ISTITUTO DI STUDI E ANALISI ECONOMICA

Convergence in per-capita GDP across European regions using panel data models extended to spatial autocorrelation effects

by

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ABSTRACT

This paper studies the convergence of per-capita GDP across European regions over a fairly long period. Most of the works in the field are based on either cross-sectional or fixed-effects estimates. We propose the estimation of convergence in per-capita GDP across European regions by making use of panel-data models extended to include spatial error autocorrelation (Anselin, 1988; Elhorst, 2003). This will allow us to extend the traditional beta-convergence model to include a rigorous treatment of the spatial correlation among the intercept terms. A spatial analysis of such intercept terms will also be performed in order to shed light on the concept of spatially conditional convergence.

Key Words: Regional Convergence, Regional spill-overs, Spatial Dependence Modelling, Spatial Panel Data Models.

JEL Classification: C21, C23, R11

NON-TECHNICAL SUMMARY

Neoclassical growth model is the natural starting point of the analysis of EU regional income disparities even if some of the assuptions that drives the neoclassical convergence process are particularly questionable for regional economics. However, there are solid empirical reasons why it make sense to fit models in which there is a significant convergence process.

The main aim of the present paper is to study the convergence process of per-capita GDP across a set of 125 European regions over a fairly long period. Most of the empirical works in this field are based on either cross-sectional or fixed-effects estimates. Both cross-sectional and fixed-effect models, however, are obtained by imposing strong a priori restrictions on the model parameters.

Many different approaches have been developed in the literature to solve these problems.

In particular, we propose the estimation of convergence in per-capita GDP across European regions by making use of panel-data models extended to include spatial error autocorrelation (Anselin, 1988; Elhorst, 2003). This will allow us to extend the traditional beta-convergence model to include a rigorous treatment of the spatial correlation among the intercept terms. A spatial analysis of such intercept terms will also be performed in order to shed light on the concept of spatially conditional convergence. In the paper we will also analyze the theoretical properties of the model and we will show some empirical results based on the per-capita GDP of the European countries at NUTS 2 level of spatial aggregation.

L’ANALISI DELLA CONVERGENZA NEL REDDITO PRO-CAPITE DELLE REGIONI EUROPEE UTILIZZANDO MODELLI PER DATI LONGITUDINALI ESTESI AGLI EFFETTI DI AUTOCORRELAZIONE SPAZIALE

SINTESI

Il punto di partenza naturale nello studio delle disparità nella distribuzione dei redditi a livello regionale è rappresentato dal modello neoclassico di crescita. Anche se l'applicazione a livello regionale delle ipotesi di base di tale modello è stata talvolta criticata, solide evidenze empiriche ne confermano l'efficacia.

Il presente lavoro ha come obiettivo l'analisi del processo di convergenza dei redditi pro-capite in un *panel* di 125 regioni Europee nel periodo compreso tra il 1980 e il 1995.

La maggior parte dei lavori empirici presenti in letteratura sono basati su modelli per dati *cross-section* o modelli per dati longitudinali. I risultati che si ottengono sono influenzati dalle forti restrizioni imposte sui parametri che descrivono il sentiero di crescita da tale modellistica. La letteratura econometria recente ha visto il fiorire di numerosi tentativi volti a superare questi limiti. Il presente lavoro si inserisce in tale filone di ricerca.

In particolare, nel presente lavoro il processo di convergenza tra regioni Europee è stimato attraverso un modello per dati *panel* esteso al trattamento formale dell'autocorrelazione spaziale (Anselin, 1988; Arbia, 1989).

Al fine di chiarire il concetto di convergenza "spazialmente" condizionata, vengono analizzate le proprietà spaziali dei termini costanti dell'equazione sia in termini analitici che grafici. Inoltre, le proprietà analitiche del modello impiegato vengono discusse nel dettaglio e vengono presentati i risultati di un'analisi empirica condotta sulle regioni Europee (NUTS2).

Parole chiave: Convergenza regionale, *Spill-overs* regionali, Dipendenza Spaziale, Modelli panel spaziali.

Classificazione JEL: C21, C23, R11

CONTENTS

1 INTRODUCTION[1]

This paper studies the convergence of per-capita GDP across European regions over a fairly long period. Many of the results obtained in the literature strongly depend on the set of regions considered, the sample period, and the estimation method used. Moreover, most of the works are based on either cross-sectional or fixed-effects estimates.

In general, studies based on fixed-effect models, produce much higher convergence rates than those obtained using cross-country regressions. Both cross-sectional and fixed-effect models, however, are obtained by imposing strong a priori restrictions on the model parameters. The first class of models imposes absolute regional homogeneity in the parameters of the process describing GDP growth. The second allow for heterogeneity, but this depends only on the intercept term as if all the differences in the GDP growth rates were determined by the starting point for each region.

An alternative approach has been proposed by Peracchi and Meliciani (2001) who postulated a panel-data model in which all parameters can differ across regions. In this way not only the model avoids the imposition of strong restrictions, but it also provides spatially distributed coefficient whose pattern can add significant insights. They find significant correlation of the growth rates across neighbouring regions and between regions belonging to the same country. Furthermore a series of papers (Arbia et al., 2002; Arbia et al., 2003; Baumont et al., 2002, amongst the others) have shown that the presence of spatial effects matters in the estimation of the beta-convergence process both in terms of different spatial regimes and in terms of significant spatial spill-overs. Spatial effects, but incorporated within a continuous time framework, were also discussed by Arbia and Paelinck (2003; 2004).

In this paper we propose the estimation of convergence in per-capita GDP across European regions by making use of panel-data models extended to include spatial error autocorrelation and spatially lagged dependent variable (Anselin, 1988; Elhorst, 2003). This will allow us to extend the traditional beta-convergence model to include a rigorous treatment of the spatial correlation among the intercept terms. A spatial analysis of such intercept terms will also be performed in order to shed light on the concept spatially conditional

1 The present paper was presented at the 44th European Congress of the European Regional Sciences Association (ERSA) Region and Fiscal Federalism, University of Porto, Porto, Portugal, 25-29 August 2004. We are grateful to J.P.Elhorst and J.P. LeSage for providing Matlab Routines. We also would like to thank an anonimous referee for his useful comments. The present paper was written while Gianfranco Piras was working as a research assistant at the ISAE.

convergence. In the paper we will analyze the theoretical properties of the model and we will show some empirical results based on the per-capita GDP of the European countries at level NUTS 2.

The remaining of the paper is organized as follows: Section 2 is devoted to a detailed discussion over the data set; in Section 3 a beta-convergence model is estimated, estimation results are presented and residuals diagnostic are discussed. In Section 4 a simple fixed effect model is estimated, while in Section 5 we introduce the correction needed to take into account the problem of spatial dependence in panel data model. A fixed effect panel data model extended to spatial error autocorrelation is also estimated. A concluding section follows where we report some indications for further research in the field.

2 PRELIMINARY DATA ANALYSIS

Although many progress has been made in recent time by the European Statistical Institute, spatial data availability is still one of the greatest problem in the European context. As a matter of fact, data availability is still very scarce and in many instances it is very difficult to avail of harmonized data-sets allowing consistent regional comparisons.

In the present work we use data on the (log) per-capita GDP expressed in PPS and drawn from the REGIO database. We include 125 regions belonging to 10 European Countries: Belgium, Denmark, France, Germany, Luxembourg, Italy, Netherlands, Portugal, and Spain. Our sample observations range from 1980 to 1995[2].

The REGIO data-base has to be considered the first and most famous data-set with spatially referred data. It is an harmonized regional statistical database (developed by Eurostat, the European Statistical Institute), covering the main aspects of economic and social life in the European Union. The database, created in 1975, is currently divided into ten statistical domains[3]. The regions are classified according to three levels of spatial aggregation, using the

2 Many works use the same data set in empirical studies: Quah, 1996; Baumont, Ertur and LeGallo, 2002; Arbia and Paelink, 2004, among others.

3 The ten domains of the REGIO database are the following: demography, economic accounts, unemployment, the labor force sample survey, energy statistics, transport, agriculture, living conditions, tourism, and statistics concerning research and development.

so-called Nomenclature of Territorial Units for Statistics (NUTS) typology[4]. In this paper we consider the second level of spatial aggregation.

When dealing with geographical phenomena, in many cases, a preliminary analysis of data is already very informative with respect to its dynamics. In our preliminary data analysis we show the quantile maps of the growth rate of per-capita GDP. In order to analysis the phenomenon graphically, we have divided the observations into six different ranges. The maps show the evidence of stability of geographical features over time. In fact, many regions belong to the same range over the entire period, and their growth path is relatively stable. Moreover, if we consider jointly the maps of the growth rate, and the maps of the GDP levels, there is a consistent evidence of spatial effects in that regions presenting a high growth rate, have also the lower initial GDP and, furthermore, in most cases have borders in common with regions with a high GDP. This evidence shows that having a neighbor with particularly high level of income, produce a positive spillover for the poor regions, their growth rate rising sensibly. In other term, the catch up effect discussed in Barro and Sala-i-Martin (1995) seem to be present in our data set. Convergence process to the own steady-state seems to be more rapid for the poor regions. Here below we show four maps (relative to years 1981, 1985, 1990, and 1995) as representative of the dynamics we have just described over the whole period 1981-1995.

In order to test for global spatial autocorrelation in per-capita GDP, we computed the Moran's *I* index over the entire period and its significance level. Both information are reported in Table 1[5]. In our elaboration we used a spatial weight matrix based on the inverse of the squared geographical distance (great circle distance between regional centroids), which is indeed strictly exogenous (for further details on the construction of a similar matrix see, among others, Baumont, Ertur, and LeGallo, 2002; Arbia, 2005). The results show that the *I*-Moran index is fairly stable across time. It takes negative values during the period ranging from 1984 to 1986, and in the period from 1981 to 1990. The values assumed during all the other years considered in our sample are positive and fall within the interval 0.17-0.47. Indeed, excluding the value in 1987, the interval may be considered much smaller, showing values that do not vary

4 The spatial aggregation levels are the following: NUTS1, representing the 78 European regions, NUTS2, corresponding to the 211 basic administrative units, and NUTS3, for 1,093 subdivisions of basic administrative units.

5 The I-Moran index is written in the following matrix form: $I_t(k) = \frac{n}{S_0}\frac{z_t^{'}Wz_t}{z_t^{'}z_t}$, where z_t is the vector of the *n* observations for year *t* in deviation from the mean and *W* is a spatial weight matrix (Cliff and Ord, 1981; Arbia, 2005).

Fig. 1 Quantile map of the growth of per-capita GDP in 1981

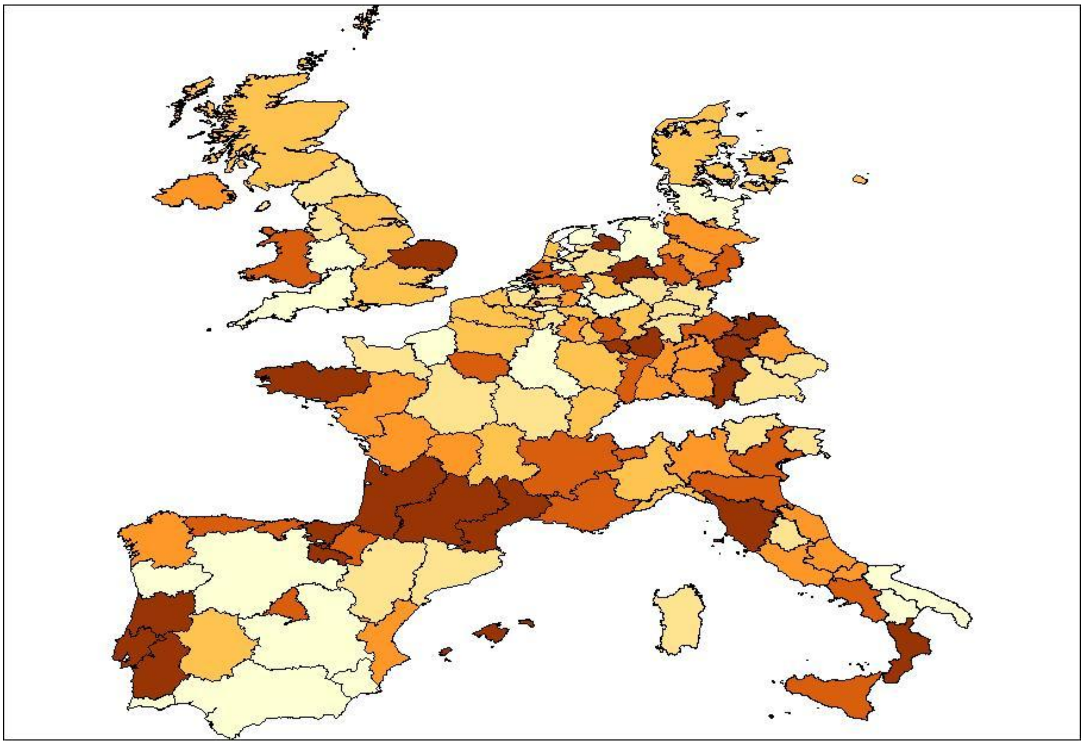


Fig. 2 Quantile map of the growth of per-capita GDP in 1985

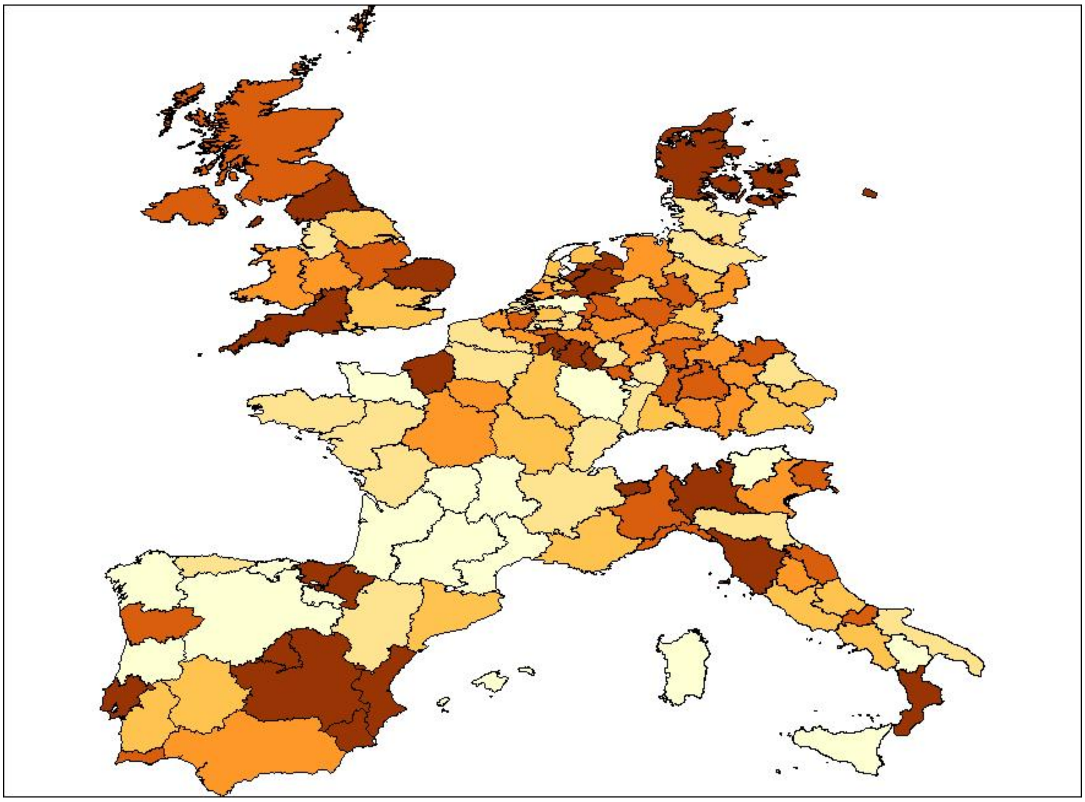


Fig. 3 Quantile map of the growth of per-capita GDP in 1990

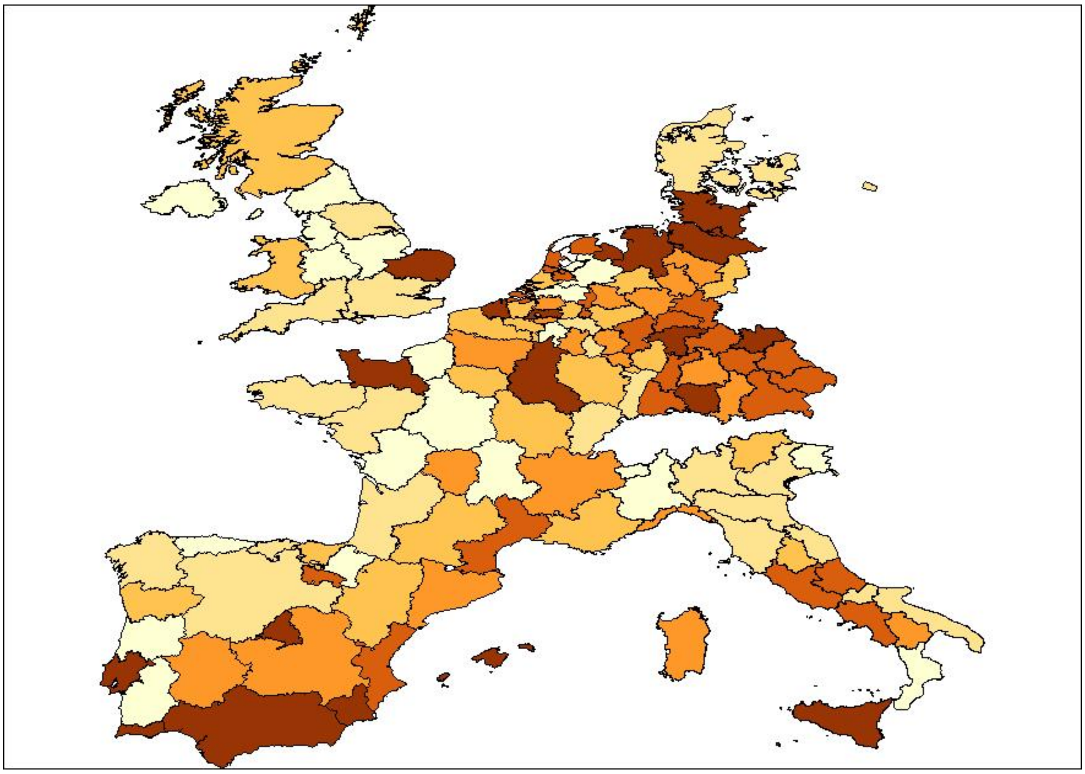
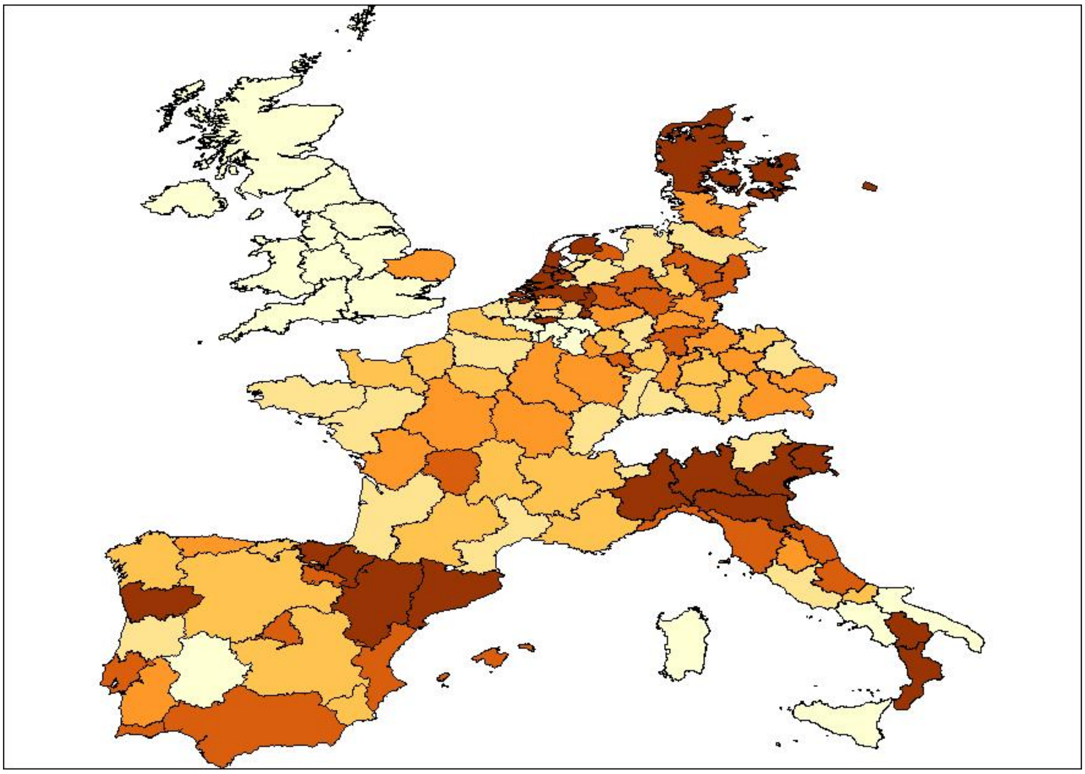


Fig. 4 Quantile map of the growth of per-capita GDP in 1995



sensibly. Values of *I* larger (or smaller) then the expected values indicate positive (negative) spatial autocorrelation. Inference is based on a permutational approach (10,000 permutations used in our computation). As shown in the fourth column of Table 1, in our sample per-capita regional GDP is, in almost all cases, positively spatially autocorrelated, since the *p*-values are near to zero for most of the years considered, the only exceptions being represented by years 1981, 1985, 1986, and 1990. These results suggest that the null hypothesis of no spatial autocorrelation can be rejected and that the OLS estimates should be improved in order to account for spatial autocorrelation. We proved this result to be particularly robust to a different choice of the spatial weight matrix computing the *I*-Moran using different specifications of the weights[6] obtaining results that do not vary sensibly.

Table 1 *I*-Moran statistic of the growth rate of per-capita GDP (1980-1995)

Variable	*I*-Moran	Z-values	p-value
Growth GDP-81	-0.048	-1.159	0.246
Growth GDP-82	0.247	7.341	0.000
Growth GDP-83	0.277	8.222	0.000
Growth GDP-84	-0.067	-1.695	0.090
Growth GDP-85	-0.023	-0.437	0.661
Growth GDP-86	-0.007	0.021	0.982
Growth GDP-87	0.170	5.134	0.000
Growth GDP-88	0.144	4.382	0.000
Growth GDP-89	0.084	2.649	0.008
Growth GDP-90	-0.002	0.166	0.867
Growth GDP-91	0.443	12.990	0.000
Growth GDP-92	0.326	9.619	0.000
Growth GDP-93	0.479	14.004	0.000
Growth GDP-94	0.354	10.420	0.000
Growth GDP-95	0.363	0.685	0.000

6 In particular, we have considered to more spatial weight matrices: a simple binary contiguity matrix, and a binary spatial weight matrix with a simple distance-based critical cut-off.

3 BETA-CONVERGENCE MODEL

Two concept of convergence appear in the literature of economic growth across countries or regions. The first, may be described by the fact that a poor economies tends to grow faster than a rich one, so that the poor spatial unit tend to catch up to the rich one in terms of level of per-capita income. Such a situation is always referred to as beta-convergence models. The second interpretation applies when country-wise inequality tends to reduce in time. This process is called sigma-convergence. Generally, convergence of the first type tends to generate convergence of the second type: when poor regions grow faster than reach ones the result is a reduction in the dispersion of per-capita income across individuals countries[7].

The framework used in the present paper to estimates convergence among European regions is described by the following cross-sectional model:

$$\ln\left[\frac{y_{T,i} - y_{0,i}}{y_{0,i}}\right] = \alpha + \beta \ln y_{0,i} + \varepsilon_i \qquad (1)$$

where the dependent variable represents the entire period growth rate, α is a constant, and $y_{0,i}$ is the log of the per-capita GDP of the first period in the sample, and ε is the error term with zero mean. If the parameter β is significantly negative one can conclude in favour of unconditional beta-convergence. Based on Equation (1) two more parameters can be computer. The first refers to the speed of convergence and the second to the time necessary to reach the steady-state, known in the literature as the *half-life*[8]. Model (1) is based on a set of assumption. Firstly, it should be assumed that all economies are structurally similar and thus they are characterized by the same steady-state. Secondly, all the spatial units may differ only for their initial conditions.

The main results obtained using the specification (1) are reported in Table 2. The parameter β is negative and significant thus confirming the presence of unconditional beta-convergence.

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7 In the literature are given two different definition of convergence: conditional and absolute. Conditional convergence occurs when the growth rate of an economy is positively related to the distance between the particular level of income of this region and its steady-state. Conversely absolute convergence occurs when poor regions tend to grow faster than the rich ones. For a detailed discussion on this two definitions see, among others, Barro and Sala-i-Martin (1995).

8 The speed of convergence is computed as: $s = -\ln(1 + T\beta)/T$. The *half-life* can be calculated as: $\tau = -\ln(2)/\ln(1+\beta)$

Table 2 Results of the estimation of the beta-convergence model

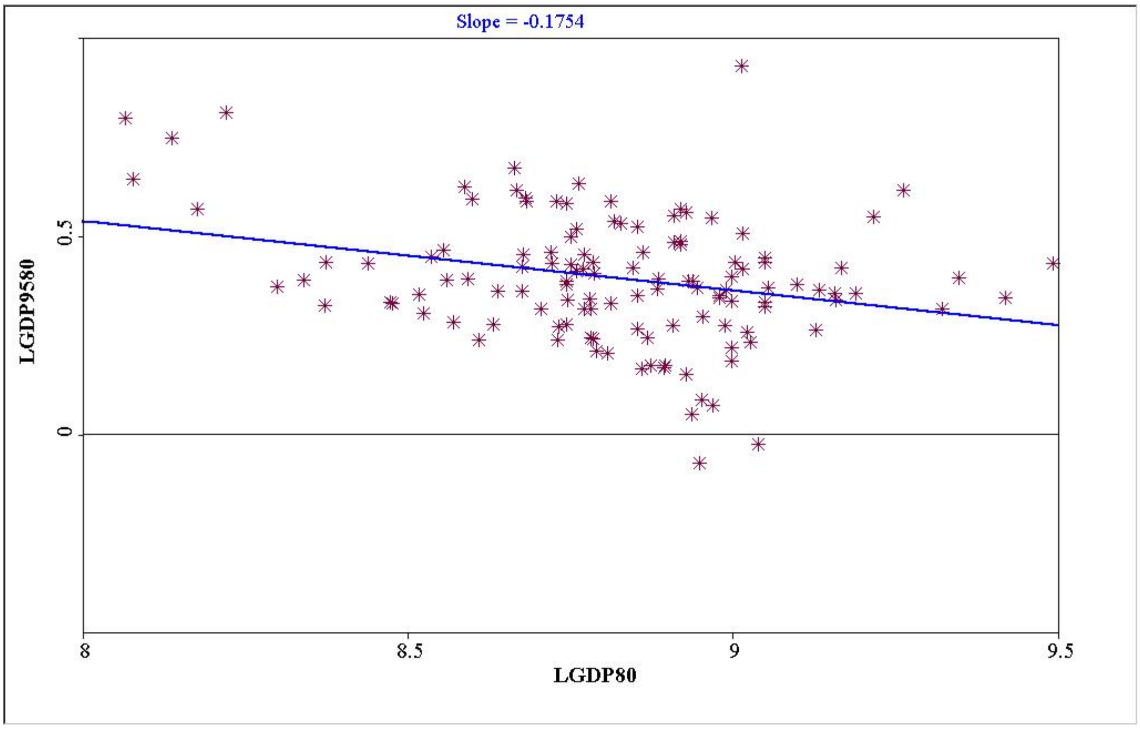
OLS ESTIMATION OF THE BETA-CONVERGENCE MODEL				
Dependent variable (1)		GDP growth rate over the period 1980-1995		
F-statistic	10.785			
Prob F-statistic	0.001			
Log-Likelihood	57.690			
Akaike	-111.381			
Schwarz	-105.725			
	Coefficient	Standard Error	t	P>|t|
Log GDP-1980	-0.175	0.053	-3.280	0.001
Constant	1.939	0.471	4.12	0.000
R-square	0.080			
Adjusted R-square	0.073			
TEST OF NORMALITY OF ERRORS				
Test	DF	Value	Prob	
Jarque-Bera	2	5.284	0.071	
DIAGNOSTIC FOR HETEROSCHEDASTICITY				
Test	DF	Value	Prob	
Breusch-Pagan	1	0.174	0.676	
Koenker-Bassett	1	0.117	0.731	
SPECIFICATION ROBUST TEST				
Test	DF	Value	Prob	
White	2	0.727	0.695	
DIAGNOSTIC FOR SPATIAL DEPENDENCE				
Test	MI	Value	Prob	
Moran's *I* test	0.341	5.786	0.000	

(1) The dependent variable is the logarithm of the growth rate over the entire period of our data set.

(2) The variable log gdp-1980 represents the logarithm of the value of per-capita GDP in the first year (1980).

In Figure 5, we show the scatter plot and the regression line of the beta-convergence model. The growth rate of per-capital income for 1980-1995, shown on the vertical axis, is negatively related to the log of per-capita income in 1980, shown on the horizontal axis. Indeed, the regression coefficient shows that the process of convergence is still rather weak.

Fig. 5 Scatter plot and regression line of the beta-convergence model (1)



(1) Dependent variable: growth rate of per-capita GDP for 1980-1995. 125 regions have been considered in the data set.

4 FIXED EFFECT ESTIMATION

A panel, or longitudinal data set, consist of a sequence of observations, repeated through time, on a set of statistical units (individuals, firms, countries, etc.). Panel data models have attracted the interest of many researcher in recent time. Baltagi (2001), in the introduction of his seminar book on panel data, list some of the benefits and some limitation in using panel data (Hsiao, 1985, 1986; Klevmarken, 1989; Solon, 1989). Firstly, they allow controlling for individuals heterogeneity. Moreover, they are more informative with respect to time series or pure cross-sectional data, present more variability, less collinearity among the variables, more degrees of freedom and more efficiency. It should be emphasized that a panel data regression differs from a time series or cross-section regression in that it consider both the temporal and the individuals dimension. Panel data offers two distinct advantages over pure cross-section or time series (Peracchi, 2001). First of all the units are observed through times and this fact simplifies the analysis of some economic problems that cannot be studied using purely cross sectional data. Furthermore, panel data allow the analysis of individual behaviour, controlling for individual heterogeneity.

On the other hand some problems arise using panel data. First of all design and data collection problems are more complicated then in the case of time series or cross-sectional data. Furthermore, measurement errors may arise producing distortions in the inferential procedures and in many cases, the time series dimension is too short. However the main problem in using panel data is selectivity, arising in the various forms of self-selectivity, non-response, attrition and new entries.

More formally, the most general formulation of a panel data model may be expressed by the following equation:

$$y_{i,t} = \alpha_i + X_{i,t}^{'}\beta + u_{it} + \varepsilon_{i,t} \tag{2}$$

with i (i=1,...,N) denoting individuals, and t (t=1,...,T), denoting time periods, and $X^{'}_{i,t}$, the observation of K explanatory variables in country i and time t. It should be noted that αi is time invariant and accounts for any individual-specific effect not included in the regression equation. Two different interpretations may be given to the α_i, and, consequently, two different basic models may be distinguished. If the α_i's are assumed to be fixed parameters to be estimated the model expressed in the equation (2) is termed *fixed effect panel data model*. Conversely, if the α_i's are assumed to be random, the so-called *random effect panel data model* is generated.

Generally speaking, fixed effect model is particularly indicated when the regression analysis is limited to a precise set of individuals, firms or regions; random effect, instead, is an appropriate specification if we are drawing a certain number of individuals randomly from a large population of reference[9].

For this reason, since our data set consists on the observation over 125 European regions, we decided to estimate a fixed effect panel data model to check for convergence. Following Islam (1995) a number of papers have tried to estimate the speed of convergence among regions using panel data sets and variant of fixed effect model. One of the main advantages obtained from the application of panel data models to convergence problems with respect to the more traditional cross-sectional approach is that it is not necessary to keep constant the steady-state, since this can be directly estimated from data by

9 For more detail on the discussion regarding the use of this two models for panel data we suggest to see specialistic books on panel data (i.e. Baltagi 2001)

using a Least Square dummy variables estimator. In the literature, there is evidence that estimates of the speed of convergence from panel data with fixed effects tend to be much larger than the 2% per year estimated from cross sections (Barro and Sala-i-Martin, 1995). Following this approach some problems may arise from the fact that, in order to obtain significative results, one should include a long time series observations. In this way the time observations tend to be close to one another thus capturing more a short-term adjustment toward the trend rather than long-term convergence.

The model we estimate in the present paper may be expressed by the following equation:

$$\ln\left[\frac{y_{t+k,i}-y_{t,i}}{y_{t,i}}\right]=\alpha_i+\beta\ln y_{t,i}+\varepsilon_{t,i} \qquad (3)$$

where the dependent variable is the annual growth rate of per-capita GDP, the regressor is represented by the (log) per-capita-GDP for region i at time t, and α_i are interpreted as parameter to be estimated as in the fixed effect model specification.

In Table 3 the estimate results of the previous equation are reported. It should be noticed that the coefficient of the growth rate variable is still significantly negative, thus confirming the hypothesis of converge among European regions. In absolute terms the value of the growth rate coefficient found using the fixed effect estimator is smaller than that found when using the simple beta-convergence model in Section 2, thus indicating that the speed of convergence is lower than those usually estimated in the literature which make use of absolute convergence models.

An interesting aspect is represented by the spatial analysis of the residuals obtained by the fixed effect estimation. Figures from 7 to 10 show the quantile map of the residuals for the years 1981, 1985, 1990, and 1995: a spatial structure is evident. This evidence is confirmed by the values of the Moran's I index computed on the residuals for each year. In fact, as it is shown in Table 4, the null hypothesis of no spatial dependence in the residuals structure should be rejected in almost all the cases. The same evidence is shown by Figures from 12 to 15 reporting the scatter plot of the Moran calculated in 1981, 1985, 1990, and 1995. The same analysis led over the estimated α coefficients leads to reject the hypothesis of spatial heteroskedasticity. In fact, the value of the Moran coefficient computed over the sequence of the estimated α leads to the acceptance the null hypothesis of no spatial dependence.

Table 3 **Fixed-effects regression**
Number of groups 125, number of observations per group 14

FIXED EFFECT PANEL DATA ESTIMATION				
Dependent variable:		Annual growth rate of the per-capita GDP		
	Coefficient	Standard Error	t	P>|t|
Log-GDP	-0.047	0.035	-13.390	0.000
Constant	0.506	0.032	15.370	0.000
Sigma-α	0.012			
Sigma-ε	0.037			
ρ	0.100			
R-square:	Within	0.099		
	Between	0.039		
	Overlall	0.061		
Corr (α_i,xβ)	-0.569			

Table 4 **Moran's I coefficient computed over the residuals of the fixed effect panel data model estimation in each time period (1981-1995)**

Variable	*I*-Moran	Z-values	p-value
residual -81	0.461	14.246	0.000
residual -82	0.464	13.594	0.000
residual -83	0.464	13.586	0.000
residual -84	0.476	13.941	0.000
residual -85	0.463	13.859	0.000
residual -86	0.476	13.940	0.000
residual -87	0.457	13.387	0.000
residual -88	0.452	13.232	0.000
residual -89	-0.443	12.983	0.000
residual -90	0.422	12.855	0.000
residual -91	0.445	13.042	0.000
residual -92	0.448	13.121	0.000
residual -93	0.415	12.187	0.000
residual -94	0.429	12.586	0.000
residual -95	0.422	12.736	0.000
Fixed effects	-0.007	0.876	0.380

Fig. 6 **Quantile map of the estimated value of the coefficient α denoting the individual-specific effect**

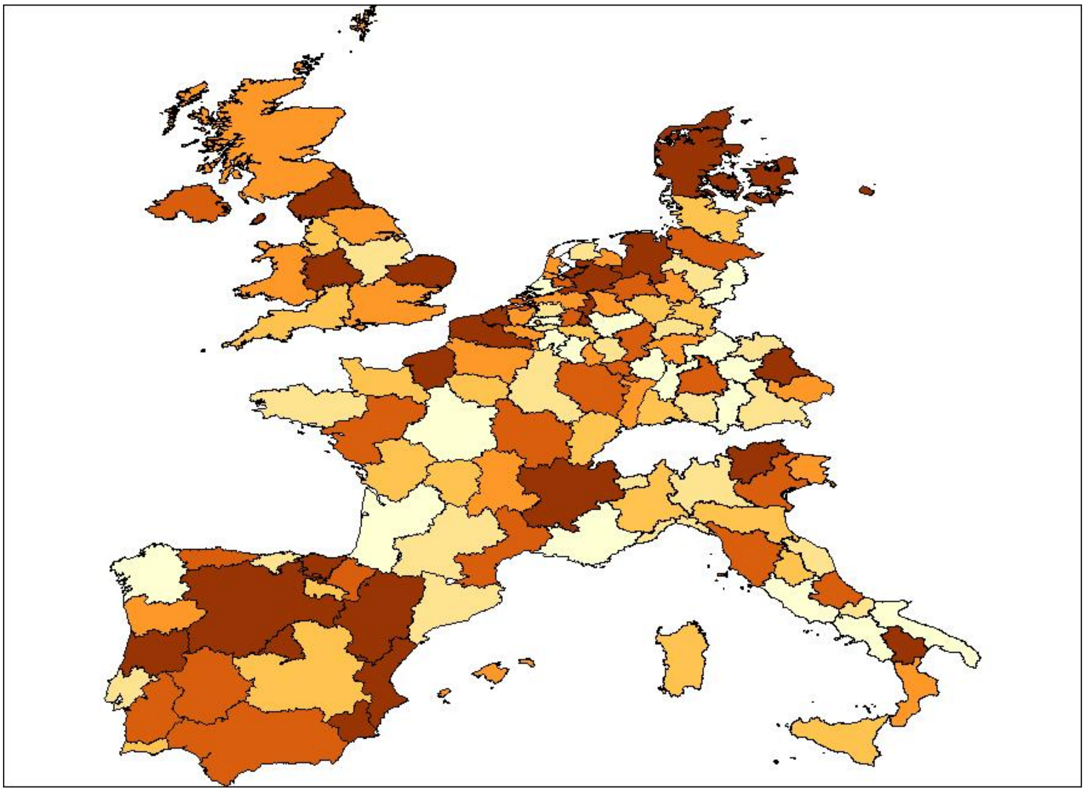


Fig. 7 **Quantile map of the residuals in 1981**

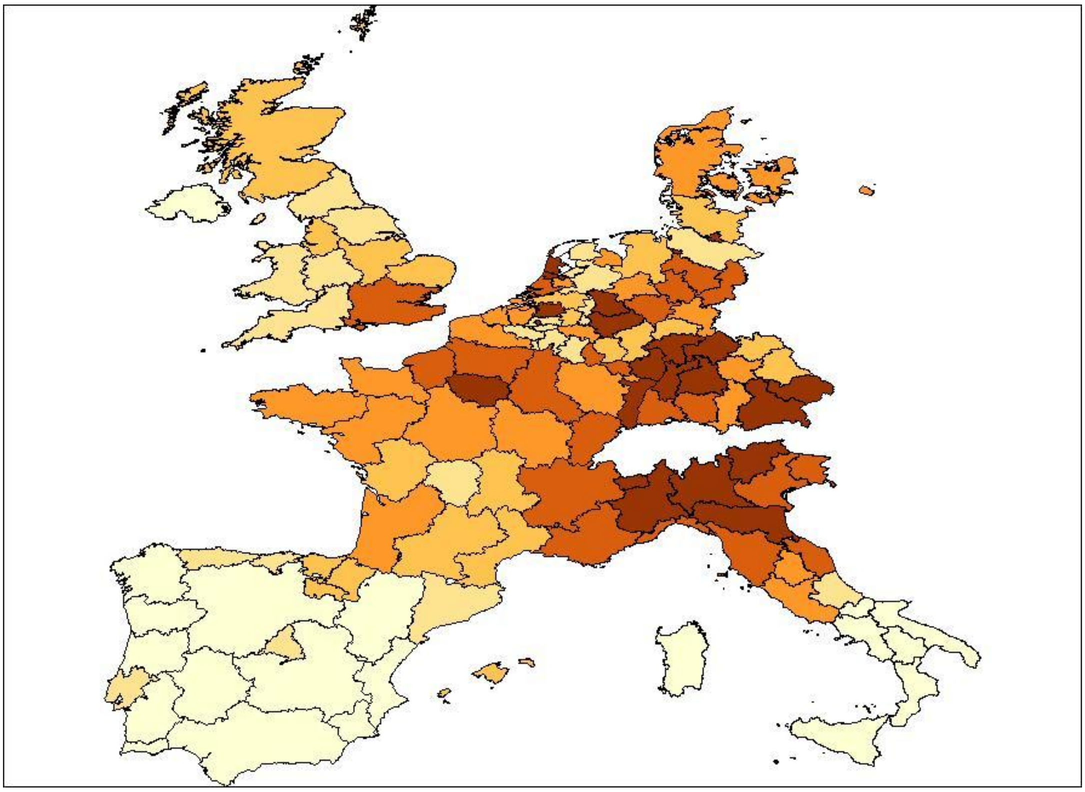


Fig. 8 **Quantile map of the residuals in 1985**

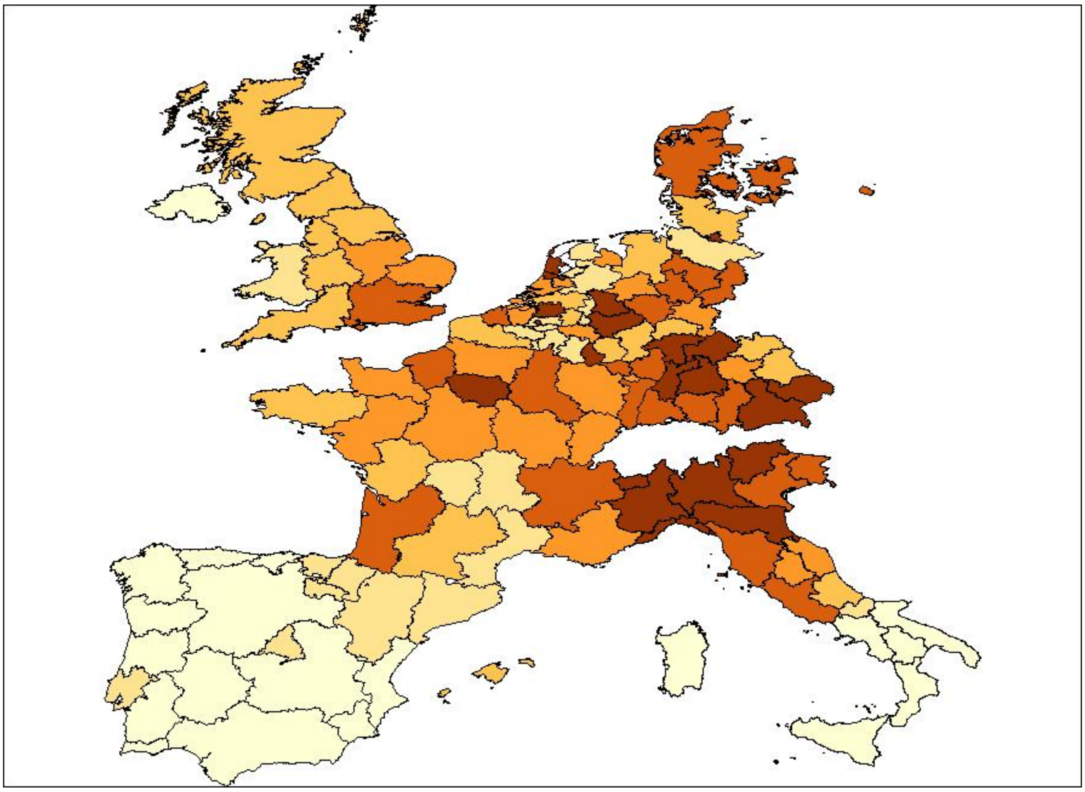


Fig. 9 **Quantile map of the residuals in 1990**

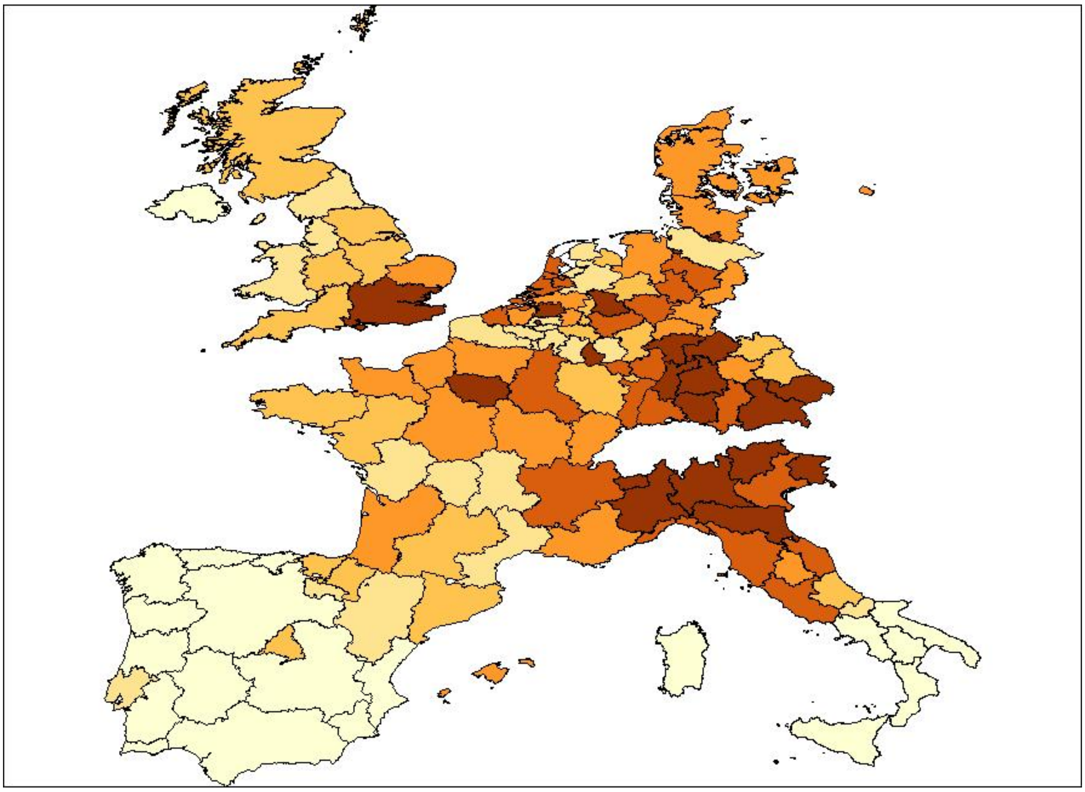


Fig. 10 Quantile map of the residuals in 1995

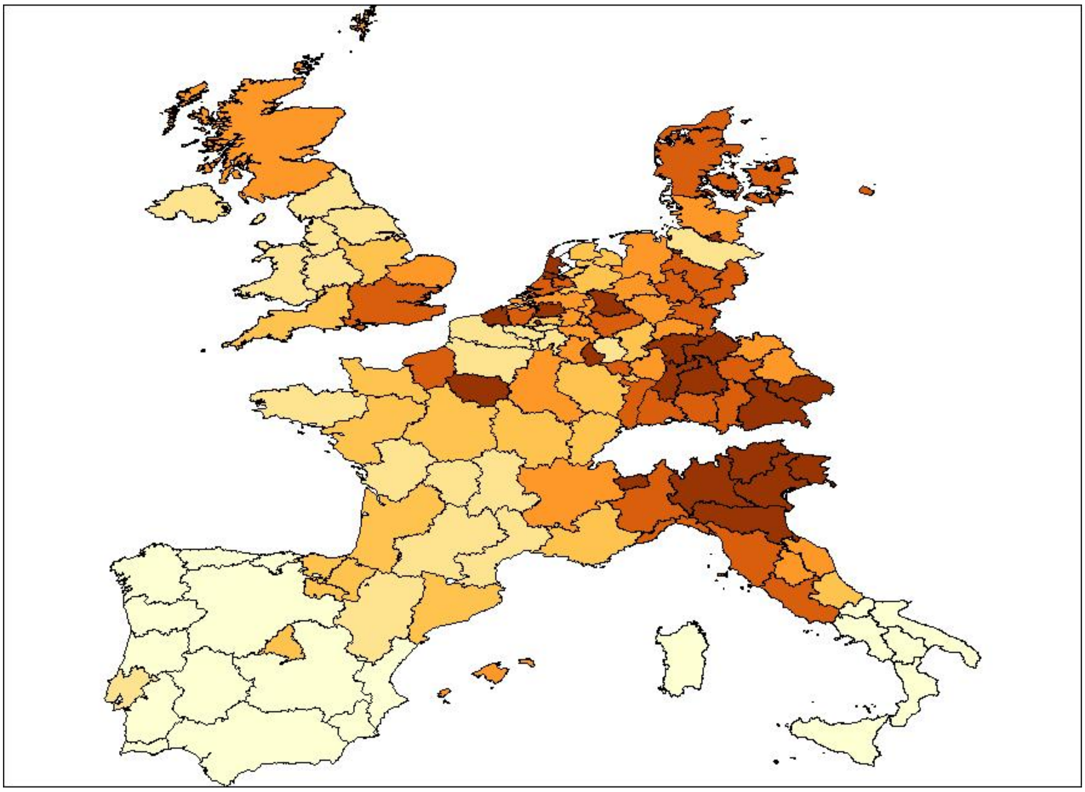


Fig. 11 Moran scatter-plot of the estimated values of the coefficient α denoting the region-specific effect in the fixed effect estimates of the convergence among the European regions over the period 1980-1995

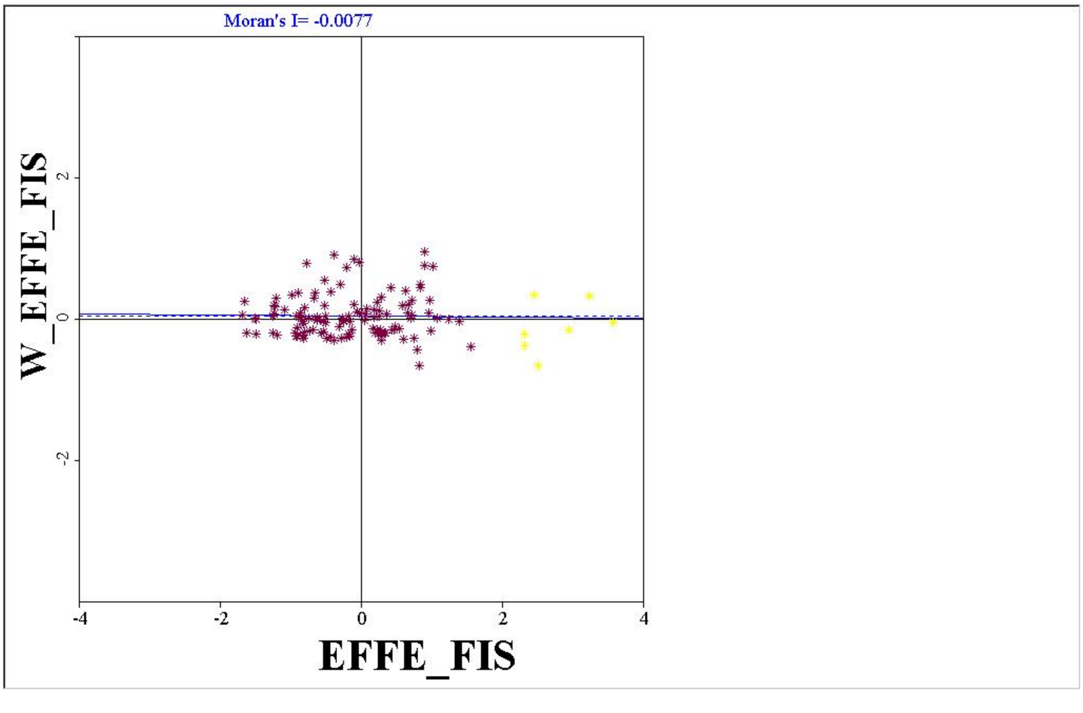


Fig. 12 **Moran scatter-plot of the residuals of the fixed effect estimates in 1981**

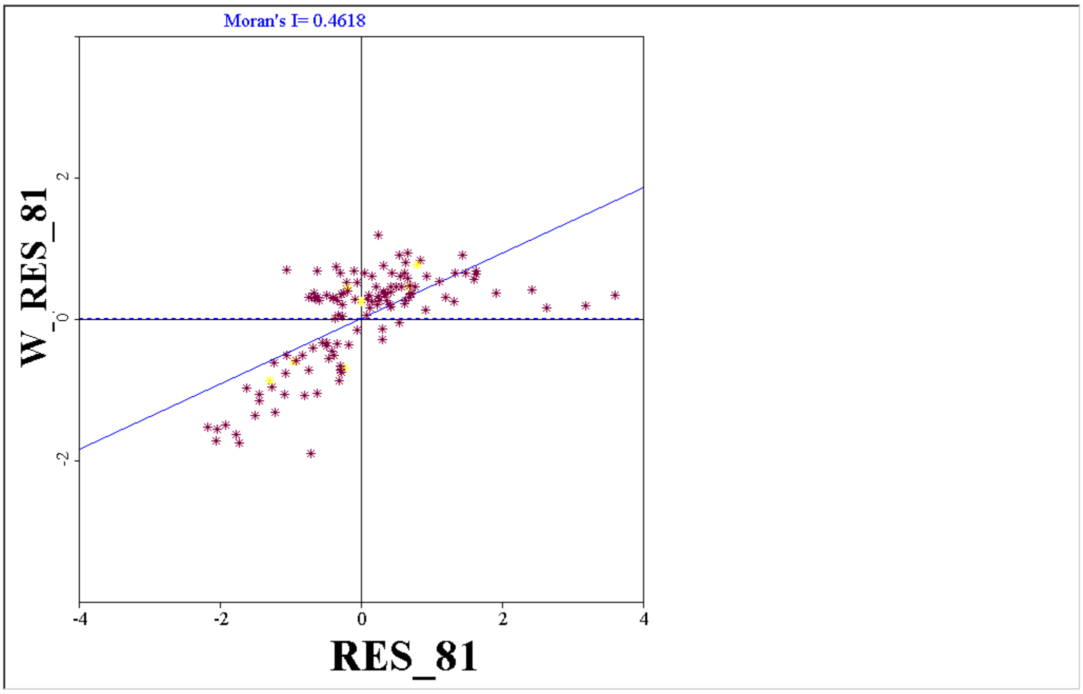


Fig. 13 **Moran scatter-plot of the residuals of the fixed effect estimates in 1985**

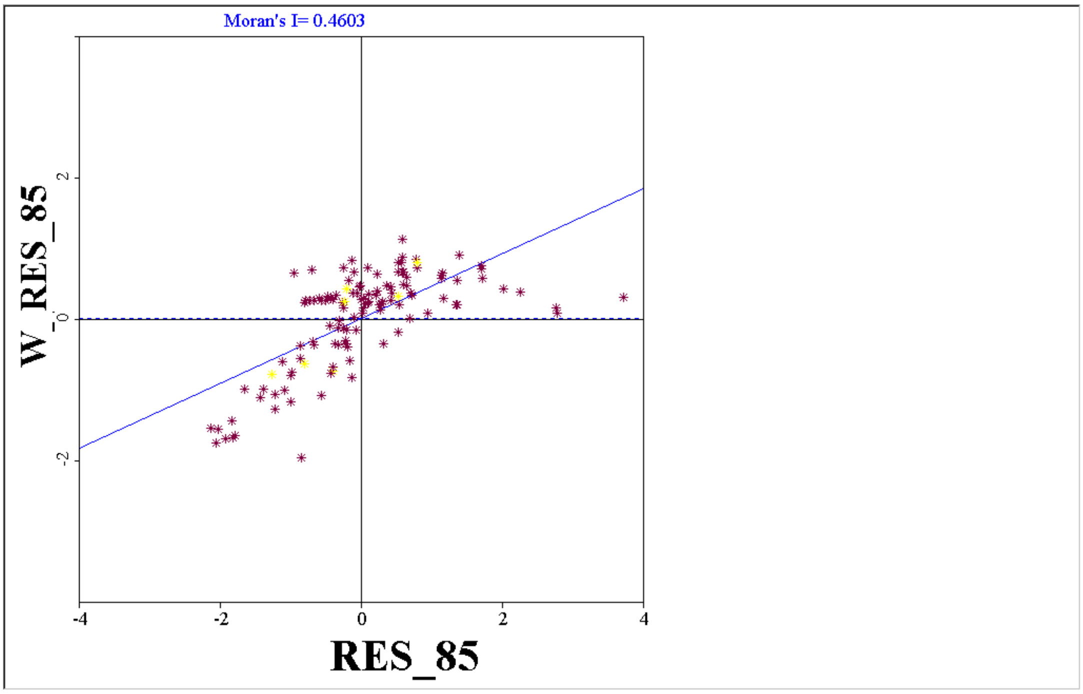


Fig. 14 **Moran scatter-plot of the residuals of the fixed effect estimates in 1990**

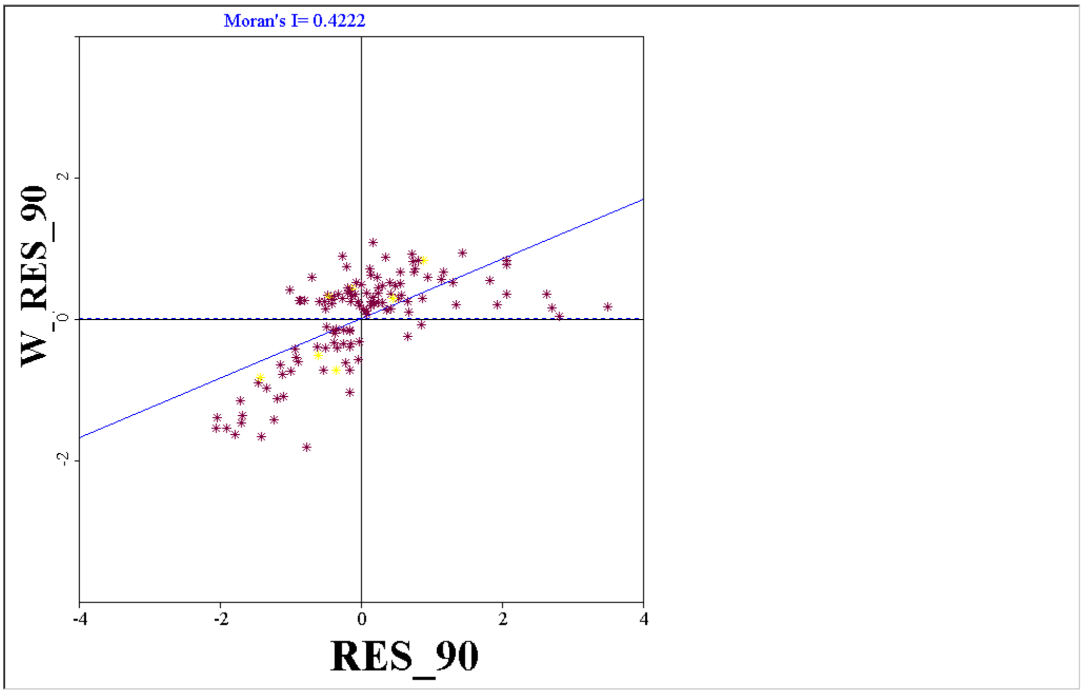
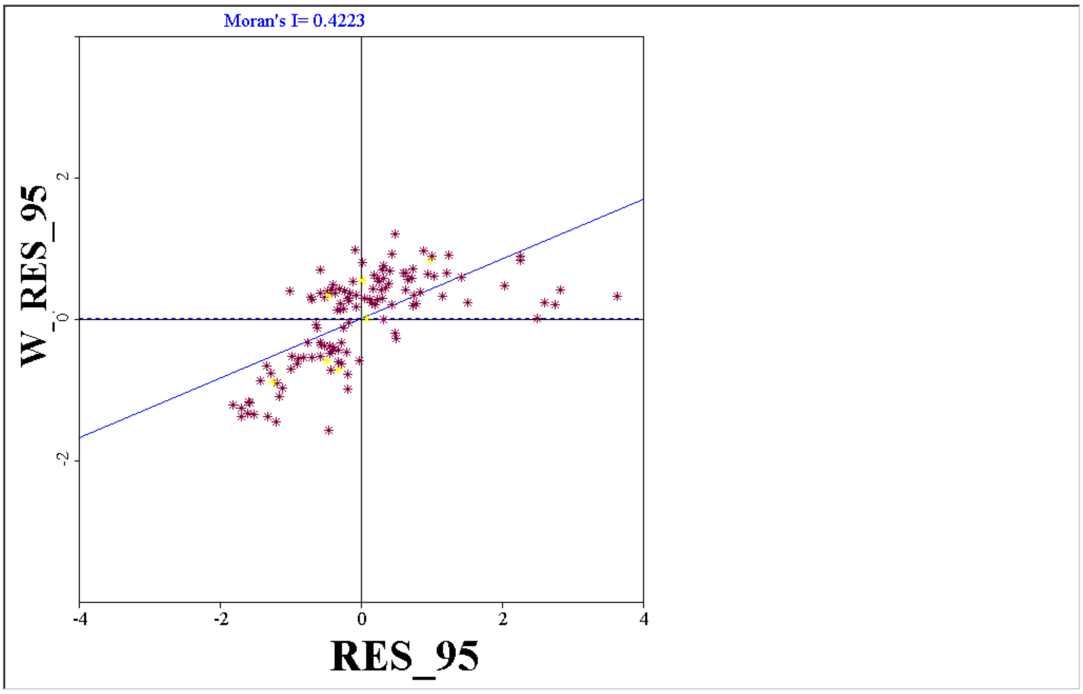


Fig. 15 **Moran scatter-plot of the residuals of the fixed effect estimates in 1995**



5 SPATIAL PANEL DATA MODELS

In traditional panel data literature, the researcher is not usually interested in cross sectional correlation. However, when the data are referred to a cross-section of countries, regions, states or counties, the aggregates are likely to exhibit cross-sectional correlation that should be considered in the analysis. With the increasing availability of micro as well as macro panel data, spatial panel data models are becoming of particular interest in empirical research[10].

The aim of this section is to estimate a fixed effect panel data model extended to account for spatial error autocorrelation. Two problems may arise when panel data models have a locational component. The first problem is spatial heterogeneity, that is the characteristic of the parameters to vary with the observational location. The second problem is that of the spatial dependence that may exist between observations at each point in time. In a recent paper Elhorst (2003) provides a thorough survey of the specification and estimation of spatial panel data models including spatial effects either in the form of error autocorrelation or of a spatially lagged dependent variable. In particular, he starts from the classical literature on panel data, and adapts what can be learned from the econometric literature by discussing the following four models: (i) the spatial fixed effect model, (ii) the spatial random effect model, and (iii) the fixed and (iv) random coefficient spatial error models. He derives the relative likelihood for each model, discuss the asymptotic properties, and the estimation procedure. The potentially problems arising from the spatial version of this four models are discussed in detail. In the present work, we consider only the fixed effect panel data model specification extended to account for spatial error correlation. It should be stressed that the application of such a model to the estimation of regional convergence, appears to be the most reasonable solution. Furthermore, the present paper represents the first application of the spatial fixed effect model to the problem of convergence among regions, and this analysis represents the most innovative aspect of our work. The spatial econometrics literature has shown that OLS estimation is inappropriate in models including spatial effects. More precisely the OLS estimators, while unbiased, became inefficient in the case of spatial error autocorrelation. In the case of a model including a spatially lagged dependent variable, the estimates not only loose their property of unbiasedness, but also became inconsistent. The most common method to overcome this problems proposed in the spatial econometrics literature is maximum likelihood (Anselin, 1988). In the quoted

10 For a few application on spatial panel data see, among others, Elhorst (2003), Case (1991), Baltagi and Li (2001), Holtz-Eakin (1994), etc.

paper, Elhorst derives the maximum likelihood function for all the models listed before. The starting point of many econometric analysis is the classical panel data model we discussed in the previous section. The starting point of our empirical analysis is the equation representing the extension of the fixed effect model to spatial error autocorrelation:

$$\begin{aligned} &\ln\left[\frac{y_{t+k,i}-y_{t,i}}{y_{t,i}}\right]=\alpha_i+\beta\ln y_{t,i}+\varepsilon_{t,i} \\ &where \\ &\varepsilon_{i,t}=\delta W\varepsilon_{i,t-1}+\xi_t \end{aligned} \tag{4}$$

where the dependent variable is the annual growth rate of the per-capita GDP of the European regions, and the regressor is the log of the initial per-capita GDP, αi denotes the vector of random country-specific effects, δ is the scalar spatial autoregressive coefficient, W is the classical spatial weights matrix discussed in Section 2, whose diagonal elements are zero, and ζt are errors assumed to be independent, identical distributed with zero mean and finite variance. For the derivation of the maximum likelihood of this model, and the formulation of the first order conditions for its maximization, as well as the LM test for δ, see Anselin (1988), or Elhorst (2003).

Table 5 Fixed effect with spatial autocorrelation

FIXED EFFECT WITH SPATIAL AUTOCORRELATION			
Dependent variable		Annual growth rate of per-capita GDP	
R-square	0.369		
Sigma squared	0.000		
Log-Likelihood	3866.959		
Number of Observations	1875		
Number of Variables	1		
Variable	Coefficient	t-stat	Probability
Log of per-capita GDP	-0.036	-9.463	0.000
Spatial autocorrelation coefficient	0.556	33.858	0.000

Table 5 reports the main results of the estimation procedure. The main advantages deriving from this new formulation is in the fact that one can take into account the spatial dependence present in the data set and more reliable estimates of the coefficients. The sign of the estimate of the parameter of interest confirms convergence, but its value is smaller than the one obtained using the previous formulation. It may be concluded that, in by taking into account spatial dependence produce a growth rate of convergence smaller than that obtained with the classical panel data model. The relatively simple model we considered in the present section represents only the first step of a possible research path concerned within the application of spatial panel data models to the problem of economic regional convergence.

Table 6 **I-Moran test of the residuals of the spatial fixed effect panel data model estimation for each time period (1981-1995)**

Variable	*I*-Moran	Z-values	p-value
residualspat -81	0.021	0.859	0.390
residualspat -82	0.234	6.971	0.000
residualspat -83	0.389	11.413	0.000
residualspat -84	0.143	4.355	0.000
residualspat -85	0.042	1.462	0.143
residualspat –86	0.297	8.786	0.000
residualspat –87	0.073	2.351	0.018
residualspat -88	0.108	3.359	0.000
residualspat -89	0.098	3.049	0.002
residualspat -90	0.155	4.688	0.000
residualspat -91	0.530	15.484	0.000
residualspat -92	0.356	10.476	0.000
residualspat -93	0.434	12.724	0.000
residualspat -94	0.361	10.627	0.000
residualspat -95	0.389	11.427	0.000

The results obtained show that the fixed effect model extended to spatial error autocorrelation does not succeed to fully correct the residuals structure of spatial dependence. In fact Table 6 shows that the I-Moran index remains significant in most cases. However, the correction introduced at least improves the estimation reducing the absolute value of the index. By inspecting the geographical map the effect of the correction is more evidently displayed (see Figures 16 to 19).

Fig. 16 **Quantile map of the residuals of the spatial error panel data model (1981)**

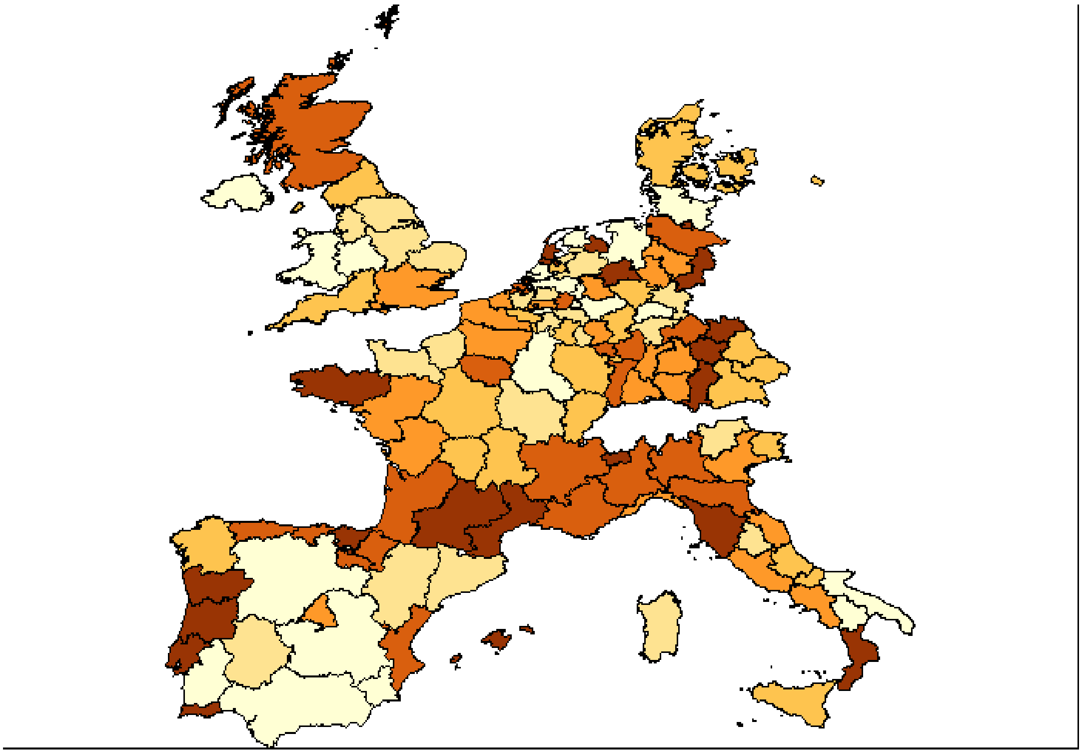


Fig. 17 **Quantile map of the residuals of the spatial error panel data model (1985)**

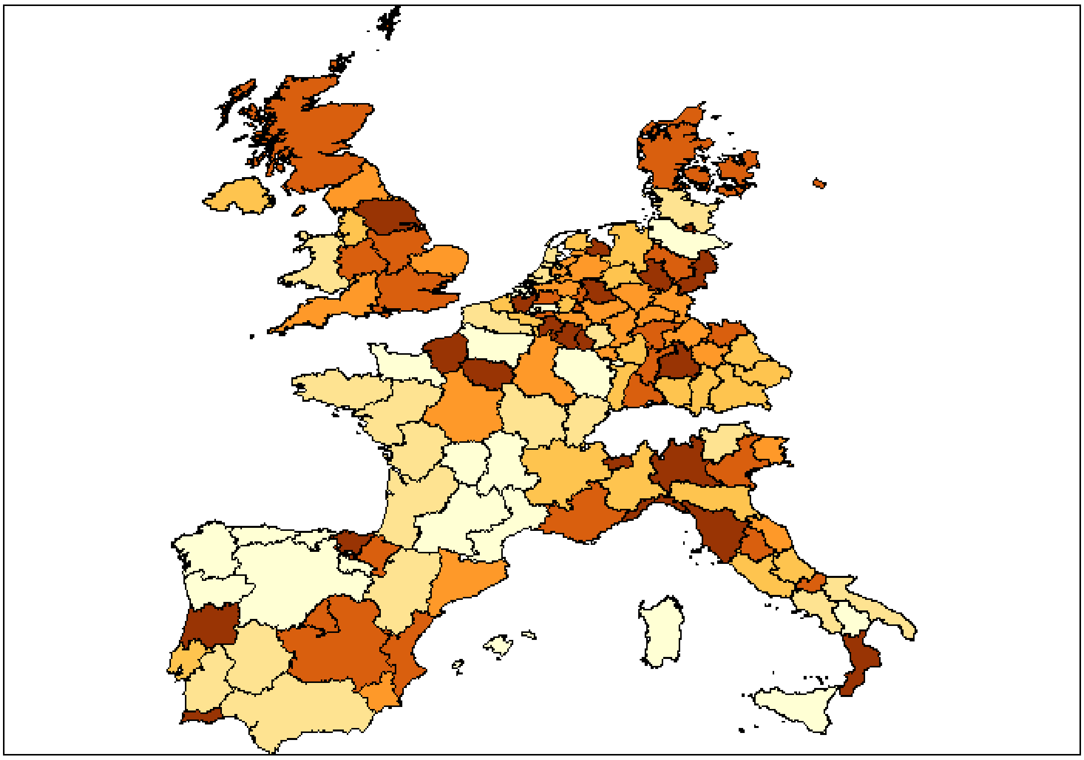


Fig. 18 **Quantile map of the residuals of the spatial error panel data model (1990)**

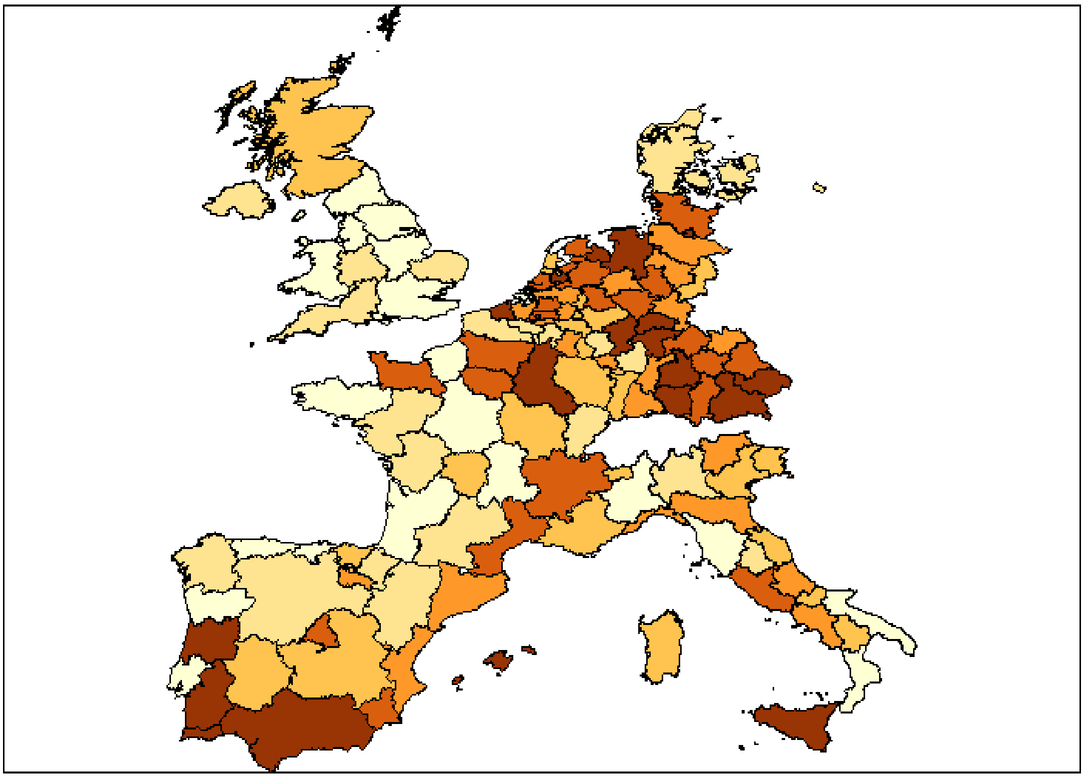
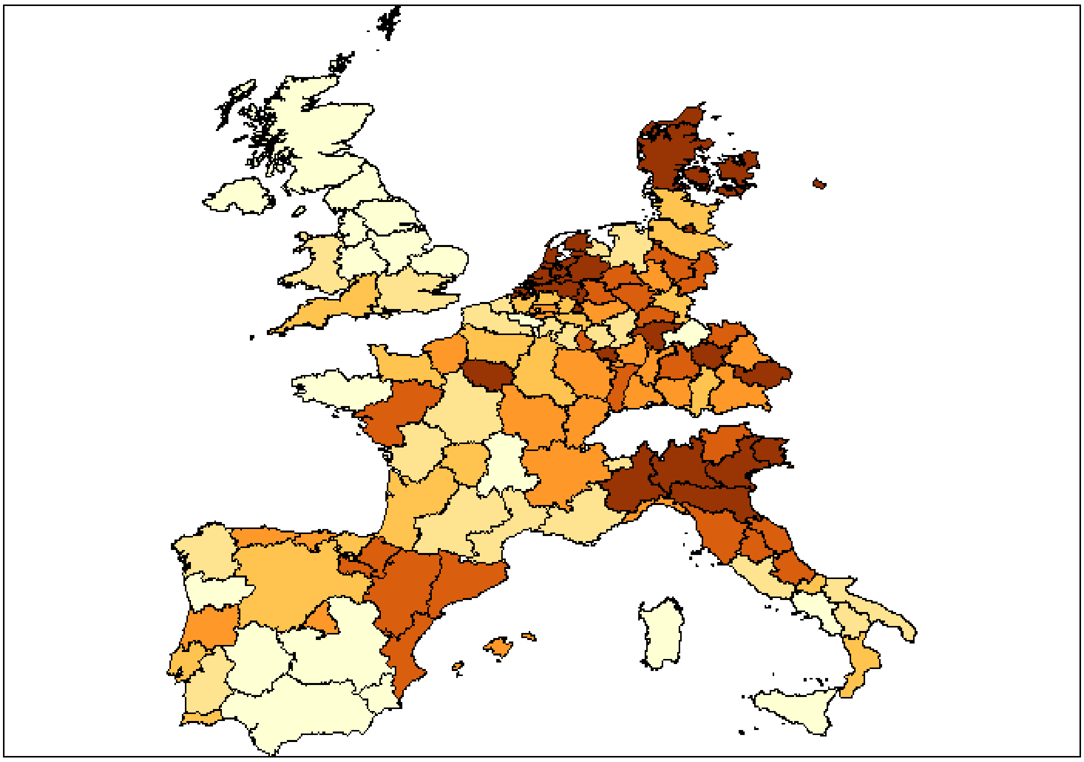


Fig. 19 **Quantile map of the residuals of the spatial error panel data model (1995)**



6 CONCLUSIONS

In the present paper we considered the problem of convergence among European regions. Many of the applied works in literature study convergence making use of fixed-effect model or cross-country regression. Our investigation starts from the observation that this two techniques both impose strong a-priori restrictions on the model parameters. On one side, cross-sectional methods do not consider heterogeneity at all, on the other fixed effect approach make it depend only on the different intercept obtained for each region and all the differences in the growth rates depend only on the different starting point.

The methodology used in the present paper allows us to extend the traditional models by considering a specific treatment of the spatial correlation among the intercept terms, and a rigorous spatial analysis of the residuals obtained in the various models. We also considered a spatial analysis of the intercept terms and of the residuals. The main result obtained is that, by taking into account the spatial dependence among the spatial units, we are able to improve the reliability of the estimates of the speed of convergence among the European regions.

The present paper can be considered as a point of departure for any future researches that can develop in various directions. First of all, the fixed effect model considered in this paper could be extended to include a spatially lagged dependent variable. Secondly, a random effect spatial panel data model could be used. Finally we could consider the framework of the dynamic panel data models extended to spatial error autocorrelation or to a spatially lagged dependent variable.

REFERENCES

Anselin, L. (1988) Spatial Econometrics: Methos and Models, Kluwer Academic Publishers, Dordrecht.

Arbia, G. (2005) Introductory spatial econometrics: with application to regional convergence, Springer-Verlag, Berlin, Forthcoming.

Arbia, G., Basile, R. and Salvatore, M. (2003) Spatial Effects on Regional Growth. A Parametric and a Nonparametric Approach, paper presented at the congress Analytical Frontiers in Spatial Aspects of Economic Development, May 29, 2003, WIDER, Helsinki

Arbia, G., Basile, R. and Salvatore, M (2002) Regional convergence in Italy 1951-1999: a spatial econometric perspective, Paper presented at the 17th annual congress of the European Economic Association, Venice, August 2002.

Arbia, G. and Paelinck, JHP (2003) Economic convergence or divergence? Modelling the interregional dynamics of EU regions 1985 – 1999, Geographical Systems, 5, 1-24, 2003

Arbia, G. and Paelinck, J.H.P., (2004) Spatial econometric modelling of Regional Convergence in Continuous Time, International Regional Science Review, 2004.

Baltagi B.H., (2001) Econometric analysis of panel data, 2nd edition Chichester, UK: Wiley.

Baltagi B.H., and Li, D., (2004) Prediction in the panel data model with spatial correlation In Advances in Spatial Econometrics: Methodology, Tools and Applications, edited by Anselin L., Florax R.J.G.M., and S.J. Rey, Heidelberg: Springer.

Barro R.J. and Sala-i-Martin X., (1995) Economic Growth, McGraw Hill, New York.

Baumont C., Ertur C., and LeGallo J., (2002), The European Regional Convergence Proces, 1980-1995: do Spatial Regimes and Spatial Dependence matter?. Economics Working Paper Archive at WUSTL.

Case A.C., (1991) Spatial patterns in household demand, Econometrica, 59: 953-965.

Cliff A.D. and J. K. Ord (1981), Spatial processes models and applications, Pion, London.

Elhorst J.P., (2001) Dynamic Models in Space and Time, Geographical Analysis, 33, 2: 119-140.

Elhorst P.J., (2003) Specification and Estimation of Spatial Panel Data Models, International Regional Sciences Review, 26, 3:244-268.

Holtz-Eakin, D., (1994) Public-sector capital and productivity puzzle, Review of Economics and Statistics , 76, 12-21.

Hsiao C., (1985) Benefits and limitations of panel data, Econometric Reviews, 4, 121-174.

Hsiao C., (1986) Analysis of panel data, Cambridge, UK: Cambridge University Press.

Islam N., (1995) Growth empirics: A panel data approach, Quarterly Journal of Economics, 4, 1127-1170.

Klevmarken N.A., (1989) Panel Studies: what can we learn from them? European Economic Review, 33, 523-529.

Peracchi F., Meliciani, (2001) Convergence in per capita GDP across European regions a reappraisal, Working Paper University of Tor Vergata, Rome.

Peracchi F., (2001) Econometrics, Wiley, Chichester, UK.

Quah D., (1996) Empirics for economic growth and convergence, European Economic Review, 40, 6, pp. 1353-7.

Solon G.S., (1989) The value of panel data in economic research, in D. Kesprzyk, G.J. Duncan, G. Kalton and M.P. Singh, eds., Panel Surveys, John Wiley, New York, 486-496.

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