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SPATIAL DEPENDENCE AND NON-LINEARITIES IN REGIONAL GROWTH BEHAVIOUR IN ITALY

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1. INTRODUCTION

One of the most striking features of empirical economic data is that some countries and regions within a country grow faster than others. Economic theory has long been aware of this problem and various explanations have been provided in the past (Barro and Sala-i-Martin, 1995; and Magrini, 2003 for a review on regional convergence). A certain school of thought reached an optimistic view of reality by predicting that a set of economies (countries or regions) will tend to assume a common level of per capita output (that is they will "converge") in the presence of constant returns to scale and decreasing productivity of capital. However, many empirical studies show contrasting, less optimistic, results.

Apart from the evident interest in the subject at a World scale, regional convergence studies have recently experienced an acceleration of interest due to the issues raised in Europe by the unification process. Since large differentials in per capita GDP across regions are regarded as an impediment to the completion of the economic and monetary union, the narrowing of regional disparities is indeed regarded as a fundamental objective for the European Union policy. Hence, the problem of testing convergence among the member States of the Union and measuring its speed emerges as a fundamental one in the view of policy evaluation.

Surprisingly enough, the literature on the empirical measurement of spatial convergence has not moved at the same speed with the increased demand. Indeed, most of the empirical work is still based on the computation of some basic statistical measures in which the geographical characteristics of data play no role. For instance, in their celebrated paper Barro and Sala-i-Martin (1992) base their models on parameters like the variance of logarithm (to identify a σ-convergence) and the simple regression coefficients (to identify a β-convergence) estimated using standard OLS procedures. In general most empirical studies in this field base their conclusions on cross-sectional data referred to geographical units almost systematically neglecting two remarkable features of spatial data. First of all, spatial data represent aggregation of individuals within arbitrary geographical borders that reflect political and historical situations. The choice of the spatial aggregation level is therefore crucial because different partitions can lead to different results in the modelling estimation phase (Arbia, 1989). Secondly, it is well known that regional data cannot be regarded as independently generated because of the presence of spatial similarities among neighbouring regions (Anselin, 1988; Anselin and Bera, 1998). As a consequence, the standard estimation procedures employed in many empirical studies can be invalid and lead to serious biases and inefficiencies in the estimates of the convergence rate.

Moreover, most of the empirical studies on regional convergence have implicitly assumed that all regions obey a common linear specification, disregarding the possibility of non-linearities (or multiple regimes) in growth behaviour. The issue of multiple regimes has instead been raised in some cross-country growth studies (Durlauf and Johnson, 1995; Liu and Stengos, 1999) that make use of non-parametric or semi-parametric approaches to model the regression function.

In this paper, we present an empirical study of the long-run β-convergence of per capita income in Italy (1951-2000) based on a level of aggregation (the NUTS 3 EU regions corresponding to the 92 Italian provinces) which is fine enough to allow for spatial dependence to be properly modelled. A non-parametric local regression model is firstly applied to identify non-linearities (i.e. multiple regimes) in the relationship between growth rates and initial conditions. Then, by using information on the presence of spatial regimes, we apply cross section regressions accounting for spatial dependence.

The layout of the paper is the following. In Section 2, we present a review of econometric techniques that incorporate spatial dependence and multiple regimes within the contest of a β-convergence modelling. In Section 3, we report the results of an empirical analysis based on the 92 Italian provinces (European NUTS-3 level) and the per capita income recorded in the period ranging from 1951 to 2000 and we show the different estimates of the convergence speed obtained by using different modelling specifications for spatial effects. Finally, in Section 4 we discuss the results obtained and outline possible extensions of the present work.

2. SPATIAL DEPENDENCE AND MULTIPLE REGIMES IN CROSS-SECTION GROWTH BEHAVIOUR

The most popular approaches in the quantitative measurement of convergence are those based on the concepts of σ- and β-convergence (Durlauf and Quah, 1999 for a review). Alternative methods are the intra-distribution dynamics approach (Quah, 1997; Rey, 2000), the "stochastic convergence" approach in time series (Carlino and Mills, 1993, Bernard and Durlauf, 1995) and, more recently, the Lotka-Volterra predator-prey specification (Arbia and Paelinck, 2004). Also within the regression approach, many innovations have been introduced. In particular, some authors introduced a panel fixed-effects specification to control for the effects of omitted variables (Islam, 1995), while others focused on the role of spatial dependence and of non-linearities in growth behaviour.

In this section, we start by reviewing the classical approaches to test convergence. Then, we propose a new specification of the empirical growth equation which simultaneously takes into account the problems of spatial dependence and multiple regimes (or non-linearities).

2.1. *σ-convergence*

The σ-convergence approach consists on computing the standard deviation of regional per capita incomes and on analysing its long-term trend. If there is a decreasing trend, then regions appear to converge to a common income level. Such an approach suffers from the fact that the standard deviation is a measure insensible to spatial permutations and, thus, it does not allow to discriminate between very different geographical situations (Arbia, 2001).[1] Furthermore, as argued by Rey and Montoury (1999), σ-convergence analysis may "*mask nontrivial geographical patterns that may also fluctuate over time*". Therefore, it is useful to analyse the geographical dimensions of income distribution in addition to the dynamic behaviour of income dispersion. This can be done, for instance, by looking at the pattern of spatial autocorrelation based on the Moran's I statistics (Cliff and Ord, 1973), that measures the spatial correlation between value at location *i* and at location *l*. Formally, Moran's I is:

$$I\text{ - }Moran = \frac{N}{\sum_{i=1}^{N}\sum_{l=1}^{N} w_{il}} \frac{\sum_{i=1}^{N}\sum_{l=1}^{N} w_{il}(x_i - m)(x_l - m)}{\sum_{i=1}^{N}(x - m)_i^2} \quad (1)$$

where N is the number of observations, w_{il} is the element in the symmetric binary contiguity matrix described in appendix 1, and x_i and x_j are observations for locations i and j (with mean μ). For the calculation of the I-Moran index, the elements w_{il} are row-standardised, that is

$$w_{il}^{rs} = \frac{w_{il}}{\sum_{l=1}^{N} w_{il}} \qquad \text{such that} \qquad \sum_{l=1}^{N} w_{il}^{rs} = 1 .$$

Positive (and significant) I-Moran values indicate spatial clustering, while negative I-Moran values are associated with spatial dispersion.

[1] Consider two regions each dominating the extreme ends of an income scale. Now let there be mobility along the income scale. For the sake of argument, say each ended up at the exact position formerly occupied by its counterpart. According to the concept of σ convergence, nothing has changed. In reality the poor has caught up with the rich while the rich has slide down to the position of the poor.

2.2. *β-convergence*

So far, the *β*-convergence approach has been considered as one of the most convincing under the economic theory point of view. It also appears very appealing under the policy making point of view, since it quantifies the important concept of the speed of convergence. It moves from the neoclassical Solow-Swan exogenous growth model (Solow, 1956; Swan, 1956), assuming a closed economic system, exogenous saving rates and a production function based on decreasing productivity of capital and constant returns to scale. This model predicts that the growth rate of one region is positively related to the distance that separates it from its steady-state. On this basis authors like Mankiw *et al.* (1992) and Barro and Sala-i-Martin (1992) suggested the following cross-sectional statistical model, in matrix form

$$\boldsymbol{g}_T = \frac{1}{T}\ln\left[\frac{\boldsymbol{y}_T}{\boldsymbol{y}_0}\right] = \boldsymbol{\mu} + \boldsymbol{\varepsilon} \qquad \boldsymbol{\varepsilon} \sim N(\boldsymbol{0}, \sigma_{\varepsilon}^2 \boldsymbol{I}) \tag{2}$$

where $\boldsymbol{g}_T$ is a $(n \times 1)$ vector of average growth rates of per capita incomes between date 0 and *T*, as $\boldsymbol{y}_T$ is the value of per capita income in the last time period considered, and $\boldsymbol{y}_0$ is the value in the first period; and ε is an identically and independently normally distributed error term. Moreover, the formal expression for the systematic component $\boldsymbol{\mu}$ is as follows

$$\boldsymbol{\mu} = \boldsymbol{\alpha} S - \frac{(1-e^{-\lambda k})}{T}\ln \boldsymbol{y}_0 \tag{3}$$

where λ is the speed of convergence, which measures how fast economies will converge towards the steady state, and *S* is the $(n \times 1)$ sum vector. The constant term $\boldsymbol{\alpha}$ is equal to $\frac{(1-e^{-\lambda k})}{T}\ln \boldsymbol{y}^*$, where $\boldsymbol{y}^*$ is the steady-state level of per capita income. In this specification all economies are assumed to be structurally identical and to have access to the same technology, so that they are characterised by the same steady-state, and differ only by their initial conditions.

Model (2) is usually directly estimated through non-linear least-squares (Barro and Sala-i-Martin, 1995) or by re-parametrizing the statistical model setting $\beta = -\frac{(1-e^{-\lambda k})}{T}$ and estimating β by ordinary least squares. Absolute convergence is said to be present if the estimate of β is negative and statistically significant. If the null hypothesis ($\beta = 0$) is rejected, we would 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.

The concept of conditional *β*-convergence is used when the assumption of similar steady-states is relaxed. Note that if economies have very different steady-states, this concept is compatible with a persistent high degree of inequality among economies. The hypothesis of conditional β-convergence is usually tested by including in the systematic component a matrix of $\boldsymbol{X}$ variables, maintaining constant the steady-state of each region. There is conditional β-convergence if the estimate of β is significantly negative once $\boldsymbol{X}$ is held constant.

2.3. *Spatial dependence in the cross section growth equation*

The neoclassical growth model discussed above has been developed starting from the hypothesis that the economies are fundamentally closed. However, this hypothesis is too strong for regions within a country, where barriers to trade and to factor flows are considerably low (Magrini, 2003). 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-over). Factor mobility means 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 (Borts and Stein, 1964). 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 be higher than in the closed-economy version.

Another possibility for poor economies to converge with richer ones is through technological diffusion or knowledge spill-over: in the presence of disparities in regional technological attainment, interregional trade can promote technological diffusion when technological progress is incorporated in traded goods (Grossman and Helpman, 1991; Segerstrom, 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 study the effect of geographical spill-over on growth, we must also distinguish between local and global geographic spill-over. With local spill-over, 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 the outcome. By global geographical spill-over, we mean that knowledge accumulation in one region improves productivity of all firms wherever they are located. Thus, a global geographical spill-over effect contributes 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 in 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 part in the explanation of convergence (Barro and Sala-i-Martin, 1995).

An alternative and indirect way to control for the effects of interregional flows (or spatial interaction effects) on growth and convergence is through spatial dependence models. A first way to take spatial dependence into account is the so-called spatial autoregressive model or SAR (Anselin and Bera, 1998; Arbia, 2006), where a spatial lag of the dependent variable is included on the right hand side of the statistical model. If $\boldsymbol{W}$ is a row-standardized matrix of spatial weights describing the structure and intensity of spatial effects (see appendix 1), equation 1 is re-specified as:

$$\boldsymbol{g}_T = \alpha S + \beta \ln \boldsymbol{y}_0 + \rho \boldsymbol{W} \boldsymbol{g}_T + \boldsymbol{\varepsilon} \tag{4}$$

where ρ is the parameter of the spatially lagged dependent variable $\boldsymbol{W}g_T$ that captures the spatial interaction effect indicating the degree to which the growth rate of per capita GDP in one region is determined by the growth rates of its neighbouring regions, after conditioning on the effect of $\ln \boldsymbol{y}_0$. The error term $\{\boldsymbol{\varepsilon}\}$ is assumed to be identically and independently normally distributed in the hypothesis that all spatial dependence effects are captured by the lagged term. The parameters of model (4) can be estimated via maximum likelihood (ML), instrumental variables or generalized method of moments (GMM) procedures.

An alternative way to incorporate the spatial effects is via the spatial error model or SEM (Anselin and Bera, 1998; Arbia, 2006). This leaves unchanged the systematic component and models the error term in equation (2) as an autoregressive random field, for instance assuming that

$$\boldsymbol{\varepsilon} = \delta \boldsymbol{W} \boldsymbol{\varepsilon} + \boldsymbol{u} \, . \tag{5}$$

The error term u is assumed to be normally distributed, with mean zero and constant variance, independently of $ln\boldsymbol{y}_0$ and randomly drawn.

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), Niebuhr (2001), and Le Gallo *et al.* (2003). All these studies, however, do not consider the possibility of multiple regimes in regional growth behaviour. In other words, it is implicitly assumed that all regions obey a common linear specification, disregarding the possibility of non-linearities.

2.4. *Multiple regimes and non-linearities in the cross section growth equation*

The concept of multiple regimes is based on endogenous growth models characterized by the possibility of multiple, locally stable, steady-state equilibria as in Azariadis and Drazen (1990). The basic idea underlying these models is that the level of per-capita GDP on which each economy converges depends on some initial conditions, so that, for example, regions with an initial per capita GDP lower than a certain threshold level converge to one steady state level while regions above the threshold converge to a different level.[2]

A common specification that is used to test this hypothesis considers a modification of the systematic component in model (2) that takes the form:

$$\boldsymbol{g}_T = \boldsymbol{\alpha}_1 S + \beta_1 \ln \boldsymbol{y}_0 + \boldsymbol{\varepsilon}_1 \qquad \text{if} \qquad \ln \boldsymbol{y}_0 < x \qquad (6)$$

$$\boldsymbol{g}_T = \boldsymbol{\alpha}_2 S + \beta_2 \ln \boldsymbol{y}_0 + \boldsymbol{\varepsilon}_2 \qquad \text{if} \qquad \ln \boldsymbol{y}_0 \geq x$$

where x is a threshold that determines whether region i belongs to the first or second regime. The same adjustment can be applied to the systematic component in the (parametric) spatial auto-covariance models.

The hypothesis of linearity has been abandoned in some cross-region studies in Europe by assuming the presence of "threshold effects" automatically produced by the membership of each region to one group or another, according to "exogenous" criteria, such as geographical criteria (e.g. Centre versus Periphery) (Basile *et al.*, 2003; and Baumont *et al.*, 2003). However, a problem with multiple regime analysis is that the threshold level cannot be (and must not be) exogenously imposed. In order to identify economies whose growth behaviour obeys a common statistical model, we must allow the data to determine the location of the different regimes. Following Liu and Stengos (1999), we argue that a non-parametric specification of the cross-region growth regression function goes a long away in addressing the issue of multiple regimes. Let us specify the empirical growth model as follows:

[2] The issue of multiple regimes in growth behaviour has been widely analysed in cross-country studies. Durlauf and Johnson (1995) propose a tree-regression approach to identify multiple regimes and find evidence that is consistent with a multiple-regime data-generating process as opposed to the traditional one-regime model. Hansen (1996) uses a Threshold Regression model to formally test for the presence of a regime shift. Liu and Stengos (1999) employ a semi-parametric approach to model the regression function and, as in Durlauf and Johnson and Hansen, emphasize the role of initial output and schooling as variables with a potential to affect growth in a non-linear way through possible thresholds or otherwise. Durlauf, Kourtellos and Minkin (2001) use a local polynomial growth regression to explicitly allow for cross-country parameter heterogeneity.

$$\boldsymbol{g}_T = m(\ln \boldsymbol{y}_0) + \boldsymbol{\varepsilon} \tag{7}$$

where $m(\ln \boldsymbol{y}_0) = E[\boldsymbol{g}_T \,|\ln \boldsymbol{y}_0\,]$ is a generic function of the conditional expected value. In order to estimate $\hat{m}(\ln \boldsymbol{y}_0)$, we use the *lowess* (locally weighted scatter-plot smoothing) regression method, that is a local polynomial regression with tricube weight function and nearest-neighbour bandwidth selection (see Cleveland, 1979; Cleveland and Devlin, 1988) (see the appendix 2).

With this specification we solve the problem of non-linearities, but we still face with that of spatial dependence. Thus, our task consists of combining non-parametric estimators with the usual parametric estimators of the spatial parameters. In our empirical analysis, we adopt the graphical output of non-parametric local regression techniques as a data sorting method which allows the data to select regimes endogenously. Then, we use this information to split the sample in two regimes and run both OLS and spatial dependent regression models with different intercepts and slopes. A different, and more systematic, way to combine non-parametrics and spatial econometrics is described in Basile and Gress (2005).

3. EMPIRICAL EVIDENCE FROM ITALIAN PROVINCES

The empirical study focuses on the case of Italian provinces, which correspond to the European NUTS-3 level in the official UE classification.[3] The analysis is based on a newly compiled database on per capita GDP for the 92 provinces over the period 1951-2000.[4]

We start with a *σ-convergence* analysis of per capita income in the 92 provinces and the related spatial patterns over the period 1951-2000 (Section 3.1). In Sections 3.2-3.4 we will move to the *β-convergence* analysis by taking explicitly into consideration the multiple regime hypothesis and the spatial dependence patterns displayed by data.

3.1. *σ-convergence and spatial autocorrelation*

Figure 1 shows the dynamics of the provinces' real per capita GDP (measured in log terms) dispersion over the period 1951-2000, synthetically measured by its coefficient of variation (the ratio between the standard deviation and the national average). Regional inequalities diminished by more than one half over the entire period, but the sharp trend towards convergence was confined to the period be-

[3] The compilation of provincial data on value added has been based on estimates elaborated by the Istituto Guglielmo Tagliacarne. These estimates have been transformed at constant prices by using sectoral/regional value added deflators. The source of population data is ISTAT (National Institute of Statistics).

[4] Italy is currently divided into 103 provinces, grouped into 20 regions. Over the period considered (1951-2000), however, the boundaries of some administrative provinces changed. Only the provinces that already existed in 1951 (92 units) have been considered for the empirical analysis.

tween 1951 and 1970. This is due partly to the significant effort to 'exogenously' implement economic development in the South (through the *Cassa del Mezzogiorno*) and partly to the 'endogenous' development of the North-Eastern regions (through the emergence of industrial districts). The following period was, instead, characterized by a substantial invariance of the income inequalities.

Figure 1 also displays the pattern of spatial autocorrelation for the provincial incomes over the same period of time, based on the Moran's I statistics. There is strong evidence of spatial dependence as the I-Moran statistics are significant (at the probability level 0.01) for each year. Differently from Rey and Montoury (1999) that examined the case of the United States, however, convergence and spatial dependence tend to move in the same direction (the simple correlation between Moran's I statistics and the coefficient of variation is –0.9). The minimum level of spatial dependence was observed for the first year of the sample (1951), when the income dispersion was at its maximum level. Then, I-Moran increased very strongly till the '70s, that is the period of strong convergence. Finally, it remained stable and high over the '90s.

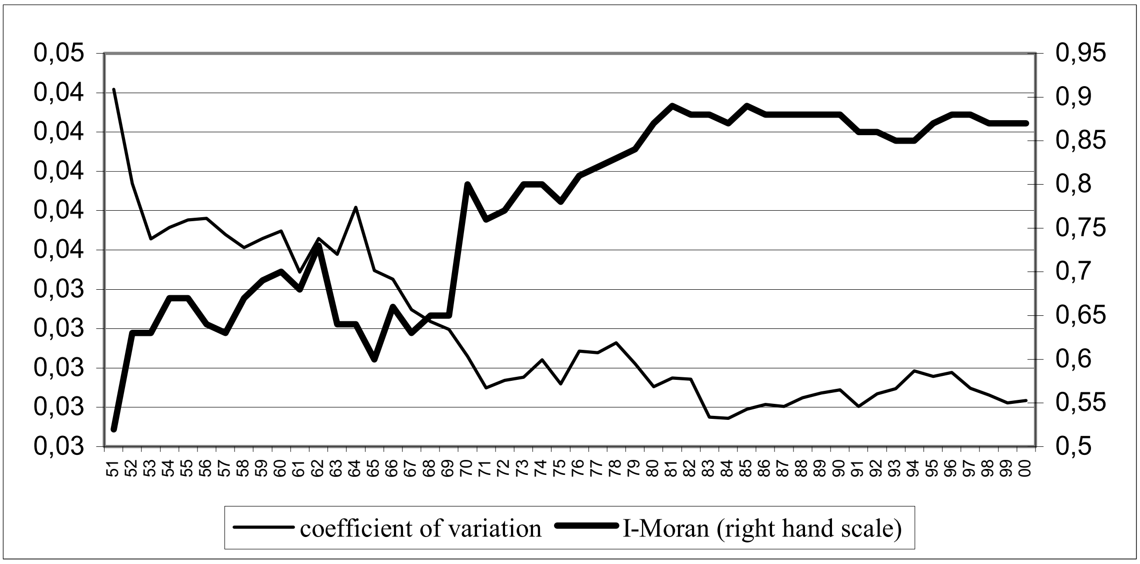


Figura 1 – Italian Provinces Convergence of Per-capita Income and Related Spatial Autocorrelation in the Period 1951-2000.

Thus, after reaching a stable level of *a-spatial* inequality (measured by the coefficient of variation) in 1970, it follows a period of strong polarization at constant levels of inequality (for a distinction between a-spatial inequality and polarization, see Arbia, 2000, 2001).

3.2. *β-convergence: basic results*

We start from the OLS estimates of the unconditional model of *β-convergence* and test for the presence of different possible sources of model misspecification (non-linearities and spatial autocorrelation). The general objective of this analysis is to assess whether the results of previous studies at provincial level (e.g. Fabiani and Pellegrini, 1997; Cosci and Mattesini, 1995), carried out using the OLS method, were actually biased for the presence of spatial dependence and multiple regimes.

Table 1 displays the cross-sectional OLS estimates of absolute convergence for the 92 Italian provinces. The dependent variable of the model is the growth rate of province's per capita income (in percentages), while the predictor introduced in each model is the initial level of per-capita income (expressed in natural logarithms). Both variables are scaled to the national average. In order to consider the trend break identified in the *σ convergence* analysis, we estimate models for the entire period and for the two sub-periods 1951-1970 and 1971-2000.

TABLE 1

Per Capita Income Growth of Italian Provinces
OLS Estimates (numbers into brackets refer to the p-values)

	1951-2000	1951-1970	1971-2000
α	0.018 (0.697)	0.067 (0.484)	0.008 (0.864)
β	-1.033 (0.000)	-2.026 (0.000)	-0.262 (0.142)
Adjusted R^2	0.435	0.418	0.013
Log Likelihood	-47.777	*-112.998*	-51.853
Schwartz Criterion	104.589	235.040	112.751
Jarque-Bera	1.419 (0.491)	2.505 (0.285)	1.458 (0.482)
Breusch-Pagan	0.920 (0.337)	0.562 (0.453)	0.000 (0.982)
Moran's I	8.806 (0.000)	6.950 (0.000)	3.722 (0.000)
LM-error	68.819 (0.000)	42.247 (0.000)	11.123 (0.001)
LM-lag	17.680 (0.000)	7.230 (0.007)	7.861 (0.005)

Notes:

- Schwartz Criterion: $-2L+p\ln(N)$, with L=log-likelihood, p=number of regressors, N=number of observations.
- Jarque-Bera = $\frac{N}{6}\left[S^2+\frac{1}{4}(K-3)^2\right]\sim\chi^2(2)$, where S is the sample skewness and K is the sample kurtosis. Under the null hypotheis of normality the Jarque-Bera test is distributed as $\chi^2(2)$.
- Breusch-Pagan. Suppose that $V(\boldsymbol{e})=\sigma^2$, where $\boldsymbol{e}$ is a vector of OLS residuals. If there are some variables $\boldsymbol{z}_1, \boldsymbol{z}_2,..., \boldsymbol{z}_r$ that influence the error variance and if $\sigma^2 = f(a_0+a_1\boldsymbol{z}_1+a_2\boldsymbol{z}_2+...+a_r\boldsymbol{z}_r)$, then the Breusch and Pagan test is a test of the hypothesis H_0: $a_1=a_2=...=a_r=0$. The function $f(.)$ can be any function. In this paper the squares of the explanatory variables were used in the specification of the error variance to test for additive heteroscedasticity. Under the null hypothesis of homoskedasticity, $S_0/2\hat{\sigma}^4$ (with the S_0 the residual sum of squares from a regression of $\hat{\boldsymbol{e}}^2$ on $\boldsymbol{z}_1$, $\boldsymbol{z}_2$, $\boldsymbol{z}_r$) has a $\chi^2(r)$.
- Moran's I = $\boldsymbol{e}'\boldsymbol{We}/\boldsymbol{e}'\boldsymbol{e}\sim N(\boldsymbol{0},\sigma_{\mathrm{I}}^2)$, where $\boldsymbol{e}$ is a vector of OLS residuals and $\boldsymbol{W}$ is the row standardised spatial weights matrix. Under the null hypothesis of no spatial dependence Moran's I is distributed as $N(\boldsymbol{0},\sigma_{\mathrm{I}}^2)$.
- LM-error = $(\boldsymbol{e}'\boldsymbol{We}/\boldsymbol{e}'\boldsymbol{e})^2/tr(\boldsymbol{W}'\boldsymbol{W}+\boldsymbol{W}^2)\sim\chi^2(1)$, where *tr* stands for the matrix trace operator. Under the null hypothesis of no spatial dependence (H_0: $\delta = 0$) LM-error is distributed as $\chi^2(1)$.
- LM-lag = $(\boldsymbol{e}'\boldsymbol{Wg}_T/\boldsymbol{e}'\boldsymbol{e})^2/\{(\boldsymbol{W}\ln\boldsymbol{y}_0 b)\boldsymbol{M}(\boldsymbol{W}\ln\boldsymbol{y}_0 b)/\boldsymbol{e}'\boldsymbol{e}+tr(\boldsymbol{W}'\boldsymbol{W}+\boldsymbol{W}^2)\}\sim\chi^2(1)$, where $\boldsymbol{Wg}_T$ is the spatial lag of the dependent variable, b is the OLS estimator for the parameter β, $\boldsymbol{M}$ is a projection matrix, $\boldsymbol{M=I-X(X'X)X'}$. Under the null hypothesis of no spatial dependence (H_0: $\rho = 0$) LM-error is distributed as $\chi^2(1)$.

Our results are consistent with the previous findings on the development of Italian regions. The coefficient of initial per capita GDP is –1.03 and significant at a level of probability $p<0.01$ for the entire period, it is –2.03 and significantly different from zero for the first period (confirming the presence of absolute convergence over that period), while it is –0.26 and non-significant for the second period (suggesting lack of absolute convergence). Similarly, the convergence rate was fairly high (2.5%) during the first period and declined substantially (to 0.3%) during the period 1970-2000; for the entire period the estimated convergence rate is 1.4% (Table 2). The lack of absolute *β-convergence* starting from the beginning of the '70s was also found by Paci and Pigliaru (1995), Cellini and Scorcu (1995) and Fabiani and Pellegrini (1997).

Table 1 also reports some diagnostics to identify misspecifications in the OLS cross-sectional model. Firstly, the Jarque-Bera normality test is always far from significant (Figure 2 displays the distribution of residuals). Consequently, we can safely interpret the results of the various misspecification tests (heteroskedasticity and spatial dependence tests) that depend on the normality assumption, such as the various Lagrange Multiplier tests.[5] The Breusch-Pagan test indicates that there are no heteroskedasticity problems.

The other specification diagnostics refers to spatial dependence. Three different tests for spatial dependence are included: a Moran's I test and two Lagrange multiplier (LM) tests. As reported in Anselin and Rey (1991), the first one is very powerful against both forms of spatial dependence: the spatial lag and spatial error autocorrelation. Unfortunately, it does not allow discriminating between these two forms of misspecification. Both LM-error and LM-lag have high values and are strongly significant, indicating significant spatial dependence, with an edge towards the spatial error.

TABLE 2

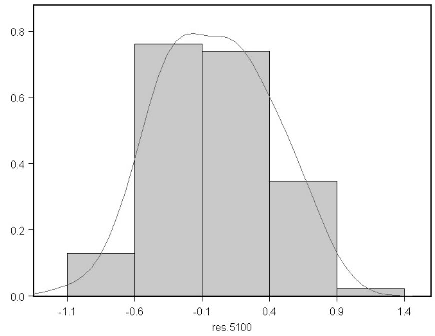
Comparison of the Convergence Rates Estimated with the Different Models

		1951-2000	1951-1970	1971-2000
Unconditional model (OLS estimates)		0.014	0.025	0.003
Spatial error model (ML estimates)		0.035	0.053	0.022
Spatial lag model (ML estimates)		0.013	0.024	0.004
Multiple regimes (OLS estimates)	I regime	0.000	-0.007	0.003
	II regime	0.030	0.059	0.001
Spatial error and multiple regimes: different intercepts and slopes (ML estimates)	I regime	0.038	0.051	0.018
	II regime	0.037	0.052	0.117
Spatial lag and multiple regimes: different intercepts and slopes (ML estimates)	I regime	0.002	-0.005	0.004
	II regime	0.023	0.054	-0.009

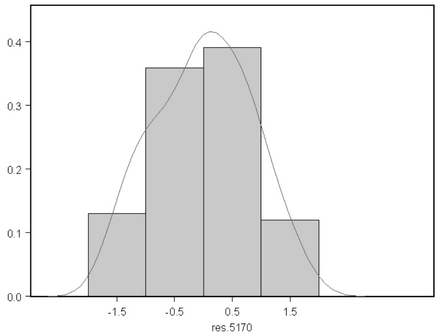
Notes: Convergence Rate = $\lambda = -\frac{\ln(1+T\beta)}{T}$.

[5] Heteroscedasticity 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 heteroscedasticity).

Period 1951-2000



Period 1951-1970



Period 1970-2000

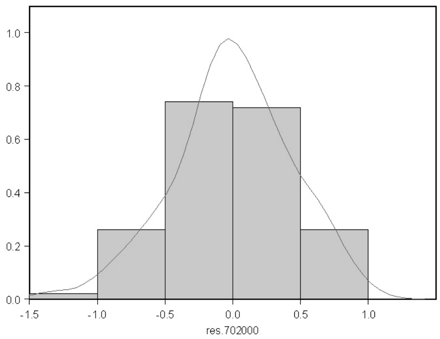


Figura 2 – Histograms and density functions of residuals from the OLS estimation.

The results described so far suggest that the original unconditional model, which has been the workhorse of much previous research, suffers from a mis-specification due to omitted spatial dependence. Thus, we attempt alternative specifications. An approach, adopted for the case of the United States by Rey and Montoury (1999), consists of the application of spatial econometric tools directly to the unconditional model.

An alternative approach, proposed in this paper, consists of firstly detect and identifying the presence of spatial regimes, and then using maximum likelihood spatial dependence models to control for the presence of spatial autocorrelation.

This approach is based on the assumption that the observed spatial autocorrelation might depend (at least in part) on heterogeneity (multiple regimes), in the form of different intercepts and/or slopes in the regression equation for subsets of the data.

3.3. *Non-linearities in cross section growth behaviour*

The main concern of this section is the identification of non-linearities in the growth behaviour of Italian provinces. In Figure 3 we plot the growth rate against initial per capita GDP for the entire period (1951-2000) and the two sub-periods (1951-1970 and 1970-2000), and a non-parametric estimation of the relationship between these two variables.[6]

The non-parametric regressions in Figure 3 identify non-linear relationships between the level of GDP and the growth rate. In particular, for the entire period and for the period 1951-70 (Panel A and B), at low income levels (that is initial levels of relative log incomes lower than –0.26, which corresponds to 77% of the national per capita GDP) growth rates are high and slightly increasing (denoting a diverging process), while regions with relative initial incomes higher than –0.26 follow a converging path. For the period 1971-2000, at low income levels, growth rates are initially high and then decreasing up to a minimum (corresponding to a relative log of GDP per capita of –0.34, which corresponds to 71% of the national per capita GDP). After that level, we cannot observe any relationship between the two variables. These results suggest that the initial income coefficient in the miss-specified linear model inherits the convergence exhibited among regions associated with a common steady state in the correctly specified multiple regime process.

By using this information, we split the sample in to two groups for both periods (see Table 3) and run OLS regression models with different intercepts and slopes (see Table 4).[7] The results clearly show that the two-regime specification is much more reliable than the one-regime used in Table 1: the two groups of provinces tend to converge to different steady states. For the entire and the first periods (characterised by strong convergence), we estimate a negative slope only for the second regime (the convergence speed is 3% for the entire period and 5.9% for the period 1951-1970); for the second period, again the coefficient on the initial income is never significant. The Chow test also confirms the presence of instability in the parameters for the entire period and the period 1951-1970, while the hypothesis of stability is not rejected for the second period.

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[6] For the first period the *lowess* has been specified as a local linear model with span = 0.5; for the second period a local quadratic model with span = 0.5 has been applied. A brief description of the lowess regression technique is given in Appendix 2.

[7] Table 3 shows that the group of low-income provinces includes mainly Southern provinces (given in bold letters), i.e. the least developed provinces in Italy. However, within the low-income group, we find over the period 1951-1970 even some central and North-Eastern provinces. On the other hand, some large southern provinces such as Napoli, Sassari, Palermo and Cagliari are included in the second group.

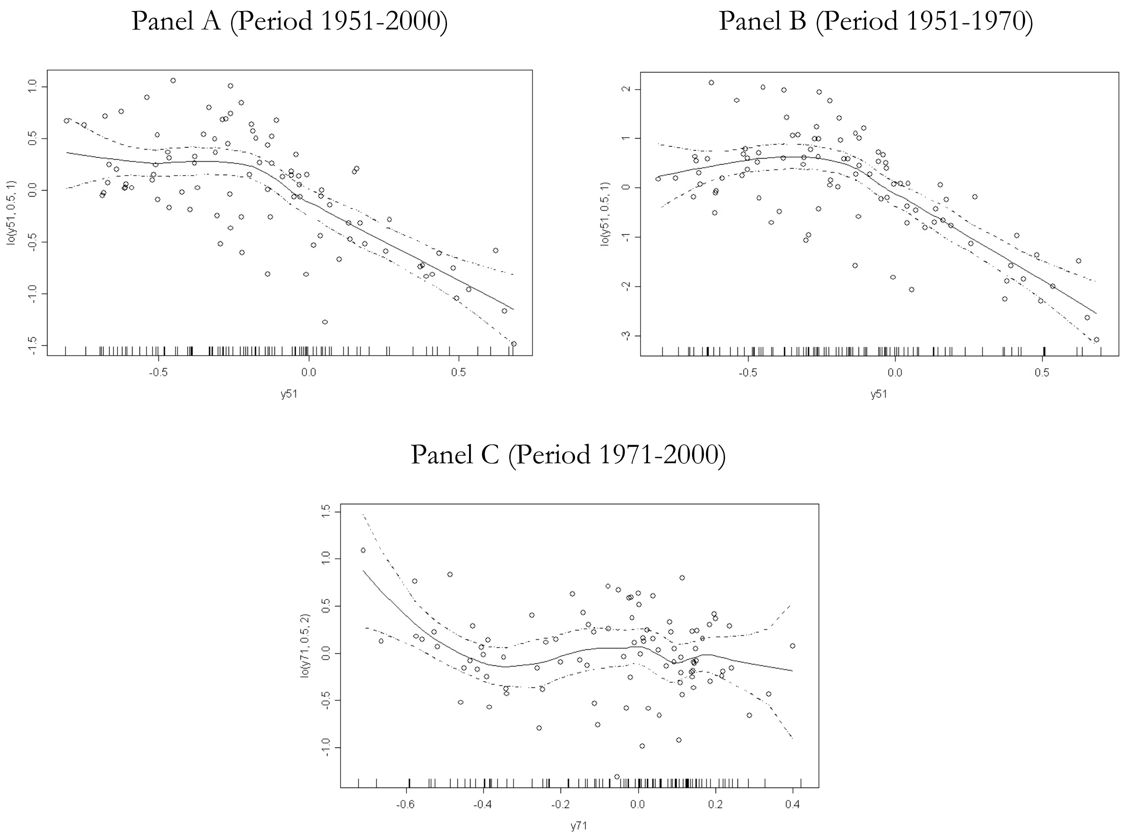

Figura 3 – Per capita GDP Levels vs Growth Rates (Nonparametric Regression).

TABLE 3

Multiple Regimes (Southern provinces are given in bold letters)

Periods 1951-1970 and 1951-2000

Group 1 (41 provinces) ($\mathbf{y}_t < -0.26$)	**Avellino, Potenza, Agrigento, Enna, Campobasso, Caltanissetta, Benevento, Caserta,** Frosinone, **Catanzaro, Lecce, Cosenza, Reggio Calabria,** Rovigo, **Salerno, Ragusa, Matera, Teramo, Trapani, Chieti, L'Aquila, Foggia,** Treviso, **Nuoro, Brindisi**, Rieti, Latina, **Siracusa,** Pesaro, Padova, Perugia, Ascoli P., **Bari, Catania**, Udine, Forlì, Arezzo, Viterbo, Belluno, **Messina,** Modena
Group 2 (51 provinces) ($\mathbf{y}_t > -0.26$)	Reggio E., **Sassari**, **Taranto**, Macerata, Mantova, Verona, Cuneo, Ferrara, **Palermo**, Brescia, Asti, Pescara, Cremona, Vicenza, Parma, Sondrio, Piacenza, Bergamo, Pistoia, Trento, Ravenna, Siena, Lucca, **Cagliari**, Venezia, Massa, Terni, Alessandria, Pisa, **Napoli**, Ancona, Grosseto, La Spezia, Pavia, Bologna, Bolzano, Como, Gorizia, Novara, Aosta, Imperia, Vercelli, Livorno, Varese, Firenze, Torino, Savona, Trieste, Milano, Roma, Genova

Period 1971-2000

Group 1 (21 provinces) ($y_t < -0.34$)	**Avellino, Agrigento, Potenza, Catanzaro, Lecce, Benevento, Cosenza, Campobasso, Enna, Reggio Calabria, Caserta, Bari, Catania, Salerno, Brindisi, Foggia, Nuoro, Caltanissetta, Ragusa, Palermo, Trapani**
Group 2 (71 provinces) ($y_t > -0.34$)	**Teramo, Matera, Napoli, Messina, Chieti,** Rieti, **L'Aquila,** Perugina, **Pescara,** Rovigo, Frosinone, Macerata, Ascoli P., **Sassari, Cagliari**, Udine, Pesaro, **Taranto**, Padova, Asti, Viterbo, Forlì, Terni, Cuneo, Imperia, Lucca, Belluno, Treviso, Pistoia, **Siracusa**, La Spezia, Ferrara, Alessandria, Grosseto, Ancona, Vicenza, Sondrio, Latina, Arezzo, Verona, Venezia, Savona, Vercelli, Massa, Gorizia, Novara, Bergamo, Pavia, Bolzano, Siena, Mantova, Livorno, Cremona, Genova, Ravenna, Piacenza, Brescia, Pisa, Firenze, Trento, Reggio E., Como, Modena, Parma, Trieste, Roma, Bologna, Torino, Varese, Aosta, Milano

TABLE 4

Per Capita Income Growth of Italian Provinces Multiple Regime Models – OLS Estimates
(Number into brackets refer to the p-values)

	1951-2000	1951-1970	1971-2000
α_1	0.478 (0.013)	1.257 (0.001)	0.011 (0.827)
β_1	0.013 (0.972)	0.719 (0.323)	-0.283 (0.124)
α_2	0.092 (0.109)	0.287 (0.009)	0.282 (0.481)
β_2	-1.586 (0.000)	-3.604 (0.000)	1.314 (0.517)
Adjusted R^2	0.505	0.560	0.001
Log-likelihood	-40.720	-99.113	-51.505
Schwartz Criterion	99.528	216.314	121.099
Test of Structural instability (Chow test)	7.295 (0.001)	15.503 (0.000)	0.333 (0.716)
Stability test of coefficient α_1	3.779 (0.055)	6.702 (0.011)	0.453 (0.502)
Stability test of coefficient β_1	13.230 (0.000)	27.147 (0.000)	0.617 (0.434)
Regression Diagnostics			
Jarque-Bera	2.683 (0.261)	4.367 (0.112)	1.454 (0.483)
Moran's I	6.988 (0.000)	5.522 (0.000)	3.834 (0.000)
LM-error	41.401 (0.000)	25.250 (0.000)	11.417 (0.000)
LM-lag	12.061 (0.000)	3.224 (0.072)	7.997 (0.000)

Notes: Chow test= $\{e_R'e_R - e_U'e_U\}/e_R'e_R \sim \chi^2(k)$, where e_R (e_U) are the residuals for a restricted (unrestricted) regression. Under the null hypothesis of no parameter instability ($\beta_1 = \beta_2$), the Chow test is distributed as $\chi^2(k)$.

Even controlling for non-linearities or multiple regime effects (when they are present), there is significant spatial dependence remaining in the cross-sectional OLS models. However, the values of I-Moran, LM-error and LM-lag tests reported in Table 4 are much lower than those reported in Table 1, especially for the period 1951-1970. This means that spatial dependence partially absorbs the non-linearity of the true function.

3.4. *β-convergence and spatial dependence*

Since the problem of spatial autocorrelation is not removed with the spatial regime specification, in the remainder of the paper we will focus on the spatial dependence modelling. Tables 5 and 6 display the results of maximum likelihood estimates of spatial error and spatial lag models for the entire and two sub-periods, respectively under the hypothesis of unique and double regimes.[8] The parameters associated with the spatial error and the spatial lag terms are always highly significant. This confirms the pronounced pattern of spatial clustering for growth rates found in Section 3.1 by looking at the Moran's I statistics.

[8] An OLS cross-regressive model, which includes a spatial lag of the initial per capita income level, has been also tested for each period and for different specifications. The coefficient of this variable, however, was never found to be significant. In fact the diagnostics indicate that there is significant spatial dependence remaining in the cross-regressive model.

Looking at these two tables, we can firstly observe that the two-regime models exhibit smaller estimates of the spatial correlation parameters than their one-regime counterparts. For example, for the first period, the estimate of the spatial autoregressive parameter in the two-regime model is 0.178, while it is 0.281 in the one-regime model. Again, we hypothesize that this is due to a 'spill-over' between the non-linearity of the underlying functions and the estimation of the spatial parameters. By forcing the data to conform to the linear parametric form, the residual non-linearities are assumed into the spatial parameter.

Again, the results of Chow tests indicate that the hypothesis of stability in the parameters can be rejected (only in the case of the spatial lag model) for the entire and the first period. This finding has two implications. First, it confirms the presence of one-common regime for the period 1970-2000; thus, for that period we will discuss only the estimates reported in Table 5. Second, it seems quite evident that the spatial error model absorbs the non-linearities in the parameters and always leads to reject the hypothesis of multiple regimes. Moreover, the fit of the one-regime spatial error model (based on the values of Schwartz Criterion) is always higher than those of OLS and maximum likelihood spatial lag one- and two-regime models.

TABLE 5

Per Capita Income Growth of Italian Provinces Spatial Dependence Models – ML Estimates
(Number into brackets refer to the p-values)

	1951-2000		1951-1970		1971-2000	
	Spatial error model	Spatial lag model	Spatial error model	Spatial lag model	Spatial error model	Spatial lag model
α	-0.110 (0.380)	-0.047 (0.264)	-0.092 (0.705)	-0.027 (0.766)	-0.135 (0.294)	-0.015 (0.740)
β	-1.687 (0.000)	-0.961 (0.000)	-3.386 (0.000)	-1.940 (0.000)	-1.652 (0.000)	-0.352 (0.042)
δ	0.819 (0.000)		0.767 (0.000)		0.719 (0.000)	
ρ		0.394 (0.000)		0.281 (0.005)		0.330 (0.006)
Log Likelihood	-1.687	-39.978	-83.317	-109.656	-40.519	-48.429
Schwartz Criterion	12.419	93.522	175.677	232.877	90.083	110.422
LR test (OLS vs. Spatial error model)	92.178 (0.000)		59.362 (0.000)		22.669 (0.000)	
LM-lag	7.088 (0.007)		9.854 (0.002)		25.382 (0.000)	
LR test (OLS vs. Spatial lag model)		15.597 (0.000)		6.684 (0.009)		6.850 (0.008)
LM-error		45.769 (0.000)		42.649 (0.000)		2.498 (0.113)

Notes:
LR (Likelihood Ratio) tests are tests on difference in fit:

1) LR test (Spatial lag model vs. OLS) = $N(\ln\sigma^2_{OLS} - \ln\sigma^2_{SAL}) + 2\sum_i \ln(1-\rho\varpi_i) \sim \chi^2(1)$

2) LR test (Spatial error model vs. OLS) = $N(\ln\sigma^2_{OLS} - \ln\sigma^2_{SEM}) + 2\sum_i \ln(1-\delta\varpi_i) \sim \chi^2(1)$

where ϖ_i are the eigenvalues of ***W***. The null hypothesis is that the two models are equivalent. In the LR test (OLS vs. Spatial lag model), when the null hypothesis is rejected, the OLS estimator is inconsistent. In the LR test (OLS vs. Spatial error model), when the null hypothesis is rejected, the OLS estimator is unbiased but inefficient.

For the entire and the first period, the coefficient of the initial level of per-capita income (and thus the implied convergence rate) decreases in the spatial lag model (both in the case of one and two regimes), while it increases in the spatial error model (which exhibits only one regime). As it is known, 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. This result is in line with the dominant opinion that the strong convergence occurred in Italy during the second world war until the early 1970s was partly due to technological transfer process (a strong regional convergence in terms of labour productivity occurred indeed over this period) and to a massive labour migration process.

TABLE 6

Per Capita Income Growth of Italian Provinces
Spatial Dependence Models with Mutiple Regimes – ML Estimates
(Number into brackets refer to the p-values)

	1951-2000		1951-1970		1971-2000	
	Spatial error model	Spatial lag model	Spatial error model	Spatial lag model	Spatial error model	Spatial lag model
α_1	-0.238 (0.438)	0.328 (0.059)	0.200 (0.709)	1.103 (0.001)	-0.072 (0.541)	-0.007 (0.882)
β_1	-1.730 (0.000)	-0.151 (0.668)	-3.328 (0.000)	0.557 (0.423)	-1.439 (0.000)	-0.383 (0.029)
α_2	-0.017 (0.919)	0.019 (0.713)	0.483 (0.051)	0.211 (0.045)	-0.618 (0.052)	0.199 (0.590)
β_2	-1.726 (0.000)	-1.394 (0.000)	-3.348 (0.000)	-3.433 (0.000)	-3.354 (0.001)	1.075 (0.567)
δ	0.806 (0.000)		0.681 (0.000)		0.671 (0.000)	
ρ		0.327 (0.000)		0.178 (0.070)		0.336 (0.004)
Log Lik.	-1.445	-35.248	-81.936	-97.582	-38.782	-47.969
Sch. Crit.	20.979	93.106	178.960	217.773	95.651	118.547
Chow test	0.581 (0.747)	10.534 (0.005)	0.695 (0.691)	28.713 (0.000)	3.897 (0.142)	0.926 (0.629)
Stability test of α_1	0.397 (0.528)	2.921 (0.087)	0.227 (0.633)	6.122 (0.013)	2.573 (0.108)	0.304 (0.581)
Stability test of β_1	0.000 (0.988)	9.675 (0.001)	0.026 (0.871)	25.020 (0.000)	3.079 (0.080)	0.598 (0.439)
LR-test (OLS vs. SEM)	78.549 (0.000)		42.354 (0.000)		25.447 (0.000)	
LM-lag	79.070 (0.000)		41.119 (0.000)		28.364 (0.000)	
LR-test (OLS vs. SAR)		10.943 (0.000)		13.062 (0.000)		7.074 (0.007)
LM-error		28.483 (0.000)		26.933 (0.000)		2.721 (0.099)

Notes: Chow test when the error term follows a spatial autoregressive progress:
$\{\boldsymbol{e}_R'(\boldsymbol{I}-\delta\boldsymbol{W})'(\boldsymbol{I}-\delta\boldsymbol{W})\boldsymbol{e}_R - \boldsymbol{e}_U'(\boldsymbol{I}-\delta\boldsymbol{W})'(\boldsymbol{I}-\delta\boldsymbol{W})\boldsymbol{e}_U\}/\boldsymbol{e}_R'\boldsymbol{e}_R \sim \chi^2(k)$ where $\boldsymbol{e}_R$ ($\boldsymbol{e}_U$) are the residuals for a restricted (unrestricted) regression.

The increase in the coefficient on initial per-capita income observed in the spatial error model for the entire and the first periods has of course a different interpretation. In this case, indeed, the correction for spatial dependence in the error term tends to capture the effect of omitted variables (different from factor migration, trade and spill-over), which have a negative effect on growth (such as the crime rate). We could say that the results of the spatial error model "obscure" the interpretation of the spatial dependence correction as a way to capture the effect of the regional openness degree on convergence. This point would suggest the necessity of using econometric tools, such as the fixed-effects model, which allow to properly capture the effects of omitted variables and thus to isolate the effect of spatial dependence.

Finally, Table 5 shows that, if compared to the OLS estimates, the coefficient of the initial per capita income (and thus the implied convergence rate) of the second period increases both in the spatial error and in the spatial lag models, suggesting that in this period regional spill-over and labour migration did not give any contribution to the regional convergence process, and thus spatial dependence parameters tend only to capture the effect of other omitted variables (which have negative effect on growth, such as the crime rate). This interpretation is in line with the common opinion according to which in the period 1970-2000 the lack of regional convergence (in particular the lack of convergence between Northern and Southern regions) has been – at least in part – due to the reduction in the opportunity for technological catching-up and to the reduction in the economic convenience for labour migration. Thus, for the second period, additional regressors should be included in the model and/or fixed effect models should be used to capture at least the effect of time invariant (unobserved) effects.

4. CONCLUDING REMARKS

Analysing regional growth behaviour and testing regional convergence within a cross-sectional regression (*β-convergence*) approach involve important economic and econometric issues, which can be grouped in three main categories: i) spatial dependence or spatial interaction, ii) omitted variables and iii) non-linearities (Magrini, 2003; Durlauf and Quah, 1999; Islam, 2003; and Temple, 1999). This paper represents a first step of a research program aimed at developing a proper econometric approach which simultaneously takes into account these three issues.

In particular, in the present paper we have examined the importance of spatial dependence and non-linearities in estimating the convergence process among Italian provinces (European NUTS-3 Regions) in the period 1951-2000 and in two sub-periods (1951-1970 and 1970-2000). Generally speaking, our results confirm that neglecting the spatial nature of data leads both to a misspecification of the growth model and to severe biases in the estimation of convergence rates.

Moreover, the evidence of two regimes for the entire and the second periods suggests that absolute convergence occurred only within a sub-group of regions. Precisely, only "relatively high income" regions followed a convergence path. Assuming a common regime (or linear) approach is therefore misleading: non-linearities are important in regional growth even when the spatial dependence, in the form of spatial lag of the growth rate, is controlled for. Moreover, one can be quite confident that the parameter of the spatial lag term of the spatial lag model tends to capture the positive effects of spatial interaction or openness (in the form of factor mobility, trade relations and knowledge spill-over) on regional convergence.

On the other hand, our findings show that controlling for spatial dependence through the spatial error model leads to obscure the effects of non-linearities in the parameters and to absorb the effects on growth of omitted variables different from factor mobility, trade relations and knowledge spill-over. This result confirms the necessity, even in the context of non-linear spatial dependent regression models, to control for the effect of heterogeneity and/or omitted variables by using panel data models.

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APPENDIX

A1. *The choice of the weight matrix*

A central issue in the specification of spatial auto-covariance models is the choice of the '**W**' spatial weights matrix. As the matrix is specified *a priori*, and as alternate specifications can have implications both for the theoretical interpretations of the model as well as the estimation of the spatial autocorrelation parameters, one of the primary criticisms of spatial auto-covariance models is the manner in which this matrix is specified.

A wide variety of methods are used in the literature to determine this matrix, including inverse functions of distances between observations, functions of the length of relative showed borders, measures based on semi-variograms, or measures based on non-spatial factors such as 'economic distance' - e.g. weighted trade ratios, or social distance as determined by social network theory. More commonly, spatial auto-covariance models deal with the relations between contiguous economic entities such as cities, regions, or nations, and the matrix is then determined based on binary relations between these entities, defining a network of interactions. In this case, functions of the contiguity of the observations or other such measures are used to create the **W** matrix.

We have chosen to use a spatial weights matrix based on the binary contiguity of the spatial regions. We believe that this should be sufficient to capture the major economic spatial interactions under consideration in our model: technological spillover, trade relations and factor mobility. By this specification, regions that are determined to be 'next to one another' by virtue of sharing a significant border have a

'1' entered in the corresponding cell of the matrix, where those that are not neighbours have a '0'. The resulting **W** matrix in this case is symmetric, with '0's along the diagonal. This matrix is then normalized to be row-stochastic, so that each row sums to unity. Normalization ensures that the estimated auto-covariance parameters are bounded between {-1,1}, allowing them to take the interpretation, in our case, of elasticities. Normalizing the **W** matrix also imposes the interpretation of 'competition between neighbours' (Anselin, 1988, pg. 24), in that the effects on growth rates between neighbouring regions is equal to *1/M*, where *M* is the number of neighbours to that region. Thus the more neighbours any region has, the less any one of its neighbours contributes to its own growth rate.

A2. *The scatterplot smoother and the lowess regression*

A scatterplot smoother helps addressing one of the simplest yet most fundament questions in data analysis: "what is our best guess of *y*, given *x*?" To define scatterplot smoothing, let $\mathbf{x}=(x_1,...x_n)'$ be the observations on an independent variable and let $\mathbf{y}=(y_1,...y_n)'$ be the observations on a dependent variable. Assume that the data are sorted by $\mathbf{x}$. A scatterplot smoother takes $\mathbf{x}$ and $\mathbf{y}$ and returns a function $\hat{y}=\hat{g}(x)$. Ordinary least squares (OLS) regression is a special case of a smoother, providing an infinite amount of smoothing. This is because in OLS regression the relationship between $\mathbf{x}$ and $\mathbf{y}$ is taken to be global, not local, and hence the smoothing neighbourhood is the entire dataset. On the contrary, in *lowess* regression the relationship between $\mathbf{x}$ and $\mathbf{y}$ is taken to be local and, thus, *lowess* is one of the most flexible nonparametric smoothing methods (Cleveland, 1979; Cleveland and Devlin, 1988).

Given a target point x_0, *lowess* yields $\hat{\mathbf{y}} \mid x_0 = \hat{g}(x_0)$ as follows:

1. Identify the *k* nearest neighbours of x_0, i.e., the *k* elements of $\mathbf{x}$ closest to x_0. This set is denoted $N(x_0)$. The analyst controls *k* via a "span" argument, which defines the size of the neighbourhood in terms of a proportion of the sample size: i.e. $k \approx span \times n$.
2. Calculate $\Delta(x_0) = \max_{N(x_0)} \left| x_0 - x_i \right|$, the distance of the near-neighbour most distant from x_0.
3. Calculate weights w_i for each point in $N(x_0)$, using the following *tricube weight function*:

$$W\left(\frac{\left|x_0 - x_i\right|}{\Delta(x_0)}\right)$$

where

$$W(z) = \begin{cases} (1-z^3)^3 \; for\, 0 \le z < 1 \\ 0 \qquad otherwise \end{cases}$$

Note that $W(x_0)=1$, and that the weights decline smoothly to zero over the set of nearest-neighbours, such that $W(x_i)=0$ for all non near-neighbours. The use of the tri-cube weight function here is somewhat arbitrary; any weight function that has smooth contact with 0 on the boundary of $N(x_0)$ will produce a smooth fitted function.

4. Regress **y** on **x** and a constant (for local linear fitting), using weighted least squares (WLS) with weights w_i as defined in the previous step. Quadratic or cubic polynomial regressions can also be used in these local regressions or even mixtures of low-order polynomials.
5. The smoothed value $\hat{g}(x_0)$ is the predicted value from the WLS fit at x_0.

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RIASSUNTO

Dipendenza spaziale e non-linearità nella crescita in Italia

In questo lavoro, presentiamo un'analisi empirica della convergenza regionale del reddito pro capite in Italia nel periodo 1951-2000, basata su un livello di aggregazione molto fine (le regioni NUTS-3 rappresentate dalle province italiane). Per quanto concerne la metodologia, usiamo sia approcci non parametrici che di econometria spaziale per catturare l'effetto sia della dipendenza spaziale che della non linearità nella relazione tra tassi di crescita e livelli iniziali di reddito pro capite. I risultati confermano l'ipotesi di *club convergence* e suggeriscono che gli *spillover* e i club di convergenza sono spazialmente concentrati.

SUMMARY

Spatial dependence and non-linearities in regional growth behaviour in Italy

In this paper, we present an empirical study of per capita income convergence in Italy over the period 1951-2000 based on a fine level of aggregation (the NUTS-3 EU regions represented by the Italian provinces). Concerning the statistical methodology, we use both nonparametric and spatial econometrics approaches to measure the effects of spatial dependence and non-linearities. Our results confirm the convergence club hypothesis and suggest that spillover and convergence clubs are spatially concentrated.