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

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June 12, 2004

*Very preliminary, please do not quote. In preparation for the 44^{th} European Congress of the European Regional Sciencs Association (ERSDA) 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.

ABSTRACT

This paper studies the convergence of per-capita GDP across European regions over a fairly long period. Most of the works 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 and spatially lagged dependent variable (Anselin, 1988; Elhorst, 2002). This will allow us to extend the traditional β-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 convergence.

1 Introduction

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 imposes absolute regional homogeneity in the parameters of the process describing GDP growth. The second allows 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 (2003) that 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 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 other) have shown that the presence of spatial effects matter in the estimation of the β-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; Helhorst, 2002). This will allow us to extend the traditional β-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 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 present paper is organized as follows: section two is devoted to a detailed discussion over the data set; in section three 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 five, the correction to take in account of spatial dependence in panel data model is introduced, and a fixed effect panel data model extended to spatial error autocorrelation is estimated. Conclusion follows in which indication for further research are reported.

2 Preliminary data analysis

Spatial data availability remains one of the greater problem in European context, although many progress has been made in recent time by the European Statistical Institute. Thus, data availability remains scarce and in many case is very difficult to dispose of harmonized data sets allowing consistent region comparisons.

In the present work we use data on the per capita GDP in logarithms expressed in PPS and drown from the REGIO database. We include 125 regions of 10 European Countries: Belgium, Denmark, France, Germany, Luxembourg, Italy, Netherlands, Portugal, and Spain. Our sample starts from 1980 to 1995.[1]

The REGIO data base has to be considered the first and most famous data set with spatially referred data. REGIO 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 [2]. The regions are classified at three levels of spatial aggregation, using the so-called Nomenclature of Territorial Units for Statistics (NUTS) typology [3]. We consider the second level of spatial aggregation.

In many cases, the preliminary analysis of data is highly significative and very informative which respect to the spatial dynamics of a particular phenomena.

In this preliminary data analysis we show the quantile maps of the growth rate of per-capita GDP. We have divided observations on the spatial units into six different ranges. The evidence that the maps show is the fact that the

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

[2] 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.

[3] 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.

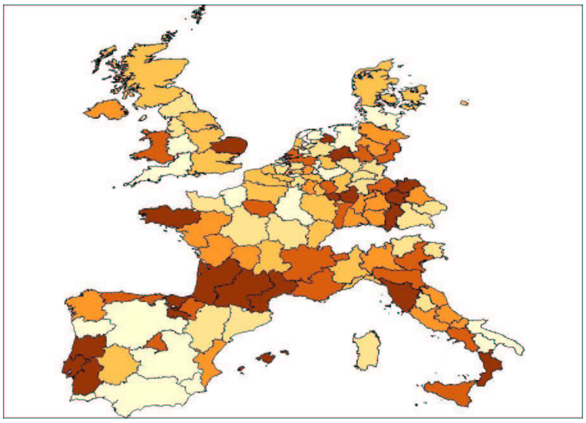

Figure 1: Quantile map of the variable growth per-capita GDP calculated in 1981

evolution over time of the phenomena under observation is not very variable. 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 same variable given in levels, there is a consistent evident of spatial effects. In fact, regions which present a high growth rate, in the most of the cases confine with spatial units in which the level belongs to the highest quantile. This evidence show that having a neighbor with particularly high level of income, produce a positive spillover for the poor regions, and their growth rate rise sensibly. In other term, the catch up effect discussed in Barro and Sala-y-Martin (1995) seem to be present in our data set. Convergence process to the own steady state seem to be more rapid for the poor regions. Thus, we only show four maps (1981, 1985, 1990, and 1995) instead of all the possible, because they are a good and representative synthesis of the dynamics we have just described over all the period 1981-1995.

In order to to test for global spatial autocorrelation in per-capita GDP in logarithm, we have calculated the Moran-I index over the entire period and its significance level which are reported in Table 1.[4]. In our elaboration we make use of a spatial weight matrix based on the inverse of squared pure

[4]The Moran-I index is written in the following matrix form: $I_t(k) = \frac{n}{S_0}\frac{z_t' W z_t}{z_t' z_t}$, 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).

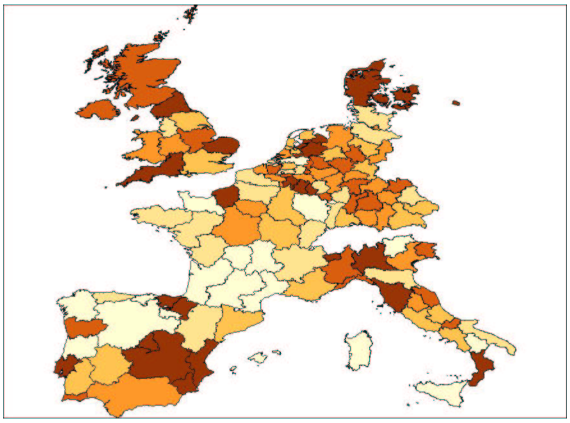

Figure 2: Quantile map of the variable growth per-capita GDP calculated in 1985

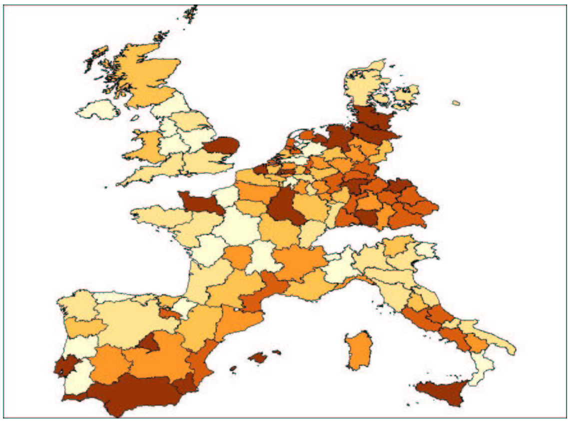

Figure 3: Quantile map of the variable growth per-capita GDP calculated in 1990

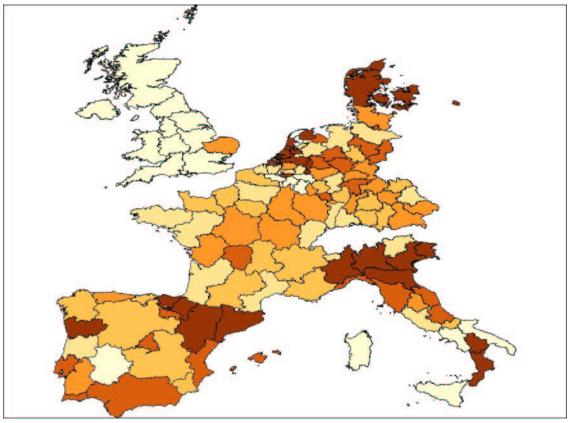

Figure 4: Quantile map of the variable growth per-capita GDP calculated in 1995

geographical distance (great circle distance between regional centroids), which is indeed strictly exogenous.(for great detail on the construction of a similar matrix see, among others, Baumont, Ertur, and LeGallo, 2002). The results show that the Moran-I index is fairly stable across time. It takes negative values during the period starting from 1984 to 1986, and in the 1981 and 1990. The values assumed during all the others years considered in our sample are positive and belongs to the interval 0.17-0.47. Really, excluding the value it takes in 1987, the interval may be considered very shorter, showing values which do not vary sensibly. Values of I larger (or smaller) then the expected values indicate positive (negative) spatial autocorrelation. Inference is based on permutation approach (10000 permutation). As shown in the fourth column of Table 1, in our sample per capital regional GDP is, in almost all cases, positive spatial autocorrelated, since the p statistics are near to zero for great part of the years considered. The only exceptions are represented by 1981, 1985, 1986, and 1990). This results suggest that the null hypothesis of no spatial autocorrelation is rejected and that OLS estimates should be improved in order to take in account spatial autocorrelation. Moreover, this latter result is particulary robust to a different choice of the spatial weight matrix. In fact, we have calculated the Moran-I by using different specification of the weights [5] obtaining very similar results, which, thus, are not reported in the present

[5]In particular, we have considered to more spatial weight matrices: a simple binary

Variable	Moran-I	Z-value	prob
ggdp81	-0.048	-1.159	0.246
ggdp82	0.247	7.341	0.000
ggdp83	0.277	8.222	0.000
ggdp84	-0.067	-1.695	0.090
ggdp85	-0.023	-0.437	0.661
ggdp86	-0.007	0.021	0.982
ggdp87	0.170	5.134	0.000
ggdp88	0.144	4.382	0.000
ggdp89	0.084	2.649	0.008
ggdp90	-0.002	0.166	0.867
ggdp91	0.443	12.99	0.000
ggdp92	0.326	9.619	0.000
ggdp93	0.479	14.004	0.000
ggdp94	0.354	10.420	0.000
ggdp95	0.363	0.685	0.000

Table 1: Moran-I calculated over the entire data set for each time peiod (1980-1995). Variable ggdp is the growth rate of per-capita GDP.

paper.

3 β-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 β-convergence models. The second interpretation applies when poor economies tend to grow faster then the rich ones. This process is called σ-convergence. Generally, convergence of the first type tends to generate convergence of the second: poor regions which grow faster than reach ones let to a reduction in the dispersion of per-capita income across

contiguity matrix, and a binary spatial weight matrix with a simple distance-based critical cut-off.

individuals[6].

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

$$Y_t = \alpha + \beta Y_0 + \varepsilon \tag{1}$$

where, Y_t is the entire period growth rate, [7] α is a constant, Y_0 is the log of the per-capita GDP of the first period in the sample, and ε is the classical error term with zero mean. If β is significantly negative, once X is held constant, may be concluded that there is unconditional β-convergence. At this point it is useful to remember that, after having estimated this cross-sectional equation, it is possible to calculate both the speed of convergence, and the time necessary to get the own steady state, known in literature as the half-life.[8]. Under the concept of unconditional β-convergence, there are some particular statements. Firstly, should be assumed that all economies are structurally similar, then, should be characterized by the same steady state. Moreover, all the spatial units may differ only for their initial conditions. In this section we do not test for the present of σ-convergence (for greater details on this arguments see Sala-I-Martin, 1996), but only say that this two concept may be used to capture conceptually different phenomena, as the σ-convergence gives information on the evolution over time of the distribution of the per-capital GDP.

Main results obtained using our simple specification are reported in Table2. In the first column the estimates of β is reported. The significantly negative value of the parameter, show the presence of unconditional β-convergence.

In Figure 5, we show the scatter plot of the regression line of the β-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. For this reason, there is evidence of the existence of absolute β-convergence for the European regions. Indeed,

[6] Always in 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 his own steady state. Absolute convergence is the event for which poor regions tend to grow faster than reach ones. For a detailed discussion on this two definition see, among others, Barro and Sala-y-Martin (1995)

[7] More precisely it is calculated by subtracting the level of per capita income in the first period from the level of the last period over observation and by dividing this difference by the level of the first period ($\frac{y_T - y_0}{y_0}$)

[8] The speed of convergence is equal to: $s = -\ln(1 + T\beta)/T$; while the half-life may be calculated as: $\tau = -\ln(2)/\ln(1+\beta)$

OLS ESTIMATION OF THE β-CONVERGENCE MODEL				
Dependent Variable			lgdp9580	
F-statistic	10.785			
Prob F-stat.	0.001			
Log-likelihood	57.690			
Akaike	-111.381			
Schwarz	-105.725			
lgdp9580	Coef.	Std.Err.	t	$P > \|t\|$
lgdp-80	-0.175	0.053	-3.28	0.001
cons	1.939	0.471	4.12	0.000
R-squared	0.080			
Adj. R-squared	0.073			
Test on 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	0.341	5.786	0.000	
Speed of convergence				
Half-life				

Table 2: Results of the estimation of the β-convergence model. The variable lgdp-9580 is the logarithm of the growth rate calculated over the entire period of our data set. The variable lgdp-80 id the logarithm of the value of per-capital GDP in the first observation period (1980). Speed of convergence and half-life have been calculated using the expressions reported in the footnote.

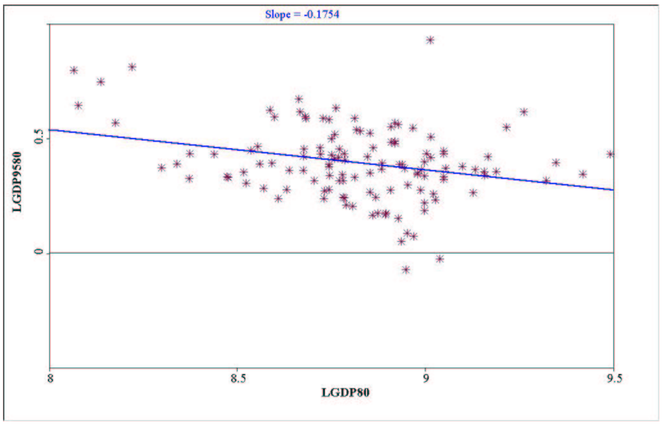

Figure 5: Scatter plot of the regression line of the β-convergence model. Dependent variable: growth rate of per-capita GDP for 1980-1995. 125 regions have been considered in data set.

the coefficient of the regression line show that the process of convergence is still rather weak.

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 has attracted the interest of many researcher in recent time. Baltagi (2001), in the introduction of his seminar book on panel data, list some benefits and some limitation in using panel data (Hsiao, 1985, 1986; Klevmarken, 1989; Solon, 1989). Firstly, they let controlling for individuals heterogeneity. Moreover, they are more informative data 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. In more details, it should be stressed that a panel data regression differs from a time series or cross-section regression as it consider both the time and the individuals dimension. Panel data offers two distinct advantages over pure cross-section or time series (Peracchi, 2001). First, the observed units are followed through times. This occurrence let simplify the analysis of some economic problems that would be more difficult to study using pure cross sections. Moreover, panel data make it possible to analyze behavior of the individual units, controlling for heterogeneity among them: the latter is not a property of time series too.

Thus, some problems rise using panel data. For example, design and data collection problems are more complicated then in the case of time series or cross-sectional data. Measurement errors may arise and due to distortions in inference. In many cases, the time series dimension is still too short. Probably, the main problem in using panel data remains selectivity, which may rise in different forms (self-selectivity, non-response, attrition).

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

$$y_{it} = \alpha_i + X_{it}^{'}\beta + u_{it} + \varepsilon_{it} \tag{2}$$

with i ($i = 1, ..., N$) denoting individuals, and t ($t = 1, ..., T$), denoting time periods, and $X_{it}^{'}$, the it-th observation on K explanatory variables. It should be noted that α_i is time invariant and accounts for any individual-specific effect not included in the regression equation. Two different interpretation may be given of the α_i, and two different basic model may be distinguish according this interpretations.
If the α_i are assumed to be fixed parameters to be estimated the model expressed in the previous equation take the name of fixed effect panel data model. If the α_i are assumed to be random, random effect panel data model is generated by the previous equation. Generally, 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, as our data set consists on the observation over 125 European regions, we have decided to estimate a fixed effect panel data model to check for convergence among them. Following Islam (1995), a number of research 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 which may be obtained from the application to convergence problems of panel data models instead that cross-sections is that it is not necessary to

[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)

hold constant the steady state, as it may be directly estimated by the fixed effects using least square dummy variables estimator. In the literature, there is a great evidence that estimates of the speed of convergence from panel data with fixed effects tend to be much larger than the 2 percent-per-year number estimated from cross sections (Barro and Sala-I-Martin, 1995). Some potential problems rise from the fact that in order to obtain significative results, one need to include many time series observations: in other words, the dependent variable should be the yearly (or over two years) growth rate of the per-capita GDP. This short time periods tend to capture 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:

$$aggdp_{i,t} = \alpha_i + lgdp_{i,t} + \varepsilon_{it}, \tag{3}$$

where $aggdp_{i,t}$ is the yearly growth rate of per-capita GDP, $lgdp_{i,t}$ is the log of the 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 notice that the coefficient of the growth rate variable is still significantly negative, and the hypothesis of converge among European regions is still confirmed. Thus, the value of the growth rate coefficient we have found using the fixed effect estimator is smaller than those founded using the simple β-convergence model, this indicating that the speed of convergence is lower than those usually estimated in the literature which make use of absolute convergence models.

A very interesting aspect, which remain to be investigate is the spatial analysis of the residuals obtained by the fixed effect estimation.

Figures from 7 to 10 show the quantile map constructed by dividing regions according to the value of the residuals into six groups for the years 1981, 1985, 1990, and 1995: a spatial structure is still evident.

This evidence is confirmed by the values of the Moran-I index calculated 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 Figure from 12 to 15 which report the scatter plot of the Moran calculated in 1981, 1985, 1990, and 1995, and added in the paper only to have a more graphical evidence. The same analysis conducted over the estimated α coefficients due to reject the hypothesis of spatial heteroschedasticity. In fact, the value of the Moran calculated over the sequence of the estimated α due to the acceptance of the null hypothesis of no spatial dependence.

growth-gdp	Coef.	Std.Err.	t	$P > \|t\|$
lgdp	-0.047	0.035	-13.39	0.000
cons	0.506	0.032	15.37	0.000
sigma-u	0.012			
sigma-e	0.037			
rho	0.100			
R-square:				
	within	0.099		
	between	0.039		
	overall	0.061		
Corr(u-i, Xb)	-0.569			

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

5 Spatial Panel Data Model

In traditional panel data literature, one does not usually worry about cross-section correlation. However, when the data are referred to be a cross-section of countries, regions, states or counties, these kind of aggregates are likely to exhibit cross-sectional correlation that has to be considered. 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]

Generally, this kind of data do not present the problem of selectivity, as the series belong to national account, which are not collected in very rare cases.

The aim of this section is to estimates a fixed effect panel data model extended to spatial error autocorrelation. In spatial research, cross-sectional data offers information on a number of spatial units at a given period in time, time series data are related to observation on a given spatial units, panel data put together this two characteristics and offers observation on a number of

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

Variable	Moran-I	Z-value	prob
res81	0.461	14.246	0.000
res82	0.464	13.594	0.000
res83	0.464	13.586	0.000
res84	0.476	13.941	0.000
res85	0.463	13.859	0.000
res86	0.476	13.940	0.000
res87	0.457	13.387	0.000
res88	0.452	13.232	0.000
res89	−0.443	12.983	0.000
res90	0.422	12.855	0.000
res91	0.445	13.042	0.000
res92	0.448	13.121	0.000
res93	0.415	12.187	0.000
res94	0.429	12.586	0.000
res95	0.422	12.736	0.000
fixed effects	−0.007	0.876	0.380

Table 4: Moran-I calculated over the residuals of the fixed effect panel data model estimation for each time period (1981-1995). Variable res are the residuals, fixed effect are the estimated α coefficients.

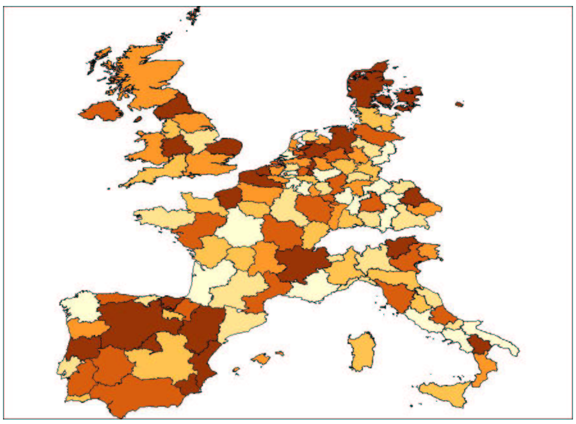

Figure 6: Quantile map constructed by dividing groups according to the estimated value of the coefficient α denoting the individual-specific effect.

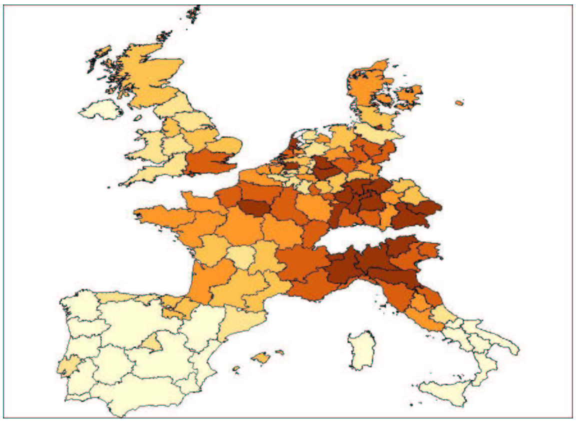

Figure 7: Quantile map constructed by dividing groups according to the value of the residuals calculated for 1981.

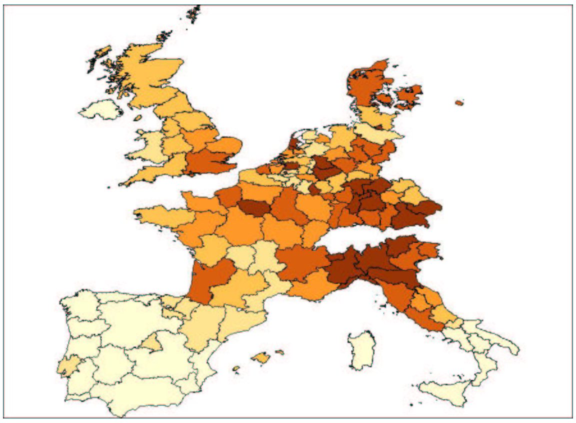

Figure 8: Quantile map constructed by dividing groups according to the value of the residuals calculated for 1985

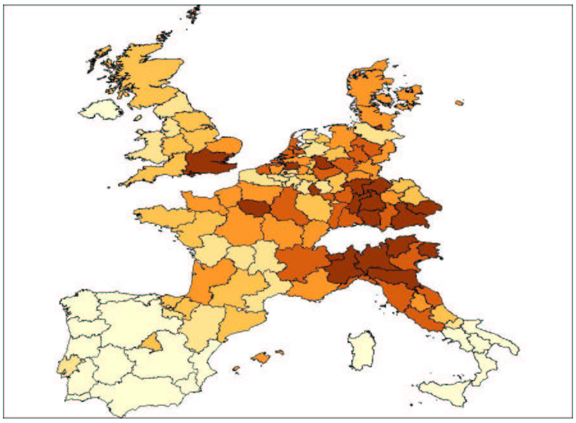

Figure 9: Quantile map constructed by dividing groups according to the value of the residuals calculated for 1990

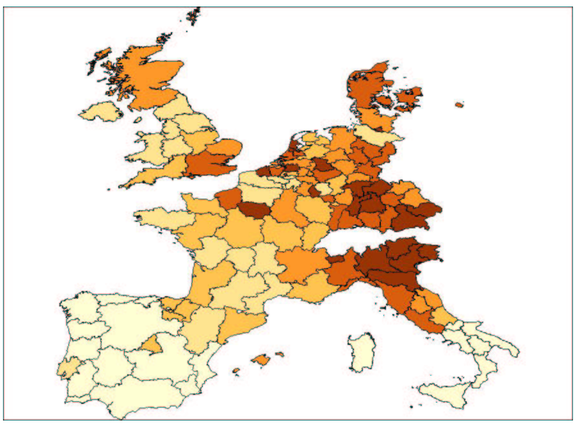

Figure 10: Quantile map constructed by dividing groups according to the value of the residuals calculated for 1995

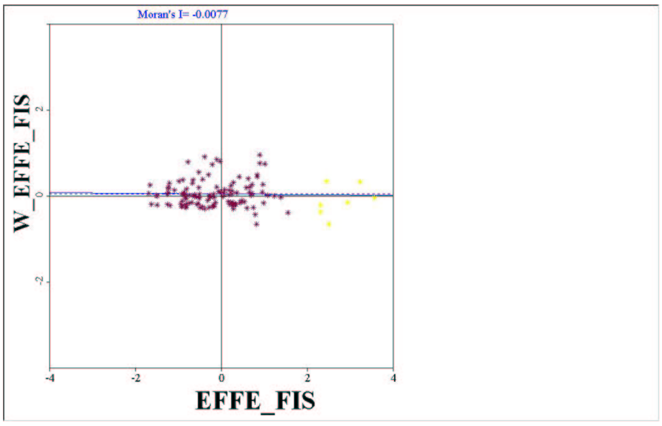

Figure 11: Moran scatter plot of the estimated values of the coefficient α denoting the region specific effect in the fixed effect estimates of the convergence among the European regions over the period 1980-1995.

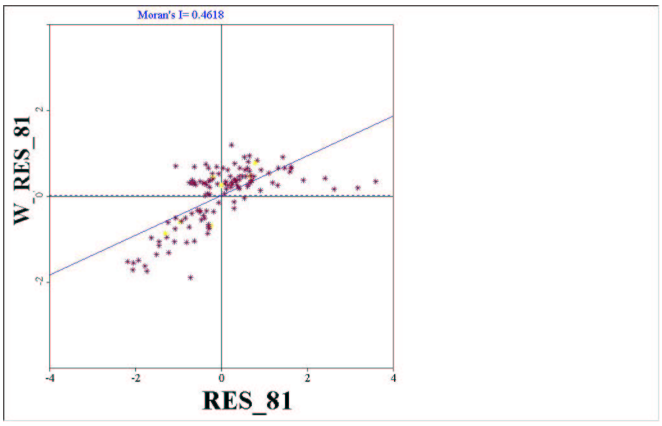

Figure 12: Moran scatter plot of the residuals of the fixed effect estimates, over the year 1981

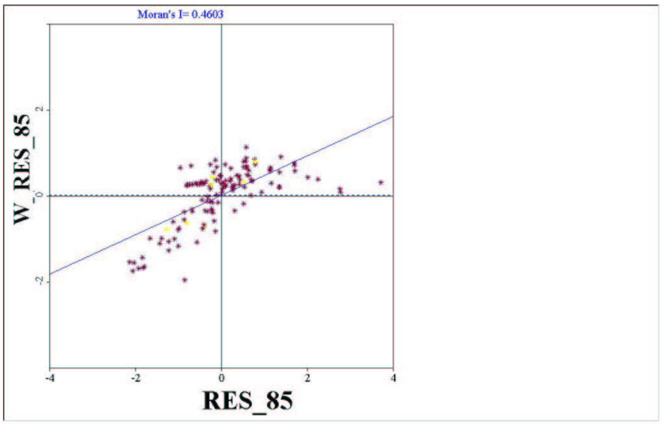

Figure 13: Moran scatter plot of the residuals of the fixed effect estimates, over the year 1985

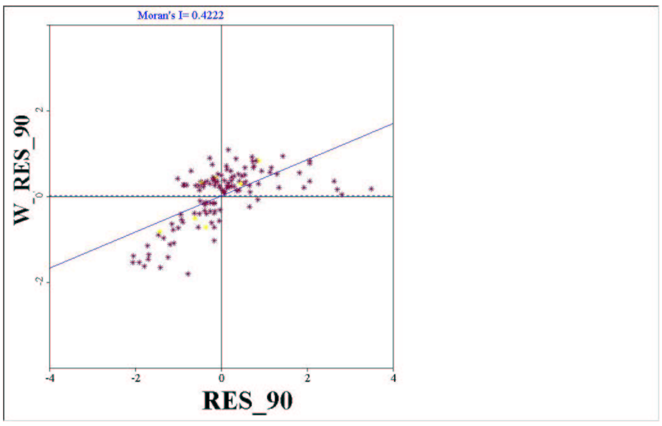

Figure 14: Moran scatter plot of the residuals of the fixed effect estimates, over the year 1990

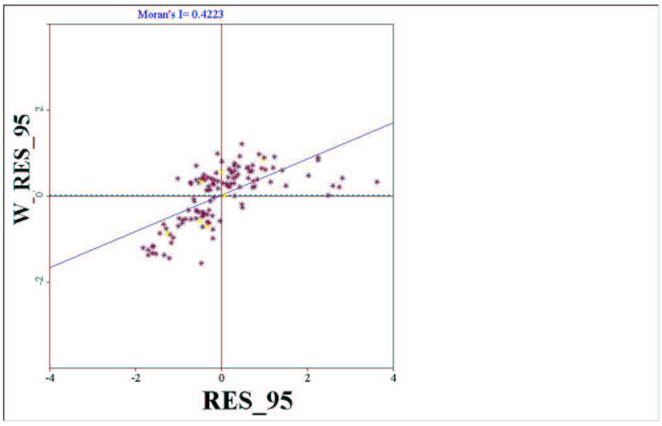

Figure 15: Moran scatter plot of the residuals of the fixed effect estimates, over the year 1995

spatial units over a precise time period. As we said in the previous section, the interest on the estimation of panel data models have been growing in recent time, thus, two problems may arise when panel data models have a locational component. The first problem is spatial heterogeneity, which can be defined as parameters that may not be homogeneous throughout the data set, but vary with location. Secondly, spatial dependence may exist between the observations at each point in time. In a recent paper Elhorst (2003)provides a survey of the specification and estimation of spatial panel data models including spatial error autocorrelation, or by extending the specification with a spatially lagged dependent variable. In particular, he starts from the classical literature on panel data, and adapt what can be learned from the econometric literature by discussing four widely used models: the spatial fixed effect model, the spatial random effect model, and the fixed and random coefficient spatial error models. He presents the relative likelihood for each model, discuss the asymptotic properties, and the estimation procedure. Moreover, the potentially problems which may rise from the spatial version of this four models are discussed in detail. In the present work, we consider only the specification considering fixed effect panel data model extended to spatial error correlation. It should be stressed that the application of such a model in the estimation of regional convergence, appear the most reasonable solution between all the possible specifications. Moreover, the present paper is the first application of spatial fixed effect model to the problem of convergence among regions, and this analysis represent the most innovative aspect of our work. The spatial econometrics literature has shown that OLS estimation in models which take in account of spatial effects is inappropriate. More in detail, it should be added that the OLS estimator of the parameter of interest, while unbiased, became inefficient in the case of spatial error autocorrelation, and that in the case of a spatially lagged dependent variable, the estimates not only lose their property of unbiadness, but also became inconsistent. As everybody knows, the latter is one of the property which should be necessary required to an estimator. The most commonly suggested method to overcome this problems proposed in the spatial econometrics literature is to estimate such models via maximum likelihood (Anselin, 1988; Anselin and Hudak, 1992). In his 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:

$$Y_t = X_t\beta + \mu + \varphi_t, \text{with} \varphi_t = \delta W \varphi_t + \varepsilon_t. \quad (4)$$

In our case, the Y_t is the annual growth rate of the per-capita GDP of the European regions, the X_t is the log of the per-capita GDP, μ_i denotes the vector of random country effect which are assumed to be independent, with the same distribution, with zero mean and finite variance; δ is the scalar spatial autoregressive coefficient (which is less then one).W is the classical spatial weights matrix discussed in section 2, whose diagonal elements are zero; and ε_t are assumed to be independent, identical distributed with zero mean and finite variance, and also independent of μ_i. 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).

In Table 5, main result of the estimation of the model we have just described are reported. The main advantage deriving from this kind of estimation is in the fact that one can take in account the spatial dependence present in the data set and to control for it in the estimation, obtaining a more confidence estimation of the coefficient of the growth GDP variable. In fact, the coefficient of interest almost show the presence of convergence to the steady state (as it is significantly negative), but it take a value smaller than the one obtained using other estimation techniques. It may be concluded that, to take in account for spatial dependence due to have a growth rate of convergence smaller than those obtained in the main literature. This relatively simple model we have estimated in the present section, is only the first step of a possible research path in the application of spatial panel data models to problem of convergence among spatial units.

Fixed effect with spatial autocorrelation			
Dependent variable			growth GDP
R-squared			0.0800
Adjusted R-squared			0.0863
Sigma squared			0.0013
Log-likelihood			2664.7055
Number of observations			1875
Number of variables			1
Adjusted R-squared			0.0863
variable	Coefficient	Asymptotic t-stat	z-probability
growth GDP	-0.0315	-18.187	0.000
δ	0.039	1.562	0.118

Table 5: Fixed effect with spatial autocorrelation.

There is not great evidence that the fixed effect model extended to spatial error autocorrelation correct the residuals structure of spatial dependence at all. From Table 6 it may be concluded that the Moran-I index remain significative for almost all years in the data set. Thus, the correction, even not exhaustive, improve the estimation, as the value of the index decrease. From the graphical analysis, the effect of the correction seems to be more evident.

6 Conclusions

In the present paper we have considered the problem of converge among European regions. Many 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. From one side, cross-section method do not consider heterogeneity at all, from the other, fixed effect approach make it depend only by the different intercept for each region. In other terms, all the differences in growth rates depends only by the different starting point for the

Variable	Moran-I	Z-value	prob
respa81	0.021	0.859	0.390
respa82	0.234	6.971	0.000
respa83	0.389	11.413	0.000
respa84	0.143	4.355	0.000
respa85	0.042	1.462	0.143
respa86	0.297	8.786	0.000
respa87	0.073	2.351	0.018
respa88	0.108	3.359	0.000
respa89	0.098	3.049	0.002
respa90	0.155	4.688	0.000
respa91	0.530	15.484	0.000
respa92	0.356	10.476	0.000
respa93	0.434	12.724	0.000
respa94	0.361	10.627	0.000
respa95	0.389	11.427	0.000

Table 6: Moran-I calculated over the residuals of the spatial fixed effect panel data model estimation for each time period (1981-1995). Variables respa are the residuals.

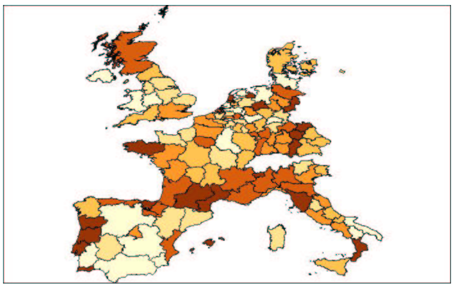

Figure 16: Quantile map of the value of the residuals of the spatial panel data model extended to spatial error autocorrelation, over the year 1981

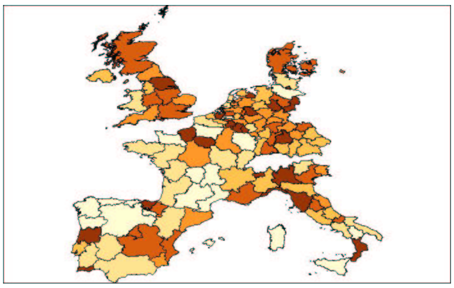

Figure 17: Quantile map of the value of the residuals of the spatial panel data model extended to spatial error autocorrelation, over the year 1985

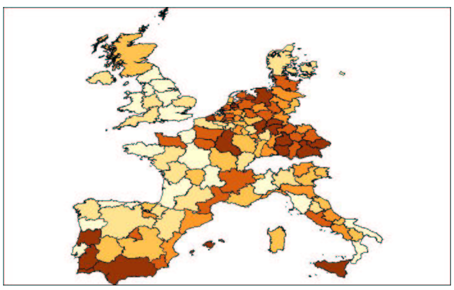

Figure 18: Quantile map of the value of the residuals of the spatial panel data model extended to spatial error autocorrelation, over the year 1990

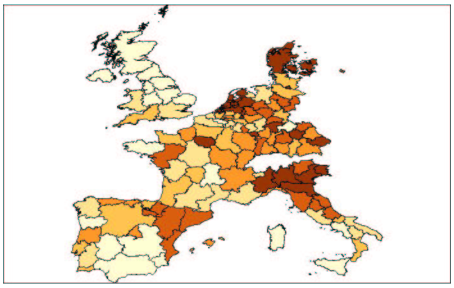

Figure 19: Quantile map of the value of the residuals of the spatial panel data model extended to spatial error autocorrelation, over the year 1995

spatial unit considered. The methodology used in the present paper allowed 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 have estimated. A spatial analysis of the intercept terms and of the residuals have been, in fact, conducted in this work. The main result we have obtained consist in the fact that taking in account of the spatial dependence among the spatial units, considerably improve the estimated values of the speed of convergence among the European regions.

The present paper may be considered as the point of departure for many future researches. Firstly, the fixed effect estimated in this work would be extended to a spatially lagged dependent variable. Then, a random effect spatial panel data model could be used to estimates the same problem, and very interesting will be to consider the framework of dynamic panel data models extended to spatial error autocorrelation or to a spatially lagged dependent variable.

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