i,t}$ and its neighbors in the previous time period $\sum_{j \neq i} w_{ij} y_{i,t-1}$; if $\phi = 0$, equation (10) takes the form of a "time-space simultaneous model" which includes the time lag $y_{i,t-1}$ and the spatial lag $\sum_{j \neq i} w_{ij} y_{i,t-1}$; finally, if $\alpha = \phi = 0$, the specification is that of a spatial model on panel data, while if $\rho = \phi = 0$ the model collapses to a "simple dynamic panel model".

Different estimation methods are developed to deal with dynamic panel issues or spatial dependence. For dynamic panel data without spatial interactions, Hsiao et al. (2002) develop a maximum likelihood estimator (MLE) with large number of regions (N) and large number of years (T). Another approach is to use a corrected least squares dummy variables model (CLSDV) (Kiviet, 1995; Hahn and Kuersteiner, 2002; Bun and Carree, 2005). Finally, dynamic panel data models are usually estimated using the GMM estimator of Arellano and Bond (1991) and Arellano and Bover (1995) and Blundell and Bond's system approach (1998).

For static panel data, spatial interactions with fixed effects are usually estimated by MLE as suggested by Elhorst (2005) or by instrumental variables methods (Anselin, 2001). A relatively recent development in the literature on spatial dynamic panel data (SDPD) seems to cross these strategies. Elhorst (2005) suggests an unconditional maximum likelihood estimator for an SDPD model with either a spatial lag or a spatial error structure under a restrictive assumption of no additional explanatory variables. Lee and Yu (2010) and Yu et al. (2008) provide the asymptotic properties of a quasi-maximum likelihood for an SDPD model with exogenous explanatory variables. More recently, Korniotis (2010) has proposed a solution based on Hahn and Kuersteiner's CLSDV (2002) and instrumental methods (Anderson and Hsiao, 1982) extended to allow for the spatial effect. Moreover, these various estimators may be complementary, depending on which specification is considered. For instance, Korniotis (2010) focuses on the 'time-space recursive' model whereas Yu and Lee (2009) work on a 'time-space dynamic' specification (10).

GMM estimator presents several important advantages. First, it enables each special case of the general specification to be estimated with only a few modifications to moment restrictions. Moreover Kukenova and Monteiro (2009) demonstrated on Monte Carlo experiments that GMM extended to allow for spatial lags are, in several cases, more efficient than MLE and QMLE. In the following, the estimation issues of spatial dynamic panel using GMM methods are briefly illustrated.

3.1. GMM methods

The dynamic panel data specification has become increasingly common in many empirical studies, especially growth convergence empirical studies. As the inclusion of the time-lagged dependent variable in the equation might lead to biased and inconsistent estimates, instrumental variable estimators are required (Arellano, 2003). A commonly employed procedure to estimate the parameters in a dynamic panel data model with unobserved individual specific heterogeneity is to transform the model into first differences. Sequential moment conditions are then used where lagged levels of the variables are instruments for the endogenous differences and the parameters estimated by GMM (see Arellano and Bond, 1991). In the first stage the individual effects are eliminated by taking first differences (GMM-DIFF) or a forward orthogonal deviation (see, for example, Arellano and Bover, 1995).

The efficiency of the estimates relies on the 'proper' choice of instruments, so the analysis refers to a common test of over-identification restrictions: the Difference-in Hansen test checks the validity of a subset of instruments. As pointed out by Roodman (2009) a large number of instruments (due to increasing time periods) can overfit endogenous variables and lead to an incorrect inference, so that the Hansen test of instruments set must be carefully interpreted. These problems prove to be serious when T is too large for a given N. In empirical applications, the instrument number can be restricted by collapsing the instruments (combining the instruments in subsets) in order to avoid redundancy between different time periods.

4. EMPIRICAL ANALYSIS

The data adopted for the empirical analysis are taken from the EUROSTAT REGIO database available at http://epp.eurostat.ec.europa.eu and are based on the log-normal agricultural gross value added per labour working unit over the period 1980 to 2007. The recent empirical literature analyses convergence focusing on the recent years, generally, starting from 1995. This is mainly due to lacking data for a large sample of observations. The dilemma between a wider time series and a larger sample is usually solved in favour of the latter.

However, convergence has a long-term nature and for this reason the analysis has tried to extend the number of years taken into consideration as much as possible. The historical series has been created up-dating the time series prepared in two previous research programmes. This procedure has required some adjustment. Among them, before 2000, the values of agricultural output in ECU have been replaced by that in EURO at the 2000 exchange rate provided by EUROSTAT and the time series has been made homogeneous rescaling with values referred to common years. The sample includes 80 regions of the EU-15 at NUTS-2 level.

Due to the specific impact of Structural Funds on convergence the empirical analysis has also been referred to two different sub-periods, 1980-1993 and 1994-2007, that represent the two different programming periods to which they are referred to. However, the analysis is not aimed at assessing any impact of the policy intervention.

4.1. Spatial autocorrelation

The second column of Table 1, illustrates the OLS estimation of the model defined in equation (1) for the time period from 1980 to 2007. The estimated β is statistically significant and negative, confirming the hypothesis of neoclassical convergence. Furthermore, the value of the parameter is 0.018, with a speed of convergence that, according to equation (2), is of 2.55% a year. This result confirms "the magic 2%" hypothesis of Quah (1997) that is the trend according to which not only the poorest economies will reach the richest, but also that it will happen within a few years[1].

[1] The literature shows that the uniformity of the rate of convergence night depend on the use of heterogenous units under the assumption that they are generated by an identical stocastic process rather than the operational of a convergence process (Canova, Marcet, 1995; Pesarant, Smith, 1995).

According to the Jarque-Brera test (1987), normality is not rejected (p-value 0.00005) and, for this reason, the testing procedure and the Maximum Likelihood estimation method adopted for the analysis of spatial effects are justified (Fingleton, 2003). The White test (1980) rejects homoskedasticity (p-value 0.005) and the Breush-Pagan test (1979) discards it versus y_0 at the 5 per cent significance level.

Table 1: Estimation results β-convergence model without and with spatial effects (1980-2007)

Model	β-convergence	Spatial error	Spatial lag
Estimation	OLS – White Equation (1)	ML Equation (3)	ML Equation (2)
$\hat{\alpha}$	0.0828 (0.0000)	0.0828 (0.0000)	0.0776 (0.0000)
$\hat{\beta}$	-0.0182 (0.0000)	-0.0181 (0.0000)	-0.0175 (0.0000)
$\hat{\lambda}$		0.3246 (0.0173)	
$\hat{\rho}$			0.1047 (0.2665)
Speed of convergence	2.55	2.54	2.41
Half-life	37.62	37.82	39.16
R^2	0.4213	0.4443	0.4298
LIK	230.144	231.395961	230.694
AIC	-456.288	-458.792	-455.389
BIC	-451.524	-454.027	-448.243
$\hat{\sigma}^2$	0.0002	0.0002	0.0002
JB	19.777 (0.0001)		
BP or BP-S	3.8271 (0.0504)	1.5212 (0.2174)	1.9733 (0.1600)
KB vs y_0	1.749 (0.1858)		
White	10.783 (0.0045)		
MORAN-I	1.783 (0.0745)		
LMerr	2.198 (0.1381)		1.101 (0.2940)
R-LMerr	1.062 (0.3025)		
LMlag	1.194 (0.2744)	2.503 (0.1135)	
R-LMlag	0.058 (0.8090)		

(…) p-values; OLS-White = use of the heterosedaticity consistent covariance matrix estimator of White in the OLS estimation; ML = Maximum Likelihood estimation; LIK = maximum likelihood function; AIC = Akaike information criterion; BIC = Schwars information criterion; JB = Jarque-Brera estimated residuals Normality test; BP = test for heteroskedasiticy, BP-S = spatially adjusted version of BP; KB = Koender-Basset test for heteroskedasticity; MORAN-I = Monan's I test adapted to estimated residuals; LMerr = Lagrange multiplier test for residual spatial autocorrelation; R-LMerr = robust version of LMerr; LMlag = Lagrange multiplier test for spatially lagged endogenous variable; R-LMlag = robust version of LMlag.

In order to investigate spatial autocorrelation, the approach suggested by Anselin *et al.* (1996) has been followed. Five tests are accounted for. First, the spatial error dependence has been tested applying the Moran's I to the residuals of the OLS estimation of the β-convergence model[2] (Cliff, Ord, 1973,1981). The test is very powerful against all forms of spatial dependence but it is not able to discriminate between spatial error dependence and omitted spatially lagged dependent variables (Anselin, Rey, 1991). This information is of specific important for investigating spatial autocorrelation that, Following Anselin and Florax (1995), has been detected through the Lagrange Multiplier (LM) tests and their robust version (R-LM). More precisely, the following four tests have been adopted:

The Lagrange Multiplier test for spatially lagged endogenous variables (LMlag), that take the form of:

$$LMlag = \frac{\hat{\varepsilon}' Wg \frac{1}{\hat{\sigma}^2}}{\hat{J}},$$

with

$$\hat{J} = \frac{1}{\hat{\sigma}^2}\left[\left(WY\hat{\rho}\right)' M \left(WY\hat{\rho}\right) + tr\left(W'W + W^2\right)\hat{\sigma}^2\right],$$

where $\left(WY\hat{\rho}\right)$ is a spatial lag for the predicted value $\left(Y\hat{\rho}\right)$, M is the projection matrix, tr is the sum of the main diagonal elements of the W matrix and $\hat{\sigma}^2$ is the maximum likelihood estimator for the error variance. The test is chi-square distributed with one degree of freedom under the null hypothesis of no spatial dependence $\left[H_0 : \rho = 0\right]$;

- The Lagrange Multiplier test for residual spatial autocorrelation (LMerr), specified as

$$LMerr = \frac{\left(\hat{\varepsilon}' W \hat{\varepsilon} \frac{1}{\hat{\sigma}^2}\right)}{tr\left(W'W + W^2\right)}$$

with notations as above; the test is chi-square distributed with one degree of freedom under the null hypothesis of no spatial dependence $\left[H_0 : \lambda = 0\right]$;

- The robust form of (a) and (b), i.e. R-LMlag and R-LMerr and given by:

$$R - LMlag = \frac{\left(\hat{\varepsilon}' Wg \frac{1}{\hat{\sigma}^2} - \hat{\varepsilon}' W \hat{\varepsilon} \frac{1}{\hat{\sigma}^2}\right)^2}{\hat{J} - tr\left(W'W + W^2\right)},$$

$$R - LMerr = \frac{\left[\hat{\varepsilon}' W \hat{\varepsilon} \frac{1}{\hat{\sigma}^2} - tr\left(W'W + W^2\right)\hat{J}^{-1}\hat{\varepsilon}' Wg \frac{1}{\hat{\sigma}^2}\right]^2}{tr\left(W'W + W^2\right)\left[1 - tr\left(W'W + W^2\right)\hat{J}\right]^{-1}}.$$

1. [2] The Moran's I test, in matrix notation, takes the form of:

2. $I = \frac{\hat{\varepsilon}' W \hat{\varepsilon}}{\hat{\varepsilon}' \hat{\varepsilon}}$ (a)

3. with $\hat{\varepsilon}$ the vector of the OLS estimation residuals.

Table 1, column 2, shows that all the five tests introduced to investigate spatial autocorrelation are not significant. As a consequence, the LIK, AIC and SC indicate that both the SEM, estimated according to equation (5), and the SLM, estimated on the basis of equation (4) and the W matrix based only on adjacency of spatial units and referred to the Queen's contiguity, do not achieve a significantly better likelihood than the OLS specification (Table 1, column 3 and 4). Only λ is significant (p-value 0.01735) and positive, but it does not affect the parameter of convergence and adds very little to the explanatory capacity of the OLS model.

Roughly speaking, a similar conclusion holds true over the two sub-period 1980-1993 and 1994-2007, as illustrated in Table 2 and 3.

Table 2: Estimation results β-convergence model without and with spatial effects (1980-1993)

Model	β -convergence	Spatial error	Spatial lag
Estimation	OLS – White Equation (1)	ML Equation (3)	ML Equation (2)
$\hat{\alpha}$	0.0911 (0.0000)	0.1018 (0.0000)	0.0868 (0.0000)
$\hat{\beta}$	-0.0186 (0.0000)	-0.0232 (0.0000)	-0.0184 (0.0000)
$\hat{\lambda}$		0.4015 (0.0017)	
$\hat{\rho}$			0.0980 (0.3515)
Speed of convergence	2.15	2.81	2.13
Half-life	36.9	29.51	37.24
R^2 or Sq. Corr.	0.2825	0.3095	0.288194
LIK	204.026	204.984	204.304
AIC	-404.052	-405.969	-402.608
BIC	-399.288	-401.205	-395.462
$\hat{\sigma}^2$	0.0003	0.0003	0.000353946
JB	5.637 (0.0596)		
BP or BP-S	2.733 (0.0982)	0.944 (0.3310)	2.380 (0.1228)
KB vs y_0	2.001 (0.1572)		
White	3.131 (0.2089)		
MORAN-I	1.294 (0.1956)		
LMerr	1.029 (0.3103)		0.556 (0.4556)
R-LMerr	0.558 (0.4547)		
LMlag	0.470 (0.4927)	1.917 (0.1661)	
R-LMlag	0.000005 (0.9982)		

(…) p-values; OLS-White = use of the heterosedaticity consistent covariance matrix estimator of White in the OLS estimation; ML = Maximum Likelihood estimation; LIK = maximum likelihood function; AIC = Akaike information criterion; BIC = Schwars information criterion; JB = Jarque-Brera estimated residuals Normality test; BP = test for heteroskedasiticy, BP-S = spatially adjusted version of BP; KB = Koender-Basset test for heteroskedasticity; MORAN-I = Monan's I test adapted to estimated residuals; LMerr = Lagrange multiplier test for residual spatial autocorrelation; R-LMerr = robust version of LMerr; LMlag = Lagrange multiplier test for spatially lagged endogenous variable; R-LMlag = robust version of LMlag.

Table 3: Estimation results β-convergence model without and with spatial effects (1994-2007)

Model	β-convergence	Spatial error	Spatial lag
Estimation	OLS – White Equation (1)	ML Equation (3)	ML Equation (2)
$\hat{\alpha}$	0.1284 (0.0000)	0.1250 (0.0000)	0.1123 (0.0000)
$\hat{\beta}$	-0.0313 (0.0000)	-0.0298 (0.0000)	-0.0281 (0.0000)
$\hat{\lambda}$		0.4502 (0.0002)	
$\hat{\rho}$			0.2294682 (0.0578522)
Speed of convergence	4.12	3.86	3.57
Half-life	21.78	22.88	24.30
R^2 or Sq. Corr.	0.273	0.3113	0.291184
LIK	173.503	174.921	174.3
AIC	-343.007	-345.842	-342.599
BIC	-338.243	-341.077	-335.453
$\hat{\sigma}^2$	0.0007	0.0007	0.0007
JB	223.8117 (0.0000)		
BP or BP-S	33.871 (0.0000)	26.210 (0.0000)	33.092 (0.0000)
KB vs y_0	6.7852 (0.0091)		
White	13.482 (0.0011)		
MORAN-I	1.580 (0.1140)		
LMerr	1.647 (0.1992)		1.592 (0.2070)
R-LMerr	0.4770 (0.4897)		
LMlag	1.1718 (0.2790)	2.835 (0.0922)	
R-LMlag	0.001 (0.9713)		

(…) p-values; OLS-White = use of the heterosedaticity consistent covariance matrix estimator of White in the OLS estimation; ML = Maximum Likelihood estimation; LIK = maximum likelihood function; AIC = Akaike information criterion; BIC = Schwars information criterion; JB = Jarque-Brera estimated residuals Normality test; BP = test for heteroskedasiticy, BP-S = spatially adjusted version of BP; KB = Koender-Basset test for heteroskedasticity; MORAN-I = Monan's I test adapted to estimated residuals; LMerr = Lagrange multiplier test for residual spatial autocorrelation; R-LMerr = robust version of LMerr; LMlag = Lagrange multiplier test for spatially lagged endogenous variable; R-LMlag = robust version of LMlag.

However, the OLS estimation, referred to the time period from 1994-2007, shows a strong increase in the speed of convergence to around 5 per cent a year (equation (2) with $\hat{\beta}$=-0.0313) and the important new element in this period is the spatially adjusted BP test that in both the SEM and SLM estimates, based on equations 5 and 4 and on a W matrix referred only on adjacency of spatial units and to the Queen's contiguity, results strongly significant, indicating the presence of remaining heteroskedasticity. According to the GWR estimations, based on equation (6), this component is related to structural instability, an effect that, from 1980-1993, is not significant as illustrated in Table 4 and 5.

Table 4: GWR estimations (1980-1993 and 1994-2007)

	1980-1993		1994-2007	
Estimation	OLS Equation (1)	GWR Equation (4)	OLS Equation (1)	GWR Equation (4)
Residual sum of squares	0.0286	0.0278	0.0612	0.0489
Sigma	0.0191	0.0190	0.0280	0.0253
Akaike Information Criterion	-401.3348	-401.7012	-340.7041	-354.5726
Coefficient of Determination	0.2862	0.3067	0.2736	0.4195
Adjusted r-square	0.2677	0.2804	0.2547	0.3900

Table 5: GWR estimation: Monte Carlo test for spatial non stationarity (1980-1993 and 1994-2007)

	p-value	
	1980-1993	1994-2007
$\hat{\alpha}$	0.9000 ns	0.0000 ***
$\hat{\beta}$	0.9001 ns	0.0000 ***

*** = significant at .1% level; ** = significant at 1% level; * = significant at 5% level; ns = not significant

Table 4 indicates that, from 1994-2007, there is a serious difference (greater than 3) in the AIC (Hurvich et al., 1998) of the OLS and GWR estimation whose values suggest that the latter is the best model. All the other GWR measures are preferable to those of the OLS. Further, the Monte Carlo test for spatial non-stationarity, illustrated in Table 5, indicates that there is a significant spatial variation in the local parameter estimates for α and β, whose extent is provided by Table 6.

Table 6: 5-number summary of the local parameter estimates (1994-2007)

	Minimum	LQ	Median	UQ	Maximum
$\hat{\alpha}$	0.0157	0.1228	0.1454	0.1632	0.1921
$\hat{\beta}$	-0.0498	-0.0420	-0.0365	-0.0302	0.0018

LQ = lower quartile; UQ = upper quartile.

Following Fotheringham at al. (2006), a preliminary information on the degree of spatial non stationarity is given comparing the interquartile range of the local parameter estimates, where 50 per cent of the local parameters are concentrated, with the confidence interval around the global estimate of the equivalent parameters, where approximately 68 per cent of values in a normal distribution are within it. Table 7 provides this information showing that the former range is greater than the latter and, thus, suggesting that the relationships taken into consideration may be non stationary. This gap is greater with reference to the intercept of the estimation equation and contradict one of the most important component of the neoclassical approach to convergence, that is, the initial level of technology and its rate of growth identical for all countries.

Table 7: Range of $1 \pm SD$ of global means and of local estimates between the interquartile range (1994-2007)

	-1SD	+1SD	LQ	UQ	+1SD-(-1SD)	UQ-LQ
$\hat{\alpha}$	0.1102	0.1467	0.1229	0.1632	0.0365	0.0404
$\hat{\beta}$	-0.0371	-0.0255	-0.0420	-0.0302	0.0116	0.0118

SD = standard deviation; LQ = lower quartile; UQ = upper quartile.

The casewise statistics indicate that there are no unusual residuals, the Standardised Residuals is within ± 3, and that there are no influential observations, the Cook's Distance (Chatfield, 1995) never exceeds the value of 1.

Figure 1 provides a more accurate information on the spatial variability of agricultural local parameters of convergence mapping their values pointing out the existence of convergence clubs. The parameter of convergence varies across the regions of the sample between a club of strongly convergent regions, geographically located in Italy, and four regions characterised by a weak convergence or divergence. The local t-value suggests a strong relationship between dependent and independent variable in nearly all the regions of the sample (Figure 2).

Figure 1. Estimated local parameters of convergence

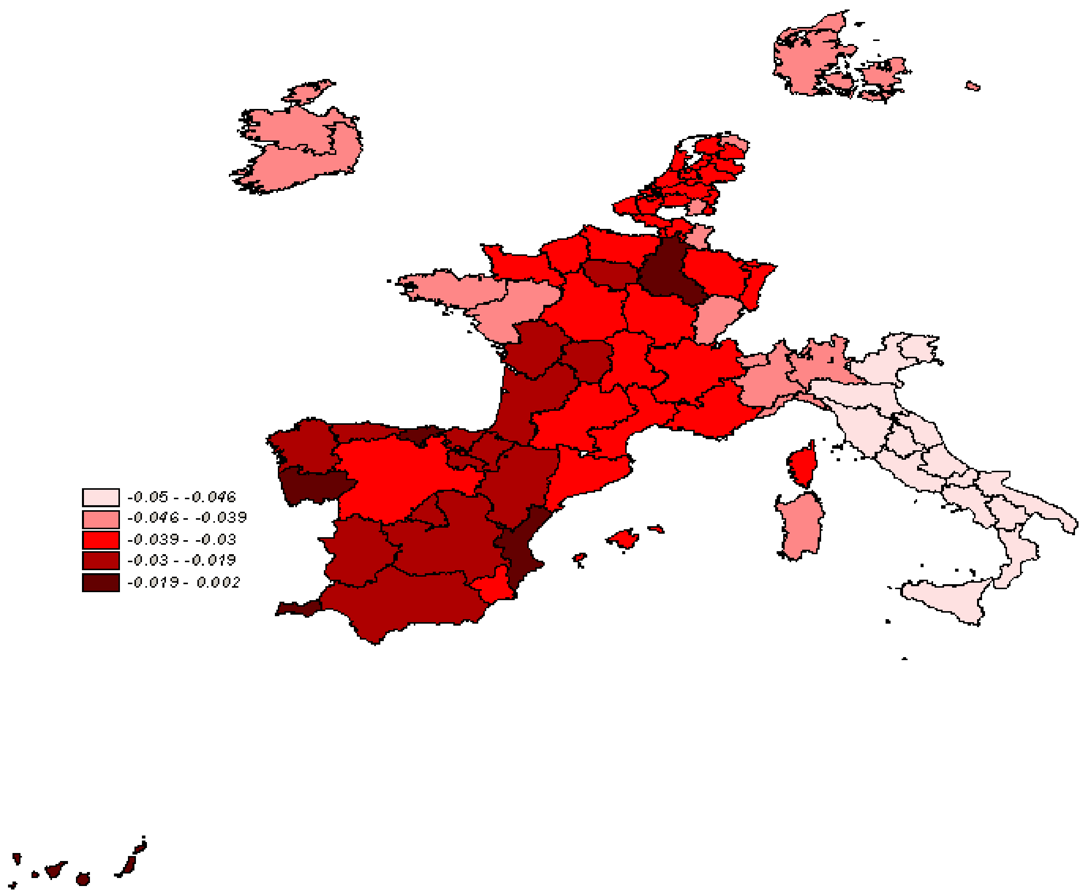
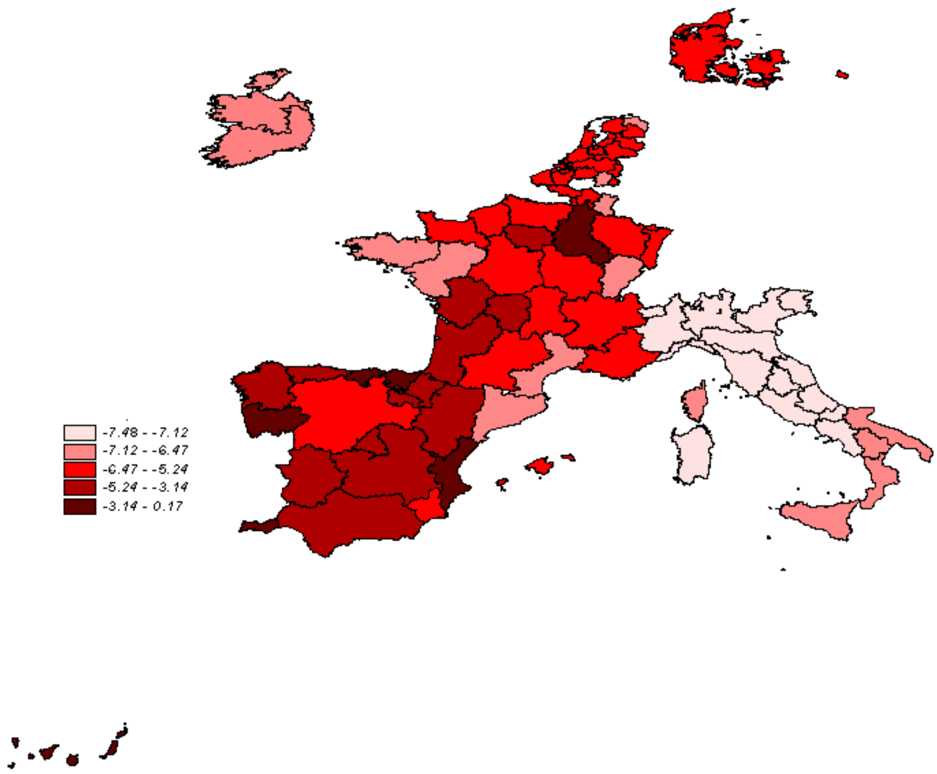


Figure 2. Estimated local t-value for local parameters of convergence



t-value	-7.48	-7.12	-6.47	-5.24	-3.14	0.17
p-value	0.00000	0.00000	0.00000	0.000001	0.001193	0.432725

Further, there is a high degree of coincidence between attribute similarity and location similarity particularly between national borders. This result suggests the effect on the convergence process of specific characteristics that seem to be connected to the national or sub-national level.

4.2. Panel econometric analysis

Tables 8-10 show the estimation results of equation (10) for the period 1980-2007.

The second columns of Table 8 illustrates the estimated values for the pooled ordinary least squares method. The estimated autoregressive parameter is positive and strongly significant. However, the implied convergence speed is very slow, 0.23%. Both the $\hat{\rho}$ "time-space" estimate and the $\hat{\phi}$ "time-space lag" are significant which means that space-effects exert a role in determining the speed of the convergence process. The third column of Table 8 shows the LSDV estimates. In this case, the autoregressive estimates is lower than that provided by the pooled regression and still significant. As a consequence, the speed of convergence is higher, 1.33%, than in the previous model. The spatial variables are significant.

As above mentioned, the pooled least squares estimator as well as the least square dummy variables estimator are biased and inconsistent when used to estimate dynamic panel models. The GMM method can help to overcame these problems.

Table 8: Estimation results for spatial dynamic model (1980 – 2007) (*)

Variables	Estimation methods		
	POLS	LSDV	GMM-Diff
$\hat{\alpha}$	0.940 (0.000)	0.702 (0.000)	0.730 (0.000)
$\hat{\rho}$	0.490 (0.000)	0.605(0.000)	0.933 (0.000)
$\hat{\phi}$	-0.482 (0.000)	-0.347(0.000)	-0.688 (0.00)
Speed of convergence	0.23	1.31	1.20
Half –life	11.2	1.9	2.20
Observations n.	2160	2160	2080
R^2	0.921	0.744	
AR(2)			1.310 (0.189)
Sargan test			101.9 (0.296)
Hansen test			78.41 (0.891)

(*) In parentheses the p-values of the test statistics. Instrument used in GMM: lag-2 and -3 for the spatial lag and the dependent variable.

Including the second and the third lags of both the spatial $\Sigma_{j \neq i} w_{ij} \, ln(y_{i,t})$ variable and of the dependent variable $ln(y_{i,t})$as instruments, the GMM estimated autoregressive parameter is closed to the LSDV estimate with an implied speed of convergence of 1.21% . Also in this case the spatial variables are strongly significant. It should be noticed that the test statistics reject the null hypothesis of autocorrelation of second order of residuals and both the Sargan and the Hansen tests confirm the overall validity of the instruments.

Table 8 also reports the half-life a unit shock statistic computed as $ln(0.5)/ln(\hat{\alpha})$. This parameter measures the number of years that it takes for deviations from the steady-state to subside permanently below 0.5 in response to a unit shock in the level of the series [3] .The half-life is about two years for the GMM estimate. This means that 50% of a unit shock is absorbed in two years. In order to examine a possible change of the estimates during the period of investigation, Table 9 and 10 provide results for the two sub-periods 1980-1993 and 1994-2007.

Focusing on GMM estimates, it first emerges that in the two sub-periods all the estimates remain significant and second, and more important, the implied speed of convergence changes dramatically.

The speed of convergence rises from the value of 2.53% during the first sub-period to the value of 10.1% in the second sub-period. Naturally, also the half-life parameter shows a

[3] Following the literature on convergence both the speed of convergence and the half-life parameters are based on $\hat{\alpha}$. However also $\hat{\rho}$ and $\hat{\phi}$ exert a role in determining the rate of convergence. Including these parameters will require the study of the impulse response function of the dynamic equation (10). This is left to further analysis.

reduction in the second period relatively to the first period. In conclusion, it seems that during the period 1994-2007 the agricultural labour productivity has shown a high rate of convergence toward the equilibrium than during the first period which covers the years 1980-1993. This result might depend not only on the action of policy interventions but also on the alternative specifications and estimators adopted (see, for example Bond et al., 2001; Esposti, Bussoletti, 2007) and introduces a future possible area of investigation.

Table 9: Estimation results for spatial dynamic model (1980 – 1993) (*)

Variables	Estimation methods		
	POLS	LSDV	GMM-Diff
$\hat{\alpha}$	0.952 (0.000)	0.598 (0.000)	0.737 (0.000)
$\hat{\rho}$	0.496 (0.000)	0.618(0.000)	0.927 (0.000)
$\hat{\phi}$	-0.493 (0.000)	-0.281(0.000)	-0.695 (0.00)
Speed of convergence	0.37	3.95	2.53
Half –life	14.1	1.3	2.3
Observations n.	1040	1040	960
R^2	0.936	0.655	
AR(2)			1.80 (0.072)
Sargan test			45.19 (0.229)
Hansen test			53.90 (0.057)

(*) In parentheses the p-values of the test statistics. Instrument used in GMM: lag -2 and -3 for the spatial lag and the dependent variable

Table 10: Estimation results for spatial dynamic model (1994 – 2007) (*)

Variables	Estimation methods		
	POLS	LSDV	GMM-Diff
$\hat{\alpha}$	0.898 (0.000)	0.482 (0.000)	0.299 (0.012)
$\hat{\rho}$	0.468 (0.000)	0.563(0.000)	0.980 (0.000)
$\hat{\phi}$	-0.456 (0.000)	-0.165(0.000)	-0.335 (0.035)
Speed of convergence	0.82	5.60	10.07
Half –life	6.4	0.9	0.5
Observations n.	1040	1040	960
R^2	0.849	0.433	
AR(2)			-1.40 (0.161)
Sargan test			25.8 (0.959)
Hansen test			34.67 (0.891)

(*) In parentheses the p-values of the test statistics. Instrument used in GMM: lag -2 and -3 for the spatial lag and the dependent variable.

5. CONCLUSIVE REMARKS

Two considerations are at the basis of this paper. On the one side, there is the renewed interest by the EU on the role of agriculture in the process of reduction of regional disparities, one of its key policy objectives, and, on the other side, there is the empirical literature on the issue that is mainly based on the neoclassical model of long-run exogenous growth of Solow-Swan-type and only rarely referred to the theoretical and empirical advancements. On this latter aspect, today the literature on economic convergence widely accepts the influence of space on regional growth (Capello, Nijlkamp, 2009). For this reason, lacking analysis on the role of spatial dependence and heterogeneity in convergence across the agricultural regions represents an important deficiency particularly from a policy-making point of view. Further, form an econometric perspective the paper confirms that the non spatial models applied to testing β-convergence suffer from errors and missspecifications due to omitted spatial effects.

From the analysis of the econometric techniques available for investigating the role of spatial autocorrelation and heterogeneity, the paper has pointed out some interesting limitations that might represent points of departure for further research in this field. Among them, there is the specification of the weight matrix. In particular, little formal guidance is available in the choice of the more appropriated spatial weights for SLM and SEM in both a cross-country and panel data environment (Anselin, 2002). Florax and de Graaff (2004) provide an overview on how the neighbouring structure of regions selected might affect results strongly, an aspect that finds confirmation in the empirical analysis developed considering 80 agricultural regions of the EU-15 at NUTS-2 level from 1980 to 2007 and in the two sub-period introduce to take into account the the two programming periods to which Structural Funds payments are referred to: the adoption of the same W matrix in spatial cross-country and panel data approaches changes evidence dramatically influencing tests and the parameter estimates. For this reason, two different spatial schemes completely exogenously constructed have been adopted selecting among different options on the basis of their influence on tests. In a certain sense they represent the W matrices that allow for the best estimates. The fact that they have resulted different according to the approach adopted might be interpreted in the sense that the structure of spatial dependence and the type of spatial weights become more complex and able to be statistically significant in affecting the speed of convergence including in the analysis of agricultural catching-up both between and within regions' variations. However, this aspect deserves a more deep understanding particularly for the related policy implications; the speed of convergence estimated by adopting the panel spatial model is much lower than that obtained with the classical β-convergence cross-country approach confirming the positive effect of factor mobility, trade relationships and knowledge spill-over on the process.

Another problem related to the weighting schemes adopted for investigating spatial autocorrelation is that they remain the same for every region in the sample. This might be a more serious problem in panel data analysis where the matrix is assumed not to change also over time.

These issues are partly overcome with the GWR approach. The software available lets the data to determine the W-matrix selecting according to specific tests among fix or adaptive bandwidth, the number of regions to retain within the kernel and the type of spatial weights. Empirical evidence from this technique have pointed out the role of spatial heterogeneity in agricultural convergence, confirming the existence of convergence clubs that should be better investigated, particularly, in the light of the different explanations provided by the theoretical literature. For example, convergence clubs may arise when saving rate out of wage is larger than saving rate out of capital within the neoclassical perspective (Dalgaard, Hansen, 2004) or due to different initial values of human capital and knowledge for the endogenous growth theory (Lucas, 1988, Romer, 1986, Gallor 1996). Further, the importance of spatial heterogeneity in agricultural convergence process suggests a further possible extension of the econometric framework to include the issue in panel data approach.

Results achieved underline absolute convergence that is affected by effects of both spatial autocorrelation and spatial heterogeneity. This means that, contrary to what prescribed by the neoclassical theory of growth, all the agricultural regions have not converged to the same steady state but to different equilibriums with some of them characterised by equilibrium values below the average. For this latter group of territorial units it should be evaluated a policy intervention aimed at promoting growth.

The importance of space for agricultural growth increase over the sub-period form 1994 to 2007 introducing a future possible area of investigation in the light of the empirical literature economic convergence that, on the topic, suggest that this result might depend not only on the action of policy interventions but also on the alternative specifications and estimators adopted (see, for example, Bond et al., 2001; Esposti, Bussoletti, 2007) .

Another issue with an impact on results particularly in analysis that take into consideration spatial effects is the delimitation of territorial units. The NUTS-2 regions are administrative units of the European Commission and EUROSTAT neither internally homogeneous nor uniformly large and, most important, with no relationship to socio-economic factors. This latter aspect is even more accentuated testing agricultural convergence across EU regions due to the fact that "agricultural regions" have different borders than that of the NUTS-2 regions (for a preliminary analysis of the different agricultural systems in the EU see, for example, Montresor *et al.*, 2007).

In the light of these considerations, it emerges that the process of agricultural regional convergence in Europe is complex and that cannot be adequately captured by the non-spatial growth regression models that have dominated the research and policy debate in this field. Spatial interaction is an important component of regional agricultural growth and convergence and spatial spill-over effects matter for the evolution of regional agricultural disparities. This suggests the need for deserving more attention to spatial dimension not only in the econometric analysis but also in the policy debate where the interaction between spatial and temporal dimension of effects introduced by policy shocks is of specific importance in an area characterised by deepening economic integration.

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