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CONVERGENCE IN PER-CAPITA GDP ACROSS EU-NUTS2 REGIONS USING PANEL DATA MODELS EXTENDED TO SPATIAL AUTOCORRELATION EFFECTS

Giuseppe Arbia and Gianfranco Piras

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Convergence in per-capita GDP across EU-NUTS2 regions using panel data models extended to spatial autocorrelation effects.*

Giuseppe Arbia † Gianfranco Piras ‡

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†University G.D'Annunzio, Faculty of Economics, viale Pindaro 42, I-65127 Pescara, Italy Tel: +39 085 4537 533 e-mail: arbia@unich.it

‡Tor Vergata University, Faculty of Economics, via Columbia 2, I-00133 Rome, Italy Tel: +39 06 7259 5625 e-mail:gianfrancopiras@gmail.com

ABSTRACT

This paper studies the long-run convergence of per-capita GDP across European regions. Most of the empirical works in this area are based on either cross-sectional or a-spatial panel data fixed-effects estimates. Here, we propose the use of panel data econometrics models that incorporate an explicit consideration of spatial dependence effects (Anselin, 1988; Elhorst, 2001; 2003). This allows us to extend the traditional convergence models to include a rigorous treatment of the regional spillovers and to obtain more reliable estimates of the parameters.

Two models are considered in particular based on the introduction of a spatial lag among the esplicatives ("spatial lag model") and imposing a spatial autoregressive structure to the stochastic component ("spatial error model"). We apply such a modelling framework to the long-run convergence of per-capita GDP of 125 EU-NUTS2 regions observed yearly in the period 1977-2002. The paper also provides a comparative study between the results obtained with the two proposed models and those obtained on the same set of data with the standard β-regression, with the standard β-regression augmented with a spatial component, and with the standard fixed-effect panel data model.

Key Words: Regional convergence; Regional spill-over; Spatial dependence modelling; Spatial panel data models.

JEL: C21, C23, R11.

1 Introduction

The most popular approaches to study the regional convergence of per-capita income are all stemming from the neo-classical Solow-Swan (Solow, 1956; Swan, 1956) model of long run growth and from the framework developed by Mankiw et al. (1992) and Barro and Sala-i-Martin (1992; 1995). This framework led to the now celebrated β-convergence approach, an empirically testable model that seeks to identify convergence by verifying the inverse relationship between the growth in per-capita income at a certain moment of time and the income level at the beginning of the time period. The β-convergence model, therefore, is not a dynamic model strictu sensu, but rather a model based on the comparison between two time periods. This is a major drawback under both the theoretical and the applied point of view. In fact an economist is usually interested in studying the full dynamics of the convergence process, that is the path followed by per-capita incomes in the various regions in the whole period considered. Indeed very different situations may lead to the same results in terms of the β-convergence and this equifinality of different models may cause problems in the phase of result interpretation and its use in political decisions and targeting resources (see Arbia, 2004).

In the present paper we propose the estimation of convergence in per-capita GDP across European regions by making use of spatial panel data models both including a spatially lagged dependent variable and a spatial error specification (Anselin, 1988; Elhorst, 2001; 2003; 2004). The main idea developed is the advantage produced by the consideration of spatial dependence within a fixed-effect approach. Indeed, the control for fixed-effects allows us to be more confident that spatial dependence may capture only regional interaction effects while heterogeneity and the effects of omitted variables are not captured in those models that do not take spatial dependence into account. The innovative aspect concern the fact that spatial dependence is not always considered in a panel data context (exception are Elhorst 2001; 2003). We introduce the spatial effects allowing for spatial autocorrelation by including in the model a spatial lag of the dependent variable and by modelling the error term with a particular spatial structure.

The empirical part of the paper concerns the estimation of the long-run convergence of per capita income in Europe (1977-2002) based on a level of disaggregation (the NUTS2 EU regions) which is fine enough to allow the spatial effects (regional spill-overs) to be properly modelled.

The remaining part of the present paper is organized as follows: Section 2 is devoted to a detailed description of the data set, in Section 3 an unconditional growth model is estimated and residuals diagnostic are discussed. Section 4 is devoted to the extension of the simple cross-sectional model to the case of spatial autocorrelation and results of the classical SAR and SER models estimation are presented. A simple fixed-effect model is estimated in Section 5, and the correction to take in account spatial dependence in panel data model is introduced in Section 6. Conclusions follow and indication for further researches are reported.

2 Preliminary data analysis

Spatial data availability is one of the greater problem in the European context, although many progresses have been made in recent time by the European Statistical Institute. Thus, data availability remains scarce and in many cases it is very difficult to have in hand harmonized data sets allowing consistent regional comparisons.

In the present work, we use data on the per capita GDP (millions of euro 1995) in logarithms drawn from the Cambridge Econometrics European Regional database, that it itself the result of extensive processing of the Eurostat REGIO database. Data drawn from the REGIO present many problems for the users: the quality of the data is always variable across countries and across time. Moreover, a continuous series at the NUTS2 level of spatial aggregation is often not available and, further, they are expressed only in current prices. In the Cambridge Econometrics dataset some principles have been followed to fill gaps and to extend the series to more recent years using national data when these are available[1]. The length of the time series dimension is very important in evaluating growth dynamics, since convergence is a long-run process, and the use of short series may produce biased results. For this, and for other reasons we have decided to make use of data drawn from the Cambridge Econometrics European Regional database. We include 125 regions[2] of 10 European Countries: Belgium, Denmark, France, Germany, Luxembourg, Italy, Netherlands, Portugal, Spain and United Kingdom. Our sample extends from 1977

[1] See the European Regional Prospect developed by Cambridge Econometrics for greater details on data treatment.

[2] The complete list of the region considered is reported in Appendix A.

to 2002[3].

We conducted a preliminarily test for global spatial autocorrelation in per-capita GDP in logarithms by calculatating the Moran-I index for each year and its significance level (the value of the standard normal distribution and the relative p-value); the results are reported in Table 1[4]. For the calculation of the index, as in all the following elaborations performed in the present work, we make use of a spatial weight matrix based on the contiguity criterion (the element of the matrix is equal to one if the two regions are neighbouring, and zero otherwise). The results show that the Moran-I index is fairly stable across time. It always takes positive values during the entire sample period (1977-2002). Values of I larger (or smaller) than the expected values indicate positive (negative) spatial autocorrelation. Inference is based on the permutational approach[5] (10000 permutations). As shown in the fourth column of table 1, in our sample per-capita income displays always significant positive spatial autocorrelation, the only exception being 1986 and 1998. This result suggests that the null hypothesis of no spatial autocorrelation can be rejected and that the estimation procedures have to be corrected to take into account the lack of independence. The result is robust to different choices of the spatial weight matrix. In fact, we calculated the Moran's I using different specification of the weights [6] obtaining very similar results, which, are not reported in the present paper for the sake of succintness.

3 The benchmarking Unconditional β-convergence model

Two concepts of unconditional convergence appear in the literature of economic growth across countries or regions. The first, proposes that poor economies tend to grow faster than rich ones, so that the poorer regions tend to catch up the rich ones in terms of the level of per-capita income. Such a situation is referred to as β-convergence models. The second concept refers to the fact

[3] The great part of the works in the literature use data drawn from the REGIO dataset in empirical studies: Quah, 1996; Baumont, Ertur and LeGallo, 2002; Arbia and Paelink, 2003; 2004, among others.

[4] The Moran-I index is written in the following matrix form: $I_t(k) = \frac{n}{S_0}(z_t' W z_t)(z_t' z_t)^{-1}$, 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).

[5] See Cliff and Ord, 1981

[6] In particular, we have considered two more spatial weight matrices: inverse square distance matrix, and a binary spatial weight matrix with a simple distance-based critical cut-off.

YEAR	Moran-I	Z-value	prob
1978	0.565	9.064	0.000
1979	0.502	8.069	0.000
1980	0.281	4.567	0.000
1981	0.160	2.657	0.007
1982	0.317	5.146	0.000
1983	0.172	2.855	0.004
1984	0.155	2.579	0.009
1985	0.148	2.478	0.013
1986	0.023	0.502	0.615
1987	0.259	4.225	0.000
1988	0.194	3.202	0.001
1989	0.207	3.406	0.000
1990	0.393	6.342	0.000
1991	0.797	12.715	0.000
1992	0.195	3.212	0.001
1993	0.474	7.617	0.000
1994	0.395	6.379	0.000
1995	0.273	4.453	0.000
1996	0.316	5.120	0.000
1997	0.234	3.825	0.000
1998	0.073	1.283	0.199
1999	0.185	3.061	0.002
2000	0.203	3.334	0.000
2001	0.437	7.045	0.000
2002	0.337	5.461	0.000

Table 1: Moran's I computed in the period 1978-2002 for the annual growth rate of per-capita income.

that, when poor regions grow faster than rich ones, we observe a reduction in the dispersion of per-capita income across regions. This second instance is referred to a σ-convergence: generally, convergence of the first type tends to generate convergence of the second (see Durlauf and Quah, 1999 for a review). In the literature, a second distinction is made between conditional and absolute convergence. 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 own steady state. Absolute convergence is the event for which poor regions tend to grow faster than rich ones. For a detailed discussion on these two definition see, among others, Barro and Sala-i-Martin (1995).

The β-convergence approach moves from the neoclassical Solow-Swan exogenous growth model (Solow, 1956; Swan, 1956). The basic equation we use in the present paper can be expressed in the following way:

$$\ln\left[\frac{y_{T,i} - y_{0,i}}{y_{0,i}}\right] = \alpha - (1 - e^{-\lambda T}) \ln y_{0,i} + \varepsilon_i \tag{1}$$

where y_T is the value of per capita income at the end of the period considered (2002 in our model), y_0 is the value in the first period (1977), ε_i is the error term, and α and λ parameters to be evaluated. In particular, λ represents the "speed of convergence", that measures how fast economies converge towards the steady state. The assumption of the probability model implicitly made in this context is that the ε_i's are normally distributed $(0, \sigma^2)$ independently of $\ln y_{0,i}$. In addition, concerning the sampling model, it is assumed that $\{\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_n\}$ are independent observations of the probability model. Equation 1 is usually directly estimated through non-linear least-squares (Barro and Sala-i-Martin, 1995) or by re-parameterizing the statistical model setting $\beta = (1 - e^{-\lambda T})$ and estimating β by ordinary least squares.

If the value of the β coefficient is significantly less than zero, absolute convergence is said to be present. In this case, we can conclude that not only do poor regions grow faster than rich ones, but also that they all converge to the same level of per capita income. After estimating this cross-sectional equation, it is possible to calculate both the speed of convergence[7] and half the time necessary to reach its own steady state, known in literature under the name of "half-

[7]That is the inverse transformation $\lambda = -\ln(1 + T\beta)/T$; while the half-life may be calculated as: $\tau = -\ln(2)/\ln(1 + \beta)$

life"[8]. The hypothesis at the basis of the unconditional β-convergence is that all economies are structurally similar (and therefore they can be characterized by the same steady state) and that all the spatial units may differ only for their initial conditions. The model expressed by Equation (1) has been subject to many empirical estimations in the literature based on different regions, different time periods and leading to different conclusions (see e.g. Le Gallo *et al.*, 2003). Here we estimate the model only because it represents the benchmark of other more sophisticated models that will be presented later in the paper.

The main results obtained estimating Equation (1) in our sample are reported in Table2. The dependent variable of this specification is the growth rate of per capita income calculated over the (25 years long) entire period. Our results are in line with previous findings on the development of European regions (e.g. Le Gallo *et al.*, 2003; Arbia and Basile, 2003). The significantly negative (-0.077) value of the parameter, confirms the presence of unconditional convergence.

Table 2 also reports some diagnostics to identify misspecifications in the OLS cross-sectional model. The value of the Jarque-Bera test is strongly significant, revealing that OLS errors are not normally distributed. Consequently, we cannot safely interpret the results of the various other misspecification tests (heteroskedasticity and spatial dependence tests) that depend on the assumption of normality[9]. The value of the Koenker-Bassett statistics indicates the possibility of problems due to the presence of heteroscedasticity. This result seems to be confirmed by the robust White statistics. The value of the log likelihood and the value of the Schwartz and AIC criterion are also reported. In order to test for the presence of spatial dependence, three different tests are included: the Moran's I and two Lagrange Multipliers tests (Anselin, 1988). The first test is very powerful against spatial dependence both in the form of error autocorrelation and spatial lag, but it does not discriminate between the two forms of misspecifications in that it does not have an explicit alternative hypothesis (Anselin and Rey, 1991). Both LM (error autocorrelation) and LM (spatial lag) are significant, indicating the presence of spatial dependence, with an edge towards the spatial lag specification. In conclusion, these results suggest that the OLS estimates may suffer from a misspecification due to omitted spatial dependence. Thus, alternative specifications will be used to account for spatial dependence.

[8] The half-life may be calculated as: $\tau = -\ln(2)/\ln(1+\beta)$

[9] Heteroskedasticity tests have been carried out for the case of random coefficient variation (the squares of the explanatory variables were used in the specification of the error variance to test for additive heteroskedasticity).

OLS ESTIMATION OF THE UNCONDITIONAL MODEL	
Constant	0.364
	(0.304)
log of income	-0.077
	(0.032)
Goodness of fit	
Adjusted R^2	0.028
Log Likelihood	-54.677
Schwartz Criterion	119.011
AIC	113.354
observations	125
Regression Diagnostic	
Jarque-Bera Normality test	16.709
	(0.000)
Koenker-Bassett heteroskedasticity test	4.714
	(0.029)
White robust test of heteroskedasticity	8.019
	(0.018)
Moran's I spatial dependence test	1.891
	(0.058)
Lagrange multiplier test on error autocorrelation	2.888
	(0.089)
Lagrange multiplier test on spatial lag	3.889
	(0.048)

Table 2: **Convergence of per capita income in the 125 European regions (1977-2002) OLS Estimates of the Unconditional β-convergence model - Equation (1) -** *(numbers into brackets refer to the p-values)*

4 Introducing Spatial dependence in the cross-sectional model

The neoclassical growth model discussed above has been developed starting from the hypothesis that the economies are fundamentally closed. However, this hypothesis is particularly strong, considering the process of unification started some years ago and is continuing in Europe. In particular, barriers to trade, to individual and factor flows have been reduced. To understand the implications for convergence of the introduction of the openness hypothesis into the theoretical framework, we must consider the role of factor mobility, trade relations and technological diffusion (or knowledge spill-overs). Factor mobility implies that labour and capital can move freely in response to differentials in remuneration rates, which in turn depends on the relative factor abundance. Thus, capital will tend to flow from the regions with a higher capital-labour ratio to the regions with a lower capital-labour ratio, while labour will tend to flow in the opposite direction. Moreover, the regions with lower capital-labour ratios will show higher per capita growth rates. Actually, if the adjustment process in either capital or labour is instantaneous, the speed of convergence would be infinite. By introducing credit market imperfections, finite lifetimes and adjustment costs for migration and investments in the model, the speed of convergence to the steady-state remains higher than in the closed economy case, but with a finite value (Barro and Sala-i-Martin, 1995). The same result can be obtained by introducing into the neoclassical growth model the hypothesis of free trade relations rather than factor mobility; convergence in interregional per-capita income will then be higher than in the closed-economy version.

Another possibility for poor economies to converge towards richer ones is through technological diffusion or knowledge spill-over. In the presence of disparities in regional levels of technology, interregional trade can promote technological diffusion when progress is incorporated in traded goods (Grossman and Helpman, 1991; Barro and Sala-i-Martin, 1997). A broader interpretation of knowledge spill-over effects refers to positive knowledge external effects produced by firms at a particular location and affecting the production processes of firms located elsewhere. However, when we investigate the regional convergence problem and we study the effects of geographical spill-overs on growth, we must also distinguish between local and global geographic spill-overs. With local spill-overs, production processes of firms located in one region only benefit from the knowledge accumulation in that region. In this case, regional divergence is likely to be observed. By global geographical spill-overs, we mean that knowledge accumulation in one region improves the productivity of all firms wherever they are located. Thus, a global geographical spill-over effect may contribute to regional convergence (Martin and Ottaviano, 1999, 2001; Kubo, 1995). In a nutshell, the speed of convergence to the steady-state predicted in the open-economy version of the neoclassical growth model as well as in the technological diffusion models is faster than in the closed-economy version of the neoclassical growth model.

A direct way to empirically test the prediction of a higher speed of convergence once openness is allowed, would consist of including interregional flows of labour, capital and technology in the growth regression model. It is quite clear, however, that such a direct approach is limited by data availability, especially with regards to capital and technology flows. Some attempts have been made to test the role of migration flows on convergence, but the results of these studies suggest that migration plays a small role in the explanation of convergence (Barro and Sala-i-Martin, 1995).

The effect of convergence is clearly more evident at the regional level than at the country level. Income disparities seem to be persistent despite the European economic integration process and the higher growth rates of some poor economies. This evidence clearly suggests the existence of different *clubs* of regions as highlighted in previous studies at a regional level (Durlauf and Johnson, 1995; Quah, 1997; and Baumont et al. 2004). Moreover, the evidence of strong spatial polarization patterns between high-income regions from one side (the central regions of EU), and low-income regions from the other (the peripherical regions), is always present in empirical studies. Finally, the influence of surrounding economies can be better observed at high levels of spatial disaggregation. A poor region surrounded by richer regions has more probability to reach a higher state of economic development and, consequently, higher per-capita income. The same evidence at a country level is probably not equally likely due to the effects of other influencing variables. All these reasons led us to analyze the convergence process by focusing our attention at the regional level.

In this section, the influence of spatial effects on regional growth in a cross-sectional framework are considered. Following Anselin (1988), spatial effects are introduced in the analysis of the convergence process among European regions using a cross-sectional approach. In fact, spatial dependence models represent a viable alternative and an indirect way to control for the effects of interregional flows (or spatial interaction effects) on growth and convergence. Initially, spatial dependence can be introduced into the model via the so-called “spatial autoregressive model" or SAR (Anselin and Bera, 1998), where a spatial lag of the dependent variable is included on the right hand side of the statistical model. If W is a row-standardized matrix of spatial weights describing the structure and intensity of spatial effects, Equation (1) can be re-specified as

$$\ln\left[\frac{y_{T,i}-y_{0,i}}{y_{0,i}}\right]=\alpha+\beta\ln y_{0,i}+\rho\sum_{j=1}^{n}w_{i,j}\ln\left[\frac{y_{T,j}-y_{0,j}}{y_{0,j}}\right]+\varepsilon_i \tag{2}$$

where $w_{i,j}\in W$, ρ is the parameter of the spatially lagged dependent variable that captures the spatial interaction effect indicating the degree to which the growth rate of per-capita GDP in one region is affected by the growth rates of its neighbouring regions, after conditioning on the effect of $\ln y_{0,i}$. The error term is again assumed normally distributed and independently of $\ln y_{0,i}$ and of $\left\{\sum_{j=1}^{n}w_{i,j}\ln\left[\frac{y_{T,j}-y_{0,j}}{y_{0,j}}\right]\right\}$, under the assumption that all spatial dependence effects are captured by the lagged term. An alternative way to incorporate the spatial effects is via the “spatial error model" or SEM (Anselin and Bera, 1998). This strategy consists of leaving unchanged the systematic component and model the error term in Equation (1) as a random field, e.g., assuming that it follows an autoregressive structure:

$$\varepsilon_i=\delta\sum_{j=1}^{n}w_{i,j}\varepsilon_j+\eta_i \tag{3}$$

In Equation (3), the error term η_i is assumed to be randomly drawn from a normal distribution, with zero mean and constant variance (σ_η^2), independently of $\ln y_{0,i}$. Some empirical studies have previously used the spatial econometric framework for testing regional convergence. The most comprehensive studies are those of Rey and Montouri (1999) and Le Gallo, Ertur and Baoumont (2003). Neither approach properly specifies a conditional growth model. Indeed, all these studies start from the minimal growth regression model specification, which includes only the initial level of per-capita income (the so-called, absolute convergence model) and then show that the unconditional convergence model is mis-specified due to spatially auto-correlated errors. However, the use of the minimal specification of the growth model might imply that at least part of the estimated spatial dependence actually absorbs the effect of the omitted explanatory variables rather than the effect of true spatial interactions.

Tables (3) and (4) display the results of maximum likelihood estimates of the spatial lag and spatial error models. The parameters associated with the spatial error and the spatial lag terms

Spatial Lag Model	
Constant	0.395
	(0.249)
log of income	-0.071
	(0.041)
Spatially lagged growth rate	0.232
	(0.037)
Goodness of fit	
Adjusted R^2	0.080
Log Likelihood	-52.748
Schwartz Criterion	119.983
AIC	111.498
observations	125
Regression Diagnostic	
Spatial Breusch-Pagan heteroskedasticity test	11.012
	(0.000)
Likelihood ratio test for spatial dependence	3.856
	(0.049)
Lagrange Multiplier test (spatial error model as an alternative hypothesis)	0.477
	(0.489)

Table 3: **Convergence of per capita income in the 125 European regions (1977-2002) Maximum Likelihood Estimates of the Spatial Lag Model - Equation (2) -** *(numbers into brackets refer to the p-values)*

Spatial Error Model	
Constant	0.292
	(0.410)
log of income	-0.069
	(0.052)
Error component spatial correlation	0.210
	(0.074)
Goodness of fit	
Adjusted R^2	0.036
Log Likelihood	-53.253
Schwartz Criterion	116.164
AIC	110.508
observations	125
Regression Diagnostic	
Spatial Breusch-Pagan heteroskedasticity test	11.622
	(0.000)
Likelihood ratio test for spatial dependence	2.846
	(0.091)
Lagrange Multiplier test (spatial lag model as an alternative hypothesis)	1.180
	(0.277)

Table 4: **Convergence of per capita income in the 125 European regions (1977-2002) Maximum Likelihood Estimates of the Spatial Error Model - Equation(3) -** *(numbers into brackets refer to the p-values)*

are always highly significant. The fit of the spatial lag model (based on the values of the Akaike and Schwartz criteria) is always higher than that of both the unconditional and the spatial lag models, even if the difference with respect to the value obtained with the OLS estimators of the unconditional model is not particularly significant.

Moreover, the coefficient of the initial level of per-capita income decreases in absolute value both in the spatial lag model and in the spatial error model specification with respect to the unconditional model, and the speed of convergence, though not particularly fast, decreases if the models account for spatial dependence. A decrease in the parameter of the initial condition, due to the inclusion of the spatial lag term in the model, indirectly confirms the positive effect of factor mobility, trade relations and knowledge spill-over on regional convergence. Furthermore, this result confirms the evidence that the convergence process is very weak. It is also remarkable that a significant positive spatial autocorrelation of the errors was found although the effect is not particularly strong with the value of λ being 0.210. In both cases, the value of the spatial version of the Breusch-Pagan test is strongly significant, suggesting the presence of heteroskedasticity.

The (absolute) decrease of the coefficient of the initial per capita income observed in the spatial models can also be interpreted under an econometric point of view. Indeed the correction introduced for spatial dependence tends to capture the effect of omitted variables which have a positive effect on growth. In summary, we could say that the above results are still characterized by a mispecification and thus are difficult to interpret in support of the thesis that spatial dependence correction is an appropriate way to capture the effects of openness on regional convergence. This point suggests the necessity to proceed to a further improvement to overcome such a drawback. In this paper we propose a new specification of the growth regression model based on the simultaneous modelling of spatial dependence and fixed-effects. The description of panel data fixed-effects spatial autocovariance models and the empirical results obtained using this specification are discussed in the next two sections.

5 The Fixed-effect panel data model

A panel, or longitudinal data set, consists of a sequence of observations, repeated through time, on a set of statistical units (individuals, firms, countries, etc.). Baltagi (2001), in the introduction of his book on panel data, lists some of the benefits and some of the limitations of using panel data (Hsiao, 1986; Klevmarken, 1989; Solon, 1989). Panel data approaches allow for controlling for individuals' heterogeneity, they are more informative with respect to purely time series or pure cross-sectional data, they present more variability, less collinearity among the variables, more degrees of freedom and more efficiency. In more detail, it should be stressed that a panel data regression differs from a time series or a cross-section regression because it considers both the time and the individuals dimension. Panel data offer two distinct advantages over pure cross-section or time series (Peracchi, 2001). First of all, the observed units are traced over time. This characteristic simplifies the analysis of some economic problems that would be more difficult to study using pure cross sectional approaches. Moreover, panel data make it possible to analyze the behavior of the individual units, controlling for heterogeneity among them. Indeed, some new problem arises when using panel data. The design and data collection phases are more complicated than in the case of time series or cross-sectional data, and measurement errors may arise and lead to distortions in inference. In many cases, the time series dimension is too short to properly account for dynamics. Probably, the main problem in using panel data is represented by the selectivity of the sample that may rise in the different forms of self-selectivity, non-response, attrition and new entries. In the case of macro data, however, this last problem is not particularly relevant.

One of the main advantages of the panel data approach to convergence is that it can be helpful to correct the bias generated by omitted variables and heterogeneity in the classical cross-sectional regression (Islam, 2003). Panel data, in fact, allow for technological differences across regions, or at least the unobservable and unmeasurable part of these differences, by modelling the regional specific effect. More formally, the panel version of the growth equation can be expressed in the following way:

$$\ln\left[\frac{y_{t+k,i} - y_{t,i}}{y_{t,i}}\right] = \alpha_i + \beta \ln y_{t,i} + \varepsilon_{t,i} \tag{4}$$

with i ($i = 1, ..., N$) denoting regions, and t ($t = 1, ..., T$), denoting time periods. The dependent variable $\ln\left[\frac{y_{t+k,i}-y_{t,i}}{y_{t,i}}\right]$ is the annual growth rate of the per capita income and $\ln y_{t,i}$ is the value of the per capita income at time t; α_i's and β are parameters to be estimated. It should be noted that α_i are time invariant and account for any individual-specific effect not included in the regression equation.

Two different interpretations may be given of the α_i, and two different basic models may be distinguished according these interpretations. If the α_i are assumed to be fixed parameters, the model expressed in the previous Equation (4) takes the form of "fixed-effect panel data model". If the α_i are assumed to be stochastic, a "random-effect panel data model" is generated by the previous equation. Generally speaking, fixed-effect models are particularly indicated when the regression analysis is limited to a precise set of individuals (firms or regions), whereas, the random effect option is more appropriate if we are drawing a certain number of individuals randomly from a larger population of reference [10]. For this reason, as our data set consists of the observations of 125 European regions, we use a fixed-effect panel data model to check for convergence. Following Islam (1995), a number of papers have been produced to estimate the speed of convergence among regions using panel data sets and various variants of the basic fixed-effect model (e.g. Canova and Marcet, 1995; Durlauf and Quah, 1999). In the main literature, there is a significant 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 problem arises from the fact that in order to obtain significant results, one needs 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 period tend to capture short-term adjustment towards the trend rather than long-term convergence. Our general objective is to prove that previous studies at the regional level for EU, carried out simply using OLS estimates, are biased because they neglect both the fixed and the spatial effects. On the other hand, studies using panel data are biased because no spatial autocorrelation effects are considered.

Thus, the interpretation of the estimated coefficients obtained using panel data models is very different from the cross-sectional case and closer to the idea of conditional convergence. In fact, convergence in this case is to a region-specific steady state, and not to a general one.

Table (5) reports the results of the estimation of a fixed-effect panel data model based on our 125 EU NUTS2 regions. The dependent variable is again the annual growth rate of the per

[10]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 like e.g. Baltagi (2001)

Fixed-effect model

Variable	Coef.	Std.Err.	t	$P > \|t\|$
log of income	-0.019	0.002	-6.800	0.000
constant	0.214	0.028	7.560	0.000
$sigma_\alpha$	0.018			
$sigma_\varepsilon$	0.028			
fraction of variance due to α_i	0.294			
F-test that all α_i=0:	2.000			
	(0.000)			
Goodness of fit				
R-square within	0.014			
R-square between	0.026			
R-square overall	0.003			
observations	3250			
Number of groups	125			
observations per group	26			
Corr(α_i, Xb)	-0.903			

Table 5: **Convergence of per capita income in the 125 European regions (1977-2002) Estimation of the fixed-effect Model - Equation(4) -** *(numbers into brackets refer to the p-values)*

capita GDP, and the only explanatory variable is the level of the income at the beginning of each period. In the most general specification, there are 125 different groups, each one corresponding to one of the European regions, and 26 observation for each group (1977-2002). Then, the total number of observations is 3250 for the entire sample. This number can be considered large enough to guarantee significant conclusions from our estimated model.

The value of the coefficient of the initial per capita income variable of European regions calculated over the entire time period is -0.019. This is significantly negative, and thus the hypothesis of convergence among European regions is again confirmed in this other framework. The value of the growth rate coefficient β, that we have found using the fixed-effect estimator is smaller than those found when using the simple unconditional convergence model (Equation (1)), indicating that, when the full dynamics of the phenomenon are accounted for, the speed of convergence is lower than that usually estimated in the literature. This happens under the hypothesis that the presence of omitted variables, captured by the presence of a country-specific effect, does not influence the value of the estimated coefficient. The value of β is also smaller than those estimated when using the spatial correction of the unconditional model (Equations (2) and (3)). The approach based on Equation (4) that is again partial in that the presence of spatial dependence, is not corrected in the previous specification. For this reason in the following section, we augment Equation (4) by introducing an explicit modelling of spatial effects.

6 Introducing Spatial effects in the Panel Data Model

Traditional panel data models do not consider the problem of cross-section correlation. However, when the data refer to a set of spatial units (like countries, regions, states or counties), we find the problem is relevant and requires a specific treatment[11].

More specifically, two problems arise when panel data models have a locational component. The first concerns spatial heterogeneity, which can be defined as parameters that may not be homogeneous throughout the data set, but vary with location. The second is represented by the spatial dependence that may exist between observations at each point in time. In the present

[11] Some examples of the use of spatial panel data see, amongs others, Elhorst (2003), Case (1991), Baltagi and Li (2004).

work, we consider only the second aspect, referring to a fixed-effect panel data model specification extended to spatial error correlation and leaving the treatment of spatial heterogeneity for further development. It should be stressed that the application of such a model in the estimation of regional convergence, appears to be the most reasonable solution among all the possible specifications. Moreover, the present paper represents the first attempt to apply the spatially corrected fixed-effect model to the problem of convergence among regions, and this feature represents the most innovative aspect of the work.

A first way to incorporate spatial effects is to start from the classical fixed-effect panel data model and account for spatial dependence by including a spatially lagged term of the dependent variable so that the model assumes the following expression:

$$\ln\left[\frac{y_{t+k,i}-y_{t,i}}{y_{t,i}}\right]=\alpha_i+\rho\sum_{j=1}^{n}w_{i,j}\ln\left[\frac{y_{t+k,j}-y_{t,j}}{y_{t,j}}\right]+\beta\ln y_{t,i}+\varepsilon_{t,i}. \qquad (5)$$

with $w_{i,j} \in W$ a weight matrix as discussed in Section 4, ρ the spatial-autoregressive coefficient, and $\varepsilon_{t,i}$ a zero mean error term assumed to be independently distributed under the hypothesis that all spatial dependence effects are captured by the spatially lagged variable term. This model takes the name of *fixed-effect spatial lag model* and represents the extension of Model 2 to the case of panel data (Elhorst, 2001; 2003). Equation (5) is estimated via Maximum Likelihood as suggested by Elhorst (2003).

A second alternative to incorporate the spatial effects is to extend Equation (4) to the case in hand by leaving unchanged the systematic component and to model the error term by assuming, for instance:

$$\begin{aligned}\ln\left[\frac{y_{t+k,i}}{y_{t,i}}\right] &= \alpha_i+\beta\ln y_{t,i}+\varepsilon_{t,i} \qquad (6)\\ \varepsilon_{t,i} &= \delta\sum_{j=1}^{n}w_{i,j}\varepsilon_{t,j}+\eta_i\end{aligned}$$

where $w_{i,j} \in W$ and W is again the spatial weight matrix, δ is the spatial autocorrelation coefficient of the error term, and the η_i are assumed to be normally distributed with zero mean, constant variance and a distribution independent from the explanatory variable. Such a model can be referred to as *fixed-effect spatial error model.* Again, the parameters may be estimated by using maximum likelihood.

Spatial Lag fixed-effect Model

Variable	Coefficient	Asymptotic t-stat	P>|t|
log of income	-0.010	-4.743	0.000
spatially lagged growth rate	0.686	49.690	0.000
Goodness of fit			
R-squared			0.0.527
Sigma squared			0.000
Log-likelihood			7597.569
Number of observations			3125
Number of variables			1

Table 6: **Convergence of per capita income in the 125 European regions (1977-2002) - Estimation of the fixed-effect Spatial Lag Model - Equation (5) -** *(numbers into brackets refer to the p-values)*

The main results of the empirical analysis performed using equations (5) and (7) are reported in tables (6) and (7). As noted earlier, these specifications allow us to solve the problem connected to unobserved factors that influence growth, and also the bias generated by the presence of spatial dependence. Table (6) reports the results of the estimation of the fixed-effect spatial lag model. The value of the estimated coefficient of the initial per-capita GDP level is -0.010 for the entire sample period. The spatial autocorrelation coefficient is highly significant, and captures the effect of spatial autocorrelation. The presence of the α_i's parameters, isolate the effect of the omitted variables, in terms of the different structural characteristics of the regional economies. The contemporaneous presence of these two different factors produces a value of the β coefficient that is lower than in the fixed-effect model, a result that is derived from the simultaneous consideration of both omitted variables and spatial autocorrelation. From an economic point of view, this result confirms the evidence obtained with the cross sectional estimates. The reduction of the coefficient of the model due to the inclusion of the spatial lag term (and, hence, the higher speed of convergence) confirms the positive effect of factor mobility, trade relationships, and the

Spatial Error fixed-effect Model			
Variable	Coefficient	Asymptotic t-stat	z-probability
log of income	-0.033	-7.620	0.000
error component spatial correlation	0.699	54.138	0.000
Goodness of fit			
R-squared			0.535
Sigma squared			0.000
Log-likelihood			7615.201
Number of observations			3125
Number of variables			1

Table 7: **Convergence of per capita income in the 125 European regions (1977-2002) - Estimation of the fixed-effect Spatial Error Model - Equation (6) -** *(numbers into brackets refer to the p-values)*

presence of spill-overs on regional convergence.

A different consideration has to be made for the results from the fixed-effect spatial error model (that are reported in Table (7)). The values of the coefficients are greater than those obtained with the classical fixed-effect model estimate and still lower than those obtained with the unconditional β-convergence cross-sectional model and of its spatially corrected versions. In this specification, it is not possible to conclude that all the effect of omitted variables has been captured by the fixed-effect coefficients. Part of the explanatory power of the model could not be explicitly considered, and, in particular, contained in the spatial autocorrelation coefficient used in modelling the error term structure. This evidence causes a bias in the coefficient describing the growth process of European regions.

For these reasons, our empirical investigation shows that a spatial lag specification fits better than the spatial error model in studying convergence among EU regions.

7 The calculation of the Moran' s I index in panel regressions

The final issue that we discuss in the present paper concerns the testing of the hypothesis of independence among residuals in a spatial panel data model. There are two obvious (although partial) approaches that can be followed. The first concerns the test of spatial autocorrelation in the T different time periods using the classical Moran' I or LM tests (Anselin, 1988). The second refers to the test of temporal autocorrelation in the n locations considered and thus involves the computation of n distinct Durbin-Watson tests (Davidson and MacKinnon, 1993). A possible way of building a general procedure to test simultaneously the two features could be obtained in the following way. Starting from the familiar Moran' I expression that (as it is known) is more general and admits the Durbin-Watson procedure as a particular case (see e. g. Arbia, 2005), a general expression may be developed:

$$I = h(\hat{e}'\hat{e})^{-1}(\hat{e}'\mathbf{W}\hat{e}) \tag{7}$$

where $\hat{e}$ are the regression residuals, and h a normalizing factor such that $h = \frac{n}{\sum_{i=1}^{n}\sum j=1nw_{ij}}$, with $w_{ij} \in \mathbf{W}$. In the case of cross-section regressions, the dimension of the matrix $\mathbf{W}$ is n-by-n, where n corresponds to the number of the spatial units considered. Conversely in the case of a panel regression, the vector of residuals has a different dimension with respect to the spatial weight matrix. In this respect, it is sufficient to build the weight matrix in a block diagonal form with the traditional spatial weight matrix repeated T times on the main diagonal. Formally the new space-time connectivity matrix $\mathbf{\Omega}$ can be expressed as

$$\mathbf{\Omega} = \begin{pmatrix} \mathbf{W} & 0 & \dots & \dots & 0 \\ 0 & \mathbf{W} & & & \dots \\ \dots & & \mathbf{W} & & \dots \\ \dots & & & \dots & \\ 0 & & & & \mathbf{W} \end{pmatrix} \tag{8}$$

where $\mathbf{W}$ are n-by-n connectivity matrices. The dimension of the $\mathbf{\Omega}$ matrix is now nT-by-nT, as each block has dimension n-by-n, and the number of blocks corresponds to the number of time periods. The computation of the Moran' I follows straightforwardly by replacing the $\mathbf{W}$ matrix in equation (7) with the $\mathbf{\Omega}$ matrix of equation (8) and stacking the n-by-T matrix of space-time residuals in one single NT-by-1 column vector.

The asymptotic distribution for the Moran statistics, derived under the null hypothesis of no spatial dependence, is still normal as in the classical (purely spatial) formulation. However the expected value and the variance need to be derived explicitly in this situation. The previous expression accounts for spatial correlation in each time period; in those cases where the model considers both spatial and serial autocorrelation, the structure of the spatial weights matrix is different. In particular, the blocks above and below the main diagonal are also non-zero and the number of diagonals that are different from zero depends on the time periods considered in the serial autocorrelation term. For instance, by limiting ourselves to lag1 temporal dependence we have:

$$\mathbf{\Omega} = \begin{pmatrix} \mathbf{W} & \mathbf{W} & \dots & \dots & 0 \\ \mathbf{W} & \mathbf{W} & \mathbf{W} & 0 & \dots \\ \dots & \mathbf{W} & \mathbf{W} & \mathbf{W} & \dots \\ \dots & & & \dots & \mathbf{W} \\ 0 & & & \mathbf{W} & \mathbf{W} \end{pmatrix} \tag{9}$$

a form that allows for simultaneous spatial and temporal ($lag1$) correlation amongst residuals to be detected. Alternative approaches have been proposed by Anselin *et al.* (2004) for the LM test in spatial lag and spatial error panel data models and by Pesaran (2004) for a diagnostic test for unspecified spatial dependence in panels.

8 Conclusions and future research guidelines

In the present paper, we considered the problem of regional economic convergence among European regions. Much of the works in the literature that focuses on convergence makes use of fixed-effect model or cross-country regression. Our investigation starts from the observation that these two techniques both impose strong a-priori restrictions on the model parameters. From one side, cross-sectional methods do not consider heterogeneity, and on the other hand, the fixed-effect panel data approach incorporates heterogeneity only in the different intercepts for each region; all the differences in growth rates depend only on the different starting point for the spatial unit considered. In addition, both approaches neglect aspects connected with spatial dependence among regions. The methodology used in the present paper allows us to extend the traditional models by considering a specific treatment of unexplained (both heterogeneity and spatial) dependence. The first evidence concerns the existence of a very slow process of convergence among European regions. This result has been obtained using the classical specification and is in line with those results obtained in the empirical literature on European regions.

Further, by taking in account the spatial dependence among spatial units, the results considerably improve the estimated values of the speed of convergence among the European regions. In fact, the coefficient of the initial GDP level estimated using models accounting for spatial dependence is considerably lower than that of the classical fixed-effect panel data model. This result shows that the value of the fixed-effect coefficient is affected by the presence in the model of the positive effect of spatial dependence.

The present paper may be considered as a point of departure for some future research in regional convergence. First of all, the estimation of a random-effect spatial panel data model could be used as an alternative to the models presented here. A second interesting possibility could be based on the framework of dynamic panel data models extended to spatial error autocorrelation or to a spatially lagged dependent variable (Elhorst, 2001). Finally, the use of semi-parametric techniques to allow the coefficients to vary among regions could be considered. The advantage of taking into account possible non-linearities within a spatial panel data framework would identify different slopes together with systematic time-invariant regional effects. Thus, greater flexibility would be guaranteed by this specification because regions may would be able to differ both in terms of their initial conditions and in their own growth path.

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Contents

List of Tables

A List of the European regions considered

be1	Brussel	be21	Antwerpen	be22	Limburg
be23	Oost-Vlaand.	be24	Vlaams Brabant	be25	West-Vlaand.
be3	Region Walonne	be31	Brabant Wallon	be32	Hainaut
be33	Liege	be34	Luxembourg	be35	Namur
dk01	Hovedstadsreg.	dk02	O. for Storebaelt	dk03	V. for Storebaelt
de11	Stuttgart	de12	Karlsruhe	de13	Freiburg
de14	Tubingen	de21	Oberbayern	de22	Niederbayern
de23	Oberpfalz	de24	Oberfranken	de25	Mittelfranken
de26	Unterfranken	de27	Schwaben	de3	Berlin
de5	Bremen	de6	Hamburg	de71	Darmstadt
de72	Giessen	de73	Kassel	de91	Braunschweig
de92	Hannover	de93	Luneburg	de94	Weser-Ems
dea1	Dusseldorf	dea2	Koln	dea3	Munster
dea4	Detmold	dea5	Arnsberg	deb1	Koblenz
deb2	Trier	deb3	Rheinhessen-Pfalz	dec	Saarland
def	Schleswig-Holstein	dk	Denmark	es11	Galicia
es12	Asturias	es13	Cantabria	es21	Pais Vasco
es22	Navarra	es23	Rioja	es24	Aragon
es3	Madrid	es41	Castilla-Leon	es42	Castilla-la Mancha
es43	Extremadura	es51	Cataluna	es52	Com. Valenciana
es53	Baleares	es61	Andalucia	es62	Murcia
fr1	Ile de France	fr21	Champagne-Ard.	fr22	Picardie
fr23	Haute-Normandie	fr24	Centre	fr25	Basse-Normandie
fr26	Bourgogne	fr3	Nord-Pas de Calais	fr41	Lorraine
fr42	Alsace	fr43	Franche-Comte	fr51	Pays de la Loire
fr52	Bretagne	fr53	Poitou-Charentes	fr61	Aquitaine
fr62	Midi-Pyrenees	fr63	Limousin	fr71	Rhone-Alpes
fr72	Auvergne	fr81	Languedoc-Rouss.	fr82	Prov-Alpes-Cote d'Azur
it11	Piemonte	it12	Valle d'Aosta	it13	Liguria
it2	Lombardia	it31	Trentino-Alto Adige	it32	Veneto
it33	Fr.-Venezia Giulia	it4	Emilia-Romagna	it51	Toscana

it52	Umbria	it53	Marche	it6	Lazio
it71	Abruzzo	it72	Molise	it8	Campania
it91	Puglia	it92	Basilicata	it93	Calabria
ita	Sicilia	itb	Sardegna	lu	Luxembourg
nl12	Friesland	nl13	Drenthe	nl2	Oost-Nederland
nl33	Zuid-Holland	nl34	Zeeland	nl41	Noord-Brabant
nl42	Limburg	pt11	Norte	pt12	Centro
pt13	Lisboa e V.do Tejo	pt14	Alentejo	pt15	Algarve
uk1	North East	uk2	Yorkshire and the Humber	uk3	East Midlands
uk4	East Anglia	uk5	South East	uk6	South West
uk7	West Midlands	uk8	North West	uk9	Wales
uka	Scotland	ukb	Northern Ireland		