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REGIONAL CONVERGENCE IN ITALY 1951-1999: A SPATIAL ECONOMETRIC PERSPECTIVE

by

Giuseppe Arbia*, Roberto Basile** and Mirella Salvatore*

*Department of Sciences, Faculty of Economics, University "G. D'Annunzio"

**ISAE

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ABSTRACT[(*)]

Testing regional convergence hypothesis involves important data issues. In empirical circumstances the problem arises of finding the best data to test the theory and the best estimators for the associated modelling. In the literature usually little attention is given to the level of spatial aggregation used and to the treatment of the spatial dependence and spatial heterogeneity. In this paper, we present an empirical study of per capita income convergence in Italy based on a fine level of aggregation (the 92 provinces). We correct estimates by modelling the spatial heterogeneity and the spatial dependence among residuals and discuss the implications in terms of convergence speed.

JEL Classification: C13, O00, R11

Keywords: Regional convergence; Regional spill-over; Spatial dependence modelling; Spatial regimes.

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NON TECHNICAL SUMMARY

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 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 the variance of logarithm (to identify a σ-convergence) and on simple regression coefficients (to identify a β-convergence) estimated using standard OLS procedures. In this field researchers that base their conclusions on cross-sectional data referred to geographical units almost systematically neglect two remarkable features of spatial data. First of all, spatial data represent aggregation of individuals within arbitrary geographical border 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. Secondly, it is well known that regional data cannot be regarded as independently generated because of the presence of spatial similarities among neighbouring regions. 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.

In this paper, we present an empirical study of the long-run convergence of per capita income in Italy (1950-1999) based on a level of aggregation (the 92 provinces) which is fine enough to allow for spatial effects (like regional spill-overs) to be properly modelled. Furthermore, we correct the estimates by modelling the spatial dependence that emerges amongst the regression residuals. Finally, we discuss the implications in terms of convergence speed, of the interpretation of results and of policy evaluation.

In the period examined, income levels and growth rates are characterised by a strong spatial correlation, thus showing the presence of strong regional interdependence and spill-overs. As a consequence, a region experiencing growth propagates positive effects onto the neighbouring regions thus producing an acceleration of the convergence process. By taking this element into consideration the rate of convergence increases from 1.2 % to a figure ranging around 3% in the different specification tested for the period 1951-1999. The underestimation appears more dramatic in a first sub-period (1951-1970), characterised by a more rapid convergence. In this period the standard OLS analysis suggests a speed of convergence of 2.3%, whereas our spatially corrected models suggest values up to 6.4% in some specification. Conversely, in the second sub-period (1970-1999) the speed of convergence is 0.3%, if estimated with the OLS, and rises up to 1.4% in some of the spatial modelling specifications.

Furthermore, by considering a spatial regime analysis, we have shown that the speed of convergence is higher in the Centre-Northern provinces if considering the first period (1951-1970) and this is due mainly to the strong spatial dependence observed.

CONVERGENZA REGIONALE IN ITALIA NEL PERIODO 1951-1999: UN'ANALISI DI ECONOMETRIA SPAZIALE

SINTESI

Il test dell'ipotesi di convergenza regionale implica la risoluzione di importanti questioni empiriche. In particolare si pone il problema di trovare i dati e lo stimatore migliore per testare le ipotesi teoriche. In letteratura si presta generalmente scarsa attenzione al livello di aggregazione spaziale adottato e al trattamento della dipendenza e dell'eterogeneità spaziale. In questo lavoro, presentiamo uno studio empirico sulla convergenza del reddito pro capite in Italia basato sull'uso di dati ad un livello di aggregazione spaziale molto fine (le 92 province). Le stime sono corrette modellando l'eterogeneità e la dipendenza spaziale nel termine di errore e discutendo le implicazioni in termini di velocità di convergenza.

Classificazione JEL: C13, O00, R11

Parole chiave: convergenza regionale; spill-over regionali; modelli di dipendenza spaziale; regimi spaziali.

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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 (Solow, 1956; and Barro & Sala-i-Martin, 1995 for a review). A certain school of thought reached an optimistic view of reality by predicting that a set of countries (or regions) will tend to assume a common level of output per capita (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 economic and monetary union, the narrowing of regional disparities is indeed regarded as a fundamental objective for the European Union policy (McGuinness and Sheehan, 1998). Hence, the problem of testing convergence among the member States of the Union and measuring its speed (Barro and Sala-i-Martin, 1992; Quah, 1996a and 1996b) 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 the variance of logarithm (to identify a σ-convergence) and on simple regression coefficients (to identify a β-convergence) estimated using standard OLS procedures. In this field researchers that base their conclusions on cross-sectional data referred to geographical units almost systematically neglect two remarkable features of spatial data. First of all, spatial data represent aggregation of individuals within arbitrary geographical border 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, 1988). 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.

In this paper, we present an empirical study of the long-run convergence of per capita income in Italy (1950-1999) based on a level of aggregation (the 92 provinces) which is fine enough to allow for spatial effects (like regional spill-overs) to be properly modelled. Furthermore, we correct the estimates by modelling the spatial dependence that emerges amongst the regression residuals. Finally, we discuss the implications in terms of convergence speed, of the interpretation of results and of policy evaluation.

The layout of the paper is the following. In Section 1, we present a review of spatial econometric techniques that incorporate spatial dependence and spatial heterogeneity within the contest of a β-convergence modelling. In Section 2, 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 1999 and show the different estimates of the convergence speed obtained by using different modelling specifications for spatial effects. Finally, in Section 3 we discuss the results obtained and outline possible extensions of the present work.

1. REGIONAL CONVERGENCE AND SPATIAL EFFECTS

The most popular approaches in the quantitative measurement of convergence are those based on the concepts of σ- and β-convergence (Barro and Sala-i-Martin, 1995 for a review). Alternative approaches are those based on (continuous) transition matrices proposed by Quah (1997) and employed by Rey (2000) in regional studies, and, more recently, the Lotka-Volterra predator-prey specification given in Arbia and Paelinck (2002).

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). Furthermore, as argued by Rey and Montoury (1998), σ-convergence analysis may "mask nontrivial geographical patterns that may also fluctuate over time" (p. 7-8). 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).

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 exogenous saving rates and a production function based on decreasing productivity of capital and constant returns to scale. On this basis authors like Mankiw *et al.* (1992) and Barro and Sala-i-Martin (1992) suggested the following statistical model

$$\ln\left[\frac{y_{t+k,i}}{y_{t,i}}\right] = \mu_{t,i} + \varepsilon_{t,i} \qquad (1)$$

with $y_{t,i}$ *(t=1,..., T; I=1,...,n)* the per capita income at time *t* in region *i*, $\mu_{t,i}$ the systematic component and $\varepsilon_{t,i}$ the error term with

$$\mu_{t,i} = \alpha + (1 - e^{-\lambda k}) \ln y_{t,i} \qquad (2)$$

with λ the speed of convergence, which measures how fast economies will converge towards the steady state. The assumption on the probability model implicitly made in this context is that $\varepsilon_{t,i}$ is normally distributed *(0, σ^2)* independently of $lny_{t,i}$. Finally, concerning the sampling model, it is assumed that $\{\varepsilon_{t,1}, \varepsilon_{t,2}, ...\varepsilon_{t,n},\}$ are independent observations of the probability model.

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

However, the sampling model of independence is inadequate to the considered case, since regional observations are likely to display positive spatial dependence with distinct geographical patterns (Cliff and Ord, 1973; Anselin, 1988).

A more correct statistical model that takes spatial correlation into account is the so-called *spatial lag model* (Anselin and Bera, 1998), where spatial dependence is accounted for by including a serially autoregressive term of the dependent variable so that the systematic component in (1) is re-specified as

$$\mu_{t,i} = \alpha + (1 - e^{-\lambda k}) \ln y_{t,i} + \gamma L\left[\frac{y_{t+k,i}}{y_{t,i}}\right] \tag{3}$$

with *L[.]* the spatial lag operator (Anselin and Bera, 1998) and the error term again assumed normally distributed independently of $lny_{t,i}$ and of $L\left[\frac{y_{t+k,i}}{y_{t,i}}\right]$. In such a model $\{\varepsilon_{t,1}, \varepsilon_{t,2}, ...\varepsilon_{t,n},\}$ again are assumed independent errors of the probability model in the hypothesis that all spatial dependency effects are captured by the lagged term. The parameters of model (3) can be estimated via maximum likelihood (ML), instrumental variables or generalized method of moments (GMM) procedures as indicated by Anselin and Bera (1998).

An alternative way to incorporate the spatial effects is to leave unchanged the systematic component and to model the error term in (1) as an autoregressive random field, for instance assuming that

$$\varepsilon_{t,i} = \delta L(\varepsilon_{t,i}) + u_{t,i} \tag{4}$$

and reformulate a probability model for the *u's* by assuming them to be normally distributed *(0, σ_u^2)* independently of $lny_{t,i}$ and randomly drawn. We call this second model *lagged error model* (Anselin and Bera, 1998). Again the parameters can be estimated by using ML or GMM procedures (Conley, 1999).

The spatial econometric literature raises also the problem of spatial heterogeneity, that is the lack of stability over space of the behavioural or other relationships under study (Anselin, 1988). This implies that functional forms and parameters vary with location and are not homogenous throughout the data set. In contrast to the spatial dependence case, the problems caused by spatial heterogeneity can for the most part be solved by means of standard econometric techniques. Specifically, methods that pertain to varying parameters, random coefficients and structural instability can easily be adapted to take into account such variation over space. However, in some situations, the problem of distinguishing between spatial dependence and spatial heterogeneity is highly complex. In those instances, the tools provided by standard econometrics are inadequate and a specific spatial econometric approach is necessary.

With regard to the cross-section growth analysis, some authors (Baumol, 1986, Neven and Gouyette, 1995, Quah, 1996, Durlauf and Johnson, 1995) suggest that regions might be interested not to a global convergence process - that is, convergence of *per capita* incomes of all regions towards a common steady state - but to a convergence by “clubs”, having common geographical (i.e., Center-periphery or North-South) or social-economic peculiarities (i.e., human capital, unemployment rate, public infrastructure, R&D activity, financial deepening). In other words, convergence within each club may be observed, without much reduction of between-club inequalities. Following upon a spatial criterion, Italian regions can be classified in two standard groupings: North-Centre and South. In order to test the hypothesis of convergence club, the systematic component (2) can be modifies to take the form

$$\begin{aligned} \mu_{t,i} &= \alpha_{CN} + (1-e^{-\lambda_{CN}k})\ln y_{t,i} && \text{if} \quad i \in North-Centre \\ \mu_{t,i} &= \alpha_{SOUTH} + (1-e^{-\lambda_{SOUTH}k})\ln y_{t,i} && \text{if} \quad i \in South \end{aligned} \qquad (2')$$

The same adjustment can be applied to the systematic component in (3).

If the convergence club hypothesis is correct, for example, if two regimes are present, with each regime converging to a different state and at a different rate, estimations based on a single regime may produce a non-significant estimate for the convergence parameter.

2. 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[1]. The analysis is based on a newly compiled database on per capita GDP for the 92 provinces over the period 1951-1999[2]. Table 1 reports some descriptive statistics, whereas Figures 1 and 2 display the geographical pattern of per capita incomes and growth rates. Figure 1 shows a marked core-periphery pattern, with the core situated in the North-Centre. Growth rates show a different spatial pattern with higher rates located in the North-East and irregularly scattered in the South.

Table 1: Descriptive statistics of per capita incomes and growth rates in the 92 Italian provinces (years 1951, 1970, 1999).

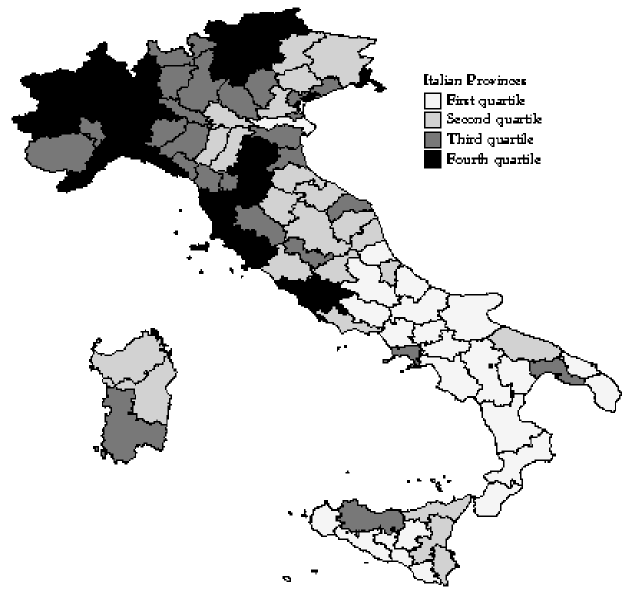
Per capita income									
Period	**Min**	**Max**	**Mean**	**First quartile**	**Second quartile**	**Third quartile**	**Coefficient of variation**	**Skewness**	**Kurtosis**
1951	3.28	14.00	6.97	4.72	5.90	7.17	0.38	1.14	3.89
1970	8.32	25.03	16.63	12.35	16.58	19.13	0.25	-0.21	2.14
1999	15.77	49.13	30.97	23.08	29.75	35.57	0.27	0.10	2.23
Growth rates									
Period	**Min**	**Max**	**Mean**	**First quartile**	**Second quartile**	**Third quartile**	**Coefficient of variation**	**Skewness**	**Kurtosis**
1951-70	2.05	6.91	4.69	4.44	5.21	5.66	0.21	-0.69	0.47
1970-99	0.94	3.33	2.17	1.87	2.18	2.49	0.22	-0.13	0.00
1951-99	1.82	4.43	3.16	2.94	3.33	3.63	0.16	-0.40	0.03

Source: Istituto Guglielmo Tagliacarne and Prometeia

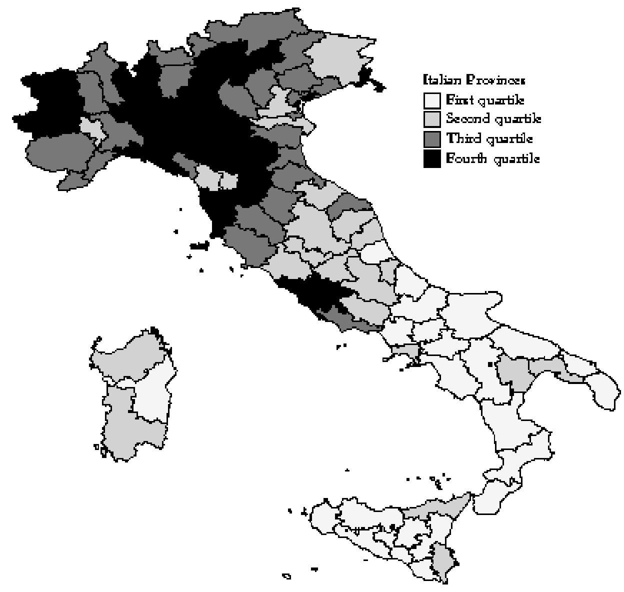
[1] The compilation of provincial data on value added has been based on estimates elaborated by the Istituto Guglielmo Tagliacarne, which involve the adoption of direct and indirect provincial indicators to disaggregate regional product within provinces. These estimates have been transformed at constant prices by using sectoral/regional value added deflators. The source of population data is ISTAT (National Institute of Statistics).

[2] Italy is currently divided into 103 provinces, grouped into 20 regions. Over the period considered (1951-1999), 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.

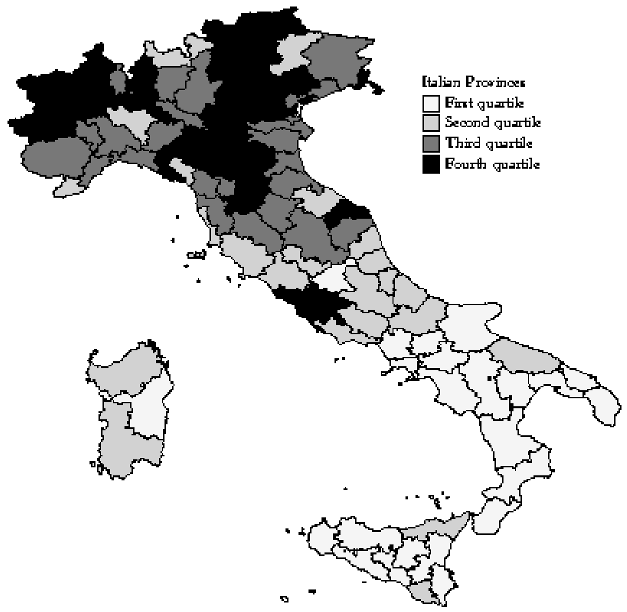
Figure 1: Distribution of provinces' per-capita incomes (natural log). (a) year 1951, (b) year 1970, (c) year 1999.



(a) natural log of per capita income in 1951



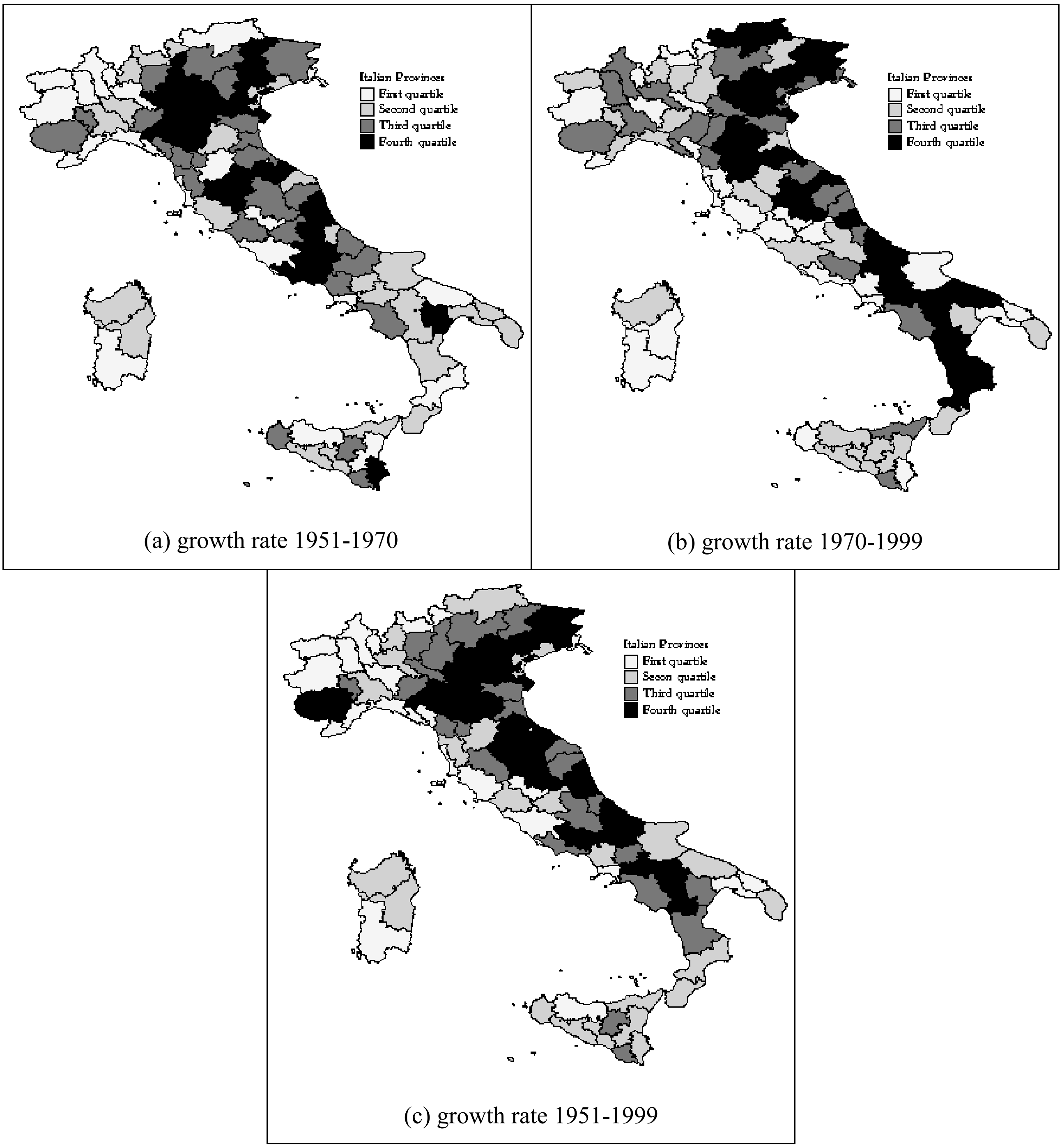
(b) natural log of per capita income in 1970



(c) natural log of per capita income in 1999

Source: Istituto Guglielmo Tagliacarne and Prometeia

Figure 2: Distribution of provinces' per capita income growth rates. (a) 1951-1970, (b) 1970-1999, (c) 1951-1999.



(a) growth rate 1951-1970

(b) growth rate 1970-1999

(c) growth rate 1951-1999

Source: Istituto Guglielmo Tagliacarne and Prometeia

We start by considering σ-convergence of per capita income in the 92 provinces and the related spatial patterns over the period 1951-1999 (Section 3.1). In Section 3.2 we will move to the β-convergence analysis by taking explicitly into consideration the spatial dependence pattern displayed by data.

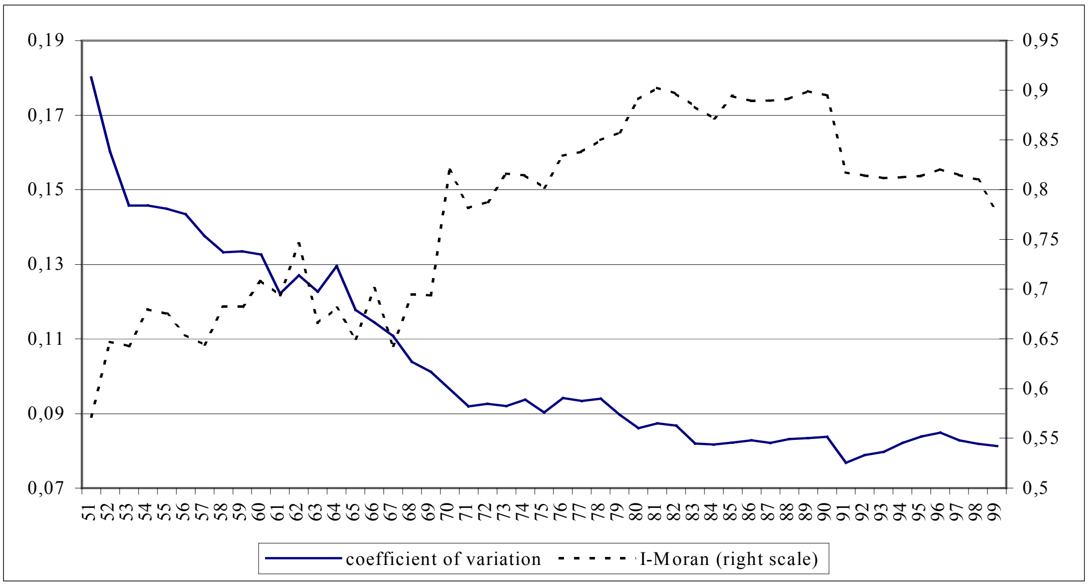
2.1 σ convergence and spatial autocorrelation: 1951-1999

Figure 3 shows the dynamics of the provinces' real per capita GDP dispersion, measured in log terms, over the period 1951-1999, 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 between 1951 and 1970. This is due partly to the significant effort to implement territorial development in the South (through the *Cassa del Mezzogiorno*) and partly to the development of the North-Eastern regions. The following period was, instead, characterized by a substantial invariance of the income inequalities. Moreover, a slight divergence of *per capita* GDP levels between Italian provinces occurred during the nineties, that is after the policy making-breakthrough taken place in 1992, when extraordinary intervention in the South was suppressed.

Figure 3 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 very 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 (1998) 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 registered 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 decreased over the '90s, a period of slight regional divergence.

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

Figure 3: Italian provinces convergence of per-capita income and related spatial autocorrelation in the period 1951-99



Source: Istituto Guglielmo Tagliacarne and Prometeia

2.2 β convergence and spatial dependence

In this section, we report the results of a β-convergence analysis of Italian provinces' per capita incomes in the period 1951-1999. 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 effects. Further, we would like to know what is the speed of catching-up and whether it has changed over time and across different parts of the country.

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 (spatial heteroskedasticity and spatial autocorrelation). Then, we use alternative specifications that extend the unconditional model by explicitly taking into account different spatial effects, namely: the presence of spatial regimes, spatial dependence in the distribution of errors, spatial autocorrelation in the dependent variable (growth rates) and in the predictor (initial per capita income).

Following Fabiani and Pellegrini (1997) and coherently with the evidence on σ convergence discussed above, we consider the existence of a break in the growth model at the beginning of the seventies. Thus, we analyse whether the break point in convergence in the early seventies is reflected in the different specifications of the econometric model.

Table 2 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, 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 by Fabiani and Pellegrini (1997) and confirmed by our σ convergence analysis reported above, we estimate models for the whole period 1951-99 and for the two sub-periods 1951-70 and 1970-99.

Table 2: Convergence of per capita income in the 92 Italian provinces (1951-1999) - Unconditional Models - OLS Estimates

(numbers into brackets refer to the p-values)

	1951-1999	**1951-1970**	**1970-1999**
Constant	-0.016 (0.735)	0.058 (0.516)	-0.045 (0.354)
Income level	-0.909 (0.000)	-1.848 (0.000)	-0.313 (0.074)
Goodness of fit			
Adjusted R^2	0.366	0.395	0.024
Log Likelihood	-48.423	-108.217	-56.066
Schwartz Criterion	105.890	225.477	121.177
Regression Diagnostics			
Jarque-Bera	2.133 (0.344)	2.422 (0.297)	1.039 (0.594)
Breusch-Pagan	0.050 (0.822)	1.345 (0.246)	0.045 (0.831)
White test	0.383 (0.825)	2.222 (0.329)	0.365 (0.833)
Moran's I	7.226 (0.000)	7.118 (0.000)	2.569 (0.010)
LM (error)	45.866 (0.000)	44.454 (0.000)	4.934 (0.026)
LM (lag)	15.959 (0.000)	10.393 (0.001)	3.644 (0.056)

Our results appear very much in line with the previous findings on the development of Italian regions/provinces. The coefficient of absolute β convergence for the whole period is highly significant with the expected sign, confirming the presence of absolute convergence over the years 1951-1999. Its value (-0.91) implies an annual rate of convergence of 1.2% (Table 3).

Table 3 - Comparison of the convergence rates estimated with the different models[a]

		1951-1999	1951-1970	1970-1999
Unconditional model (OLS estimates)		**0.012**	**0.023**	**0.003**
Spatial error model (ML estimates)		0.024	0.049	0.005
Spatial lag model (ML estimates)		0.010	0.021	0.003
Spatial regimes: different intercepts and slopes (OLS estimates)	Center-North	0.033	**0.061**	0.008
	South	0.023	**0.020**	0.022
Spatial regimes: different intercepts and common slope (OLS estimates)		**0.030**	0.050	**0.014**
Spatial error and spatial regimes: different intercepts and slopes (ML estimates)	Center-North	0.031	**0.064**	0.007
	South	0.024	**0.026**	0.025
Spatial lag and Spatial regimes: different intercepts and slopes (ML estimates)	Center-North	0.026	0.057	0.006
	South	0.023	0.021	0.021
Spatial error and spatial regimes: different intercepts and common slope (ML estimates)		**0.028**	0.051	**0.014**
Spatial lag and spatial regimes: different intercepts and common slope (ML estimates)		0.026	0.046	0.013

[a] Convergence Rate= $\lambda = -\dfrac{\log(1-\beta)}{k}$

By splitting the entire period into the two sub-periods, shows an abrupt change in the process of growth between 1951-1970 and 1970-1999. The coefficient of initial per capita GDP is –1.85 and significant at $p<0.01$ for the first period, while it is –0.313 and significant only at $p<0.10$ for the second period. Similarly, the convergence rate was fairly high (2.3%) during the first period and declined substantially (to 0.3%) during the period 1970-1999. The lack of β-convergence starting from the beginning of the '70s was also suggested by Paci and Pigliaru (1995), Cellini and Scorcu (1995) and Fabiani and Pellegrini (1997).

Table 2 also reports some diagnostics to identify misspecifications in the OLS cross-sectional model. Firstly, the Jarque-Bera normality test is always far from significant. Consequently, we can safely interpret the results of the various misspecification tests (heteroscedasticity[3] and spatial dependence tests) that depend on the normality assumption, such as the various Lagrange Multiplier

[3] 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).

tests. Since no problems were revealed with respect to a lack of normality, the Breusch-Pagan statistic is given. Its values are far from significant, indicating that there are no heteroscedasticity problems. This is confirmed by the robust White statistics.

The last specification diagnostics refers to spatial dependence. Three different tests for spatial dependence are included: a Moran's I test and two Lagrange multiplier 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 autocorrelation) and LM (spatial lag) have high values and are strongly significant especially in 1951-99 and in 1951-70, indicating significant spatial dependence, with an edge towards the spatial error.

The results described so far suggest that the original unconditional model, which has been the workhorse of much previous research, suffers from a misspecification due to omitted spatial dependence. Thus, we attempt alternative specifications. An approach, adopted for the case of the United States by Rey and Montoury (1998), consists of the application of spatial econometric tools directly to the unconditional model[4].

An alternative approach, proposed in this paper, consists of firstly applying the OLS method to test for 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, in the form of different intercepts and/or slopes in the regression equation for subsets of the data.

Table 4 reports OLS estimates of spatial regime models under the hypothesis of both different intercepts and slopes and different intercepts and common slopes. The table also reports the results of a "spatial" Chow test on the stability of the regression coefficients over the two regimes. This test has been implemented for the two coefficients (intercept and slope) jointly, as well as for the coefficients separately[5].

[4] Table 3 also reports the convergence rates estimated with the spatial error and the spatial lag econometric tools applied directly to the unconditional model.

[5] In the OLS framework, the Chow statistic is distributed as an F variate with K, N-MK degrees of freedom (N as the number of observations, K as the number of parameters, M as the number of regimes). In maximum likelihood spatial dependence models, the test is based on the asymptotic Wald statistic, distributed as χ^2 with (M-1)*K degrees of freedom.

Table 4: Convergence of per capita income in the 92 Italian provinces (1950-1999)– Spatial Regime models - OLS Estimates

(numbers into brackets refer to the p-values)

	1951-1999		1951-1970		1970-1999	
	Different intercepts and slopes	**Different intercepts and common slope**	**Different intercepts and slopes**	**Different intercepts and common slope**	**Different interceptsa nd slopes**	**Different intercepts and common slope**
Constant		0.154 (0.000)		0.407 (0.000)		0.078 (0.207)
Initial Income level		-1.612 (0.000)		-3.284 (0.000)		-1.155 (0.000)
Mezzogiorno		-0.783 (0.000)		-1.602 (0.000)		-0.560 (0.002)
Constant North-Center	0.156 (0.000)		0.415 (0.000)		0.039 (0.555)	
Initial Income level North-Center	-1.661 (0.000)		-3.671 (0.000)		-0.691 (0.120)	
Constant Mezzogiorno	-0.537 (0.000)		-0.463 (0.041)		-0.673 (0.000)	
Initial Income level Mezzogiorno	-1.411 (0.000)		-1.684 (0.000)		-1.635 (0.000)	
Goodness of fit						
Adjusted R^2	0.662	0.663	0.758	0.718	0.122	0.110
Log-likelihood	-18.515	-18.866	-64.928	-72.470	-50.144	-51.304
Schwartz Criterion	55.117	51.299	147.944	158.506	118.377	116.174
Regression Diagnostics						
Jarque-Bera	0.668 (0.716)	0.814 (0.665)	0.993 (0.608)	0.577 (0.749)	1.664 (0.434)	1.339 (0.511)
Chow test	40.298 (0.000)		68.757 (0.000)		6.044 (0.003)	
Stability of individual coefficients						
- Constant	24.201 (0.000)		14.205 (0.000)		12.023 (0.000)	
- Initial Income level	0.675 (0.413)		15.677 (0.000)		2.245 (0.137)	
Breusch-Pagan	0.330 (0.565)	0.542 (0.762)	0.907 (0.341)	3.879 (0.143)	0.041 (0.837)	0.145 (0.929)
Moran's I	3.602 (0.000)	3.697 (0.000)	3.857 (0.000)	4.438 (0.000)	2.559 (0.010)	2.152 (0.031)
LM (error)	9.726 (0.001)	10.489 (0.001)	11.311 (0.001)	15.625 (0.000)	4.269 (0.038)	3.040 (0.081)
LM (lag)	8.334 (0.003)	9.116 (0.003)	1.738 (0.187)	4.700 (0.030)	3.020 (0.082)	2.550 (0.110)

The results suggest that the null hypothesis on the joint equality of coefficients can always be rejected. The same indication is not always provided by the tests on the individual coefficients. Specifically, for the entire period and for the second sub-period there is a significant difference in the intercept term (in both cases the dummy variable Mezzogiorno is strongly significant) but not in the slope coefficient. Thus, comparing the conditional and the unconditional models, it appears that the coefficient of the initial per capita income increases from –0.91 to –1.61 for the overall period and from –0.31 to –1.16 for the period

1970-1999; so, the convergence rate also increases from 1.2 to 3% for the entire period (1951-1999) and from 0.3 to 1.4% for the second sub-period (see Table 4). Note also that the fit of these models, both in terms of information criteria and adjusted R^2, is much better than that of the unconditional specification.

For the first sub-period (characterised by strong convergence), instead, both the intercept and the slope coefficients are significantly different from North-Centre and South. Thus, we consider the spatial regime model as a more reliable specification. The adjusted R^2 is now 0.76, while it was 0.40 in the unconditional model; the log-likelihood of –64.9 (it was –108.2) shows also a much better fit and the Schwartz Criterion (147.9 vs. 225.5) indicates that this is sufficient for the decrease in degrees of freedom. The coefficients are significantly different from zero in both spatial regimes, but the intercept term has an opposite sign in the two regimes (positive for the North-Center and negative for the Mezzogiorno). The value of the slope coefficient is much higher for the North-Center (-3.67) than for the South (-1.68). Thus, during the period 1951-1970, the two geographical areas have been interested by different convergence paths. The convergence speed is 6.1% for the North-Center and 2% for the South.

However, the most remarkable feature is that, even controlling for spatial regime effects, there is significant spatial dependence remaining in the cross-sectional OLS models especially in the first sub-period. Conversely, the Breusch-Pagan test for heteroscedasticity is not significant in any of the sub-samples.

Since the problem of spatial autocorrelation among the residuals is not removed with these specifications, in the remainder of the paper we will restrict attention to the spatial dependence modelling and will leave out of consideration the problem of spatial heterogeneity.

Tables 5 and 6 display the results of maximum likelihood estimates of spatial error and spatial lag models over the entire period and for the two sub-periods, using the spatial regime specification[6]. The parameters associated with the spatial error and the spatial lag terms are highly significant in 1951-1999 and in 1951-1970; they are only marginally significant for the error model and are not significant for the lag term when the second sub-period (1970-1999) is considered. This confirms the pronounced pattern of spatial clustering for growth rates found in Section 3.1 by looking at the Moran's I statistics.

[6] 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.

Table 5: Convergence of per capita income in the 92 Italian provinces (1950-1999)- Spatial Dependence Models with spatial regimes (different intercepts and common slope)- ML Estimates

(numbers into brackets refer to the p-values)

	1951-1999		**1951-1970**		**1970-1999**	
	Spatial error model	**Spatial lag model**	**Spatial error model**	**Spatial lag model**	**Spatial error model**	**Spatial lag model**
Constant	0.122 (0.046)	0.110 (0.003)	0.369 (0.001)	0.332 (0.000)	0.064 (0.382)	0.069 (0.242)
Initial Income level	-1.549 (0.000)	-1.482 (0.000)	-3.324 (0.000)	-3.129 (0.000)	-1.179 (0.000)	-1.087 (0.000)
Mezzogiorno	-0.687 (0.000)	-0.707 (0.000)	-1.479 (0.000)	-1.506 (0.000)	-0.547 (0.004)	-0.523 (0.003)
δ	0.437 (0.000)		0.486 (0.000)		0.236 (0.065)	
γ		0.265 (0.001)		0.189 (0.020)		0.196 (0.118)
Goodness of fit						
Log Likelihood	-13.380	-14.487	-64.853	-70.103	-49.807	-50.123
Schwartz Criterion	40.326	47.061	143.272	158.293	113.181	118.334
Regression Diagnostics						
Breusch-Pagan	1.107 (0.575)	0.682 (0.711)	6.196 (0.045)	3.410 (0.181)	0.194 (0.907)	0.114 (0.944)
LR test (Spatial error model vs. OLS)	10.973 (0.000)		15.233 (0.000)		2.992 (0.083)	
LM (lag)	0.307 (0.578)		0.067 (0.795)		0.623 (0.429)	
LR test (Spatial lag model vs. OLS)		8.759 (0.003)		4.734 (0.029)		2.361 (0.124)
LM (error)		2.167 (0.141)		10.936 (0.001)		0.305 (0.580)

As we expected from the diagnostic tests reported in Tables 2 and 4, the fit of spatial error models (based on the values of Schwartz Criterion) is higher than that of both OLS cross-sectional and maximum likelihood spatial lag models. The spatial lag model outperforms the OLS one only when the entire period is considered. As a consequence, the spatial error model (with spatial regimes for the first period and with different intercepts for the whole and the second periods) must be regarded as the most appropriate specification for the examined data. Compared to the OLS estimates, the initial per capita income coefficients and the implied convergence rates did largely remained the same for the whole and the second sub-period. Conversely, they increased for the first period (the one of fast convergence), especially in the Southern regime.

Table 6: Convergence of per capita income in the 92 Italian provinces (1950-1999)– Spatial Dependence Models with spatial regimes (different intercepts and slopes) (ML Estimates)

(numbers into brackets refer to the p-values)

	1951-1999		**1951-1970**		**1970-1999**	
	Spatial error model	**Spatial lag model**	**Spatial error model**	**Spatial lag model**	**Spatial error model**	**Spatial lag model**
Constant North-Center	0.146 (0.014)	0.111 (0.003)	0.433 (0.000)	0.368 (0.000)	0.022 (0.789)	0.026 (0.671)
Initial Income level North-Center	-1.618 (0.000)	-1.502 (0.000)	-3.780 (0.000)	-3.542 (0.000)	-0.624 (0.185)	-0.584 (0.168)
Constant Mezzogiorno	-0.551 (0.000)	-0.563 (0.000)	-0.615 (0.006)	-0.517 (0.017)	-0.749 (0.000)	-0.658 (0.000)
Initial Income level Mezzogiorno	-1.439 (0.000)	-1.410 (0.000)	-2.064 (0.000)	-1.734 (0.000)	-1.811 (0.000)	-1.598 (0.000)
δ	0.421 (0.000)		0.438 (0.000)		0.283 (0.022)	
γ		0.259 (0.002)		0.115 (0.148)		0.212 (0.085)
Goodness of fit						
Log Likelihood	-12.034	-14.435	-57.281	-64.004	-47.808	-48.740
Schwartz Criterion	42.156	51.479	132.650	150.618	113.705	120.089
Regression Diagnostics						
Chow test	42.623 (0.000)	71.273 (0.000)	84.800 (0.000)	123.184 (0.000)	12.300 (0.002)	11.929 (0.002)
Stability of individual coefficients						
- Constant	21.919 (0.000)	26.616 (0.000)	18.074 (0.000)	15.423 (0.000)	12.161 (0.000)	11.926 (0.000)
- Initial Income level	0.436 (0.508)	0.106 (0.745)	14.979 (0.000)	13.522 (0.000)	3.316 (0.0685)	2.817 (0.093)
Breusch-Pagan	0.977 (0.322)	0.504 (0.477)	3.346 (0.067)	1.030 (0.310)	0.119 (0.729)	0.020 (0.885)
LR test (Spatial error model vs. OLS)	12.961 (0.000)		15.295 (0.000)		4.672 (0.030)	
LM (lag)	0.249 (0.617)		0.556 (0.455)		1.818 (0.177)	
LR test (Spatial lag model vs. OLS)		8.159 (0.004)		1.848 (0.174)		2.809 (0.093)
LM (error)		2.183 (0.139)		10.391 (0.001)		1.338 (0.247)

In conclusion, the results reported in Tables from 2 to 6 provide strong evidence of spatial effects in the unconditional convergence model widely applied in the literature. These effects have some important implications in terms of the estimated convergence speed. In particular, our results clearly suggest that, in the presence of a strong positive spatial autocorrelation both in the per capita income levels and in the growth rates, the OLS rate of convergence is strongly under-estimated and this in turn is due to the fact that regional spill-over effects allow regions to grow faster than one would expect. Indeed, in the presence of significant spatial error dependence, the random shocks to a specific province are propagated throughout the country. The introduction of a positive shock to the error for a specific province has obviously the largest relative impact (in terms of growth rate) on this province. However, there is also a spatial propagation of this shock to the other provinces. The magnitude of the shock spill-over dampens as the focus moves away from the immediate neighbouring provinces (see also Rey and Montoury, 1998).

3. CONCLUDING REMARKS

In the present paper we have examined the importance of spatial dependence and spatial heterogeneity amongst data in estimating the convergence rate of the regional per capita incomes. In particular, by examining the time evolution of per-capita income of the 92 Italian provinces (European NUTS-3 Regions) in the period 1951-1999, we have shown that, by neglecting the spatial nature of data, the convergence rates are substantially underestimated by the standard OLS procedures.

In the period examined, income levels and growth rates are characterised by a strong spatial correlation, thus showing the presence of strong regional interdependence and spill-overs. As a consequence, a region experiencing growth propagates positive effects onto the neighbouring regions thus producing an acceleration of the convergence process. By taking this element into consideration the rate of convergence increases from 1.2 % to a figure ranging around 3% in the different specification tested for the period 1951-1999. The underestimation appears more dramatic in a first sub-period (1951-1970), characterised by a more rapid convergence. In this period the standard OLS analysis suggests a speed of convergence of 2.3%, whereas our spatially corrected models suggest values up to 6.4% in some specification. Conversely, in the second sub-period (1970-1999) the speed of convergence is 0.3%, if estimated with the OLS, and rises up to 1.4% in some of the spatial modelling specifications.

Furthermore, by considering a spatial regime analysis, we have shown that the speed of convergence is higher in the Centre-Northern provinces if considering the first period (1951-1970) and this is due mainly to the strong spatial dependence observed.

The present results are of paramount importance in terms of policy evaluation and suggest that spatial effects captured by the models presented here are important elements to be considered in targeting resources.

The analysis reported here is preliminary in many respects. First of all, the convergence analysis carried out here uses data in the per capita income. Yet growth theories make predictions about labour productivity not income! Growth models concentrate on aggregate production function and assume full employment. Thus, they make no predictions about unemployment and labour force participation. As it was suggested elsewhere (e. g. Boldrin and Canova, 2001) this makes all the difference in the empirical analysis. Indeed, the observed inequalities at the provincial level can be due to the combination of three factors namely: i) differences in labour productivity, ii) differences in employment rates, and iii) interactions between productivity and employment rates. In a future paper, we will address this aspect by looking at a recently compiled database on labour productivity and employment rates for the 95 Italian provinces. Some preliminary analysis on this database reveals a very strong process of productivity convergence, but the effects of spatial dependence need to be accounted for.

Secondly, in the present paper we have not considered the effect of explanatory variables other than the initial income level. Future research effort should move towards the testing for the presence of conditional convergence by introducing into consideration conditioning variables like human capital and infrastructure in the presence of spatial dependence.

Finally, the analysis of spatial dependence can be extended in order to include different approaches to regional convergence, like e. g. the transitional matrices analysis employed by Quah (1997) and Rey (2000).

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