Vol.4.Issue.4.2016 (October -December)

BULLETIN OF MATHEMATICS AND STATISTICS RESEARCH

A Peer Reviewed International Research Journal

http://www.bomsr.com
Email:editorbomsr@gmail.com

RESEARCH ARTICLE

ISSN:2348-0580

SPATIAL MODELS THE ANALYSIS OF β–CONVERGENCE AT MICRO-TERRITORIAL LEVEL

EMANUELE TAUFER, DIEGO GIULIANI, GIUSEPPE ESPA, MARIA M. DICKSON
Department of Economics and Management, University of Trento
Trento - Italy

ISSN:2348-0580
BOMSR
BULLETIN OF MATHEMATICS AND STATISTICS RESEARCH
www.bomsr.com

ABSTRACT

In the paper, the presence of β-convergence effects at micro area level are analyzed by means of econometric and spatial econometric models. Typically, convergence effects are studied for large geographical units; with the present work it is shown that convergence is present at a finer level of resolution. Models are applied to local labor districts of a region in Italy. The use of spatial models improves the analysis of the phenomenon.

Keywords: β-convergence, σ-convergence, spatial regression, Durbin model.

1. INTRODUCTION

In the study of economic growth and disparities in income distribution at regional or national level one often refers to two fundamental concepts of convergence. A first type of convergence occurs when a poorer economy grows faster than a richer economy, achieving parity in terms of level of income, value added or GDP per capita. This phenomenon is referred to as β-convergence and was developed in particular by Mankiw (1992), Barro and Sala-I-Martin (1995). A second type of convergence occurs if the dispersion of the GDP or per capita income in different economies decreases; in this cases we speak of σ-convergence. The convergence of the first type usually tends to generate that of the second type.

The basic model for the study of *β*-convergence refers to the equation (see, for example, Arbia (2005, p.8) for further details)

$$\ln(y_t) = \left(1 - e^{-bt}\right)\ln(y^*) + e^{-bt} \ln y_0,$$

where y_t and y_0 represent, respectively, the GDP (or income or value added) in period t and in the initial period; y^* is the equilibrium value of the system, given the technology. As one can see, the value $\ln(y_t)$ is a linear combination of the initial value and the equilibrium point. The speed of convergence towards the equilibrium is determined by the parameter *b* which is defined *speed of convergence*.

Another key parameter to analyze the convergence of an economy is the so-called *half-life*, defined as the time necessary to $\ln(y_t)$ to arrive at the midway point between the initial value and that of equilibrium, i.e. $t_{hl} = \ln(2)\, b^{-1}$.

Considering a whole period $[0, T]$, through appropriate computations we obtain the average rate of convergence in the period through the equation

$$\ln\left(\frac{y_T}{y_0}\right) = \beta_0 + \beta_1 \ln(y_0), \tag{1}$$

where β_0 is a constant related to the existing technological level and the equilibrium income and β_1 is related to the speed of convergence, $\beta_1 = -(1 - e^{-bT})$, from which

$$b = -\frac{\ln(1+\beta_1)}{T}. \tag{2}$$

The study of convergence by means econometric models is a fundamental tool to verify the effectiveness of economic policies aimed at reducing regional disparities. Among the various econometric contributions in the literature we cite in particular those of Bollino and Polinori (2007) and Arbia and Piras (2005), Arbia e Paelink (2003), Peracchi e Meliciani (2001) and the references therein.

This paper is organized as follows: section 2 discusses econometric and spatial econometric models used for the analysis of *β*-convergence. Section 3 contains an analysis of data published by the Italian Statistical Institute (ISTAT) regarding the added value for 35 labour local systems (LLS) in the region of Trentino Alto-Adige (TAA) – Italy in the period from the late 90s to the early years of 2000. In particular, the aim of this study is to test the hypothesis of *β*-convergence at micro-territorial level for the TAA and the presence of spatial effects as well as to illustrate and discuss the application of econometric models discussed in Section 2. Some final thoughts are contained in section 4.

2. ECONOMETRIC MODELS FOR β-CONVERGENCE

2.1 A traditional approach

Consider equation (1), concerning average growth in the period [0,T]. Authors such as Mankiw et al. (1992), Barro e Sala-I-Martin (1995), suggest to augment equation (1) with a random error term and consider it in a context of regression analysis. More precisely, if $Y_{t,i}$ represents per capita income for region i at time t, with $i = 1,2, \dots, n$ and $t = 0,1, \dots, T$, a regression model for the analysis of *β*-convergence is defined by

$$\ln\left(\frac{Y_{t,i}}{Y_{0,i}}\right) = \beta_0 + \beta_1 \ln Y_{0,i} + \varepsilon_i \tag{3}$$

where ε_i is a random variable with null mean and variance σ^2. Typically the model is estimated through ordinary least squares (OLS) assuming independence of errors. To implement inferential procedures, a normality assumption is introduced.

If one considers the entire period between time 0 and time T, the average growth rate of income per capita is still obtained through a simple linear regression model

$$\ln\left(\frac{Y_{T,i}}{Y_{0,i}}\right) = \beta_0 + \beta_1 \ln Y_{0,i} + \varepsilon_i. \tag{4}$$

Note that the parameters β_0 and β_1 not necessarily coincide in formulas (3) and (4); In the case of formula (4) the relationship between β_1 and the speed of convergence *b* is defined by equation (2).

In this paper we will focus on the analysis of average convergence in a given period. Trying to maintain the traditional notation of econometric models, we define the dependent and independent variables of the model with

$$Y_i = ln\left(\frac{Y_{T,i}}{Y_{0,i}}\right), \quad X_i = ln(Y_{0,i}), \quad i = 1,2,\dots,n,$$

moreover, introduce a matrix notation by $y = (Y_1, Y_2, \dots, Y_n)'$ the n-vector of observations of the outcome and with $X = [X_{ij}]_{1\le i\le n, 1\le j\le k}$ the matrix of independent variables. Denote $\varepsilon = (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n)'$ the n-vector of disturbances which is multivariate normal with null mean vector and diagonal covariance matrix, i.e. $\varepsilon \sim NM(0, I_n\sigma^2)$; where I_n is the identity matrix of dimension *n*. With $\beta = (\beta_0, \beta_1)'$, model (4) becomes

$$y = X\beta + \varepsilon. \tag{5}$$

2.2 An approach with spatial models

Introduce now some spatial econometric models that we will use in the analysis of *β*-convergence. In this case the models take into account the spatial proximity of the n observations through a proximity matrix W. A general formulation for a spatial econometric model is given by

$$y = \rho Wy + \tilde{X}\beta + \varepsilon, \tag{6}$$

where

i. $W = [w_{ij}]_{1\le i\le n, 1\le j\le n}$ is a matrix of distances between points $i, j = 1,2,\dots n$, of dimension $n \times n$. Typical choices for W are

$$w_{ij} = \begin{cases} 1 & \text{if } i,j \text{ are neighbors} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

or $w_{ij} = d_{ij}^{-p}$, where d_{ij} is a measure of distance between points and $p > 0$ is a parameter. Often the matrix W is row-normalized, i.e,

$$w_{ij} = \frac{d_{ij}^{-p}}{\sum_{i=1}^{n} d_{ij}^{-p}}, \tag{8}$$

in such a case the maximum eigenvalue of W is 1; as we will see, this information will be useful in the estimation procedure. In this work, in the application to spatial data of the TAA, the use of weights of type (7) does not seem appropriate given the morphology of the territory for which, neighboring areas may be, from the economic point of view, very far if separated by high mountain ranges. In the analysis we will then use weights of type (8) with *p=1* and where d_{ij} represents the distance in kilometers between points *i, j*.

ii. The basic assumption is that $\varepsilon \sim NM(0, I_n\sigma^2)$; typically one can define vector ε with spatial dependence through the equation

$$\varepsilon = \lambda W_2 \varepsilon + u, \tag{9}$$

where $u \sim NM(0, \Omega)$, Ω is a generic variance/covariance matrix and W_2 is a distance matrix (not necessarily equal to W). In our case, the analysis seems to indicate that an error of type (9) is not needed. Instead, the parameter ρ in equation (6) will be exploited to capture spatial relations.

iii. The matrix $\tilde{X}$ contains the independent variables. In some cases $\tilde{X} = X$, however it is possible to define spatial dependence through a matrix $\tilde{X} = [X \quad WX^*]$; where X^* can coincide with X or include only a subset of X. By introducing $\tilde{X}$, the variable *Y* at site *i*, is also function of the other dependent variables at sites $j \neq i$; their relationship being weighted by W. Under these hypotheses model (6) can be explicitly written as

$$y = \rho Wy + X\beta_1 + WX^*\beta_2 + \varepsilon. \tag{10}$$

Model (10) is referred to in the literature as the model of Durbin (Le Sage, 1999) and is the reference model in our case. Note that to estimate the intercept (necessary if the X and Y variables do not have zero mean) one can simply consider a unitary column in the matrix $\tilde{X}$. Note that in some cases the matrix $[X \quad WX^*]$ can bring multicollinearity problems.

It is well known that the OLS method for model (6) does not necessarily produce consistent estimators, see Anselin (1988) for further information. Conditioning the model to the values of the independent variables, the likelihood function is obtainable in a relatively simple manner by using the likelihood of the vector of independent errors ε and the transformation $\varepsilon = (I_n - \rho W)y - \tilde{X}\beta$. Let $A = (I_n - \rho W)$ and $\vartheta = (\beta, \rho, \sigma)$, the likelihood of model (6) is given by

$$L(\vartheta; y, X) = (2\,\pi\,\sigma^2)^{-n/2}|A|exp\left\{-\frac{1}{2\sigma^2}(Ay - \tilde{X}\beta)'(Ay - \tilde{X}\beta)\right\},$$

where $|A|$ is the determinant of A. Note that the presence of $|A|$ in the likelihood implies that OLS and maximum likelihood (ML) estimates do not coincide. From the computational point of view, the problem of minimizing $-L(.;.)$ is well defined even if numerical difficulties might arise from the necessity of computing $|A|$ which contains the unknown ρ. The condition $|A| > 0$ is necessary for determining the estimates and regularity of the likelihood. To that end it is necessary to restrict the possible values of ρ in the interval $((\lambda_{min})^{-1}, (\lambda_{max})^{-1})$ where λ_{min} e λ_{max} are, respectively, the maximum and minimum eigenvalues of W. If W is row normalized, $\lambda_{max} = 1$.

An estimation procedure for model (10) is given in Anselin (1988), or Le Sage (1999), and is the following:

1. Estimate by OLS the model $y = \tilde{X}\beta_0 + \varepsilon_0$.
2. Estimate by OLS the model $Wy = \tilde{X}\beta_L + \varepsilon_L$.
3. Compute $e_0 = y - \tilde{X}\hat{\beta}_0$ and $e_{\mathrm{L}} = y - \tilde{X}\hat{\beta}_L$, where $\hat{\beta}_0$ e $\hat{\beta}_L$ indicate, respectively, the OLS estimates of β_0 e β_L obtained at steps 1 and 2.
4. Given e_0 and e_{L}, determine the value ρ which maximizes the concentrated likelihood:
$$\ln\big(L_C(\rho;.)\big) = C - \ln|I_n - \rho W| - \frac{n}{2}ln(e_0'e_0 - 2\rho\, e_0'e_{\mathrm{L}} + \rho^2 e_{\mathrm{L}}'e_{\mathrm{L}}).$$
5. Given $\hat{\rho}$ maximizing L_C, compute the estimates $\hat{\beta} = \hat{\beta}_0 - \hat{\rho}\hat{\beta}_L$.
6. An estimate of σ^2 is given by
$$\hat{\sigma}^2 = \frac{1}{n}\big(y - \hat{\rho}\,\mathrm{W}y - \tilde{X}\hat{\beta}\big)'\big(y - \hat{\rho}\,\mathrm{W}y - \tilde{X}\hat{\beta}\big).$$

The asymptotic variance of estimators, necessary for the hypothesis testing procedure is obtainable through the inversion of the Fisher information matrix, whose formulas are reported by Anselin (1988, p.65). We report for convenience the formulas for the asymptotic variance of the estimators for the case of the model (6); we have:

$$Var\big(\hat{\beta}\big) = \sigma^2(\tilde{X}'\tilde{X})^{-1}, \tag{10}$$

$$Var(\hat{\rho}) = \frac{1}{\sigma^2}tr\left\{W'W\left[\big(A^{-1}\tilde{X}\beta\big)'\big(A^{-1}\tilde{X}\beta\big) + \sigma^2A^{-1}A^{-1}\right]\right\}. \tag{11}$$

Formal hypotheses about the parameters can be tested using Wald test and the likelihood ratio (LRT) test. Indicating by ϑ_0 and ϑ_1 the parameter values respectively specified by the null (H_0) and alternative (H_1) and with $\hat{\vartheta}_0$ e $\hat{\vartheta}_1$ the ML estimates then

$$LRT = -2ln\frac{L(\hat{\vartheta}_0; y, x)}{L(\hat{\vartheta}_1; y, x)},$$

that, under the null, has a Chi-square distribution with q degrees of freedom where q is the number of constraints in the hypothesis.

Note that Arbia (1995) analyzes the problem of β-convergence through a SEM (Spatial Error Model)

$$y = X\beta + e \tag{12}$$

where $e = \rho We + \varepsilon$, with $\varepsilon \sim MVN(0, I\sigma^2)$. The SEM, after some computations, can be rewritten as

$$y = \beta_0 + \rho Wz + (\beta_1\rho)Wx + \beta_1 x + \varepsilon,$$

that is model (6) with $X = [1_n \quad x]$ and $\tilde{X} = [X \quad Wx]$ with 1_n a vector of ones of dimension n, and $x = [X_i]_{1\le i\le n}$ the vector of the logarithm of the GDP (or income or added value) at time 0. From the above formula one can see, even if the two models can be formulated in an equivalent way, that the SEM imposes constraints on parameters (note that the coefficient of Wx is $\beta\rho$).

3 ANALYZING DATA FOR THE TAA REGION

Consider an application to data for the TAA region in Italy. In 2005, the Italian Statistical Institute (ISTAT) published estimates, for the years 1996 to 2002, of the value added (VA) and the number of employed in inner Local Labour Systems (LLS), broken down by macro-activity branch (Agriculture, Industry and Services). For the TAA, 35 LLS have been identified on the basis of working commuting flows detected with the Census of Population in 1991. There are two sets of data of interest in this context:

a) The value added (VA) per capita for the years 1996-2000.
b) The value added (VA), per SSL for the years 1996-2002.

Analysis of β-convergence will be carried out on both series either by using regression and spatial econometric models. It is of interest to verify the presence of spatial effects in these series.

3.1 Analysis VA per-capita 1996-2000

Consider the series of VA per capita in the years 1996-2000 and analyze the average convergence in the period. In Table 1 one finds mean and standard deviation for *Y=Log(VA₀₀/VA₉₆)* and *X=Log(VA₉₆)* by province (Trento-TN and Bolzano-BZ).

Table 1. Mean and standard deviation (SD) by province

	Y=Log(VA_{00}/VA_{96})			X=Log(VA_{96})		
	TN	BZ	Tot	TN	BZ	Tot
Mean	0,1866	0,2312	0,2070	9,7370	9,8016	9,7665
SD	0,0969	0,0812	0,0916	0,2268	0.2379	0,2308

Looking at the values, we note a certain stability in the SD, however there seems to be a marked difference between the dependent variables in the two provinces, as evidenced by the mean. To see if there is a significant difference we define a binary variable to be included in the regression model. Begin our analysis by using model (5) where, in this case, one needs to estimate

$$E(Y) = \beta_0 + \beta_1 X + \beta_2 BZ, \tag{13}$$

where,

$$BZ_i = \begin{cases} 1 & \text{if unit } i \text{ is in the province of BZ} \\ 0 & \text{otherwise.} \end{cases},$$

The output of regression analysis is in tables 2 and 3

Table 2. OLS estimates for model (13): coefficients (Beta); standard error (SE). *Y=Log(VA_{00}/VA_{96})*; *X=Log(VA_{96}) and BZ = 1 if Bolzano, 0 otherwise.*

	Beta	SE	t-stat	Sig.
Constant	1,9830	0,5883	3,367	0,002
X	-0,1845	0,0604	-2,052	0,004
BZ	0,0565	0,0276	2,047	0,049

Table 3. ANOVA table for model (13). *Y=Log(VA$_{00}$/VA$_{96}$); X=Log(VA$_{96}$) and BZ = 1 if Bolzano, 0 otherwise.*

	SS	Df	MS	F	Sig.
Regression	0,0777	2	0,0388	5,9901	0,006
Residual	0,2075	32	0,0065		
Total	0,2852	34			

Note that all variables in the model are significant and the F-test of the table ANOVA is significant. In particular, the negative coefficient for the independent variable X indicates the presence of *β*-convergence in the period considered with an average speed of convergence, for $T = 4$, equal to $b = 0.051$. For a comparison, we cite Arbia and Piras (2005) that, for the period 1980-1995, obtained with the model (13), a coefficient β_1 equal to -0,175 for 125 European regions.

Model (13) has an adjusted R^2 equal to 0.23, quite low. To better understand what happens one should reason about the basic formulation in expression (4). Model (4) is obtained through the non-linear transformation of the original values of VA_{00} and VA_{96}. With a further transformation it is possible to rewrite the model (4) as

$$\ln VA_{00,i} = \beta_0 + (1+\beta_1)\ln VA_{96,i} + \varepsilon_i, \tag{14}$$

from which, one could proceed to estimating directly $\beta'_1 = (1+\beta_1)$. In such a case the fit of the model improves substantially (adjusted R^2 equal to 0,85), however the two models are equivalent and produce the same results on convergence.

Figure 1 and Figure 2 report the data (by province) and regression lines for models (13) and (14) respectively. Note that the coefficient β'_1 from regression (13) is 0,8155, that is *1 - 0,1845*. As already said, in such a case adjusted R^2 is 0,85.

Consider now an analysis by means of a spatial econometric model. Consider equation (6) and write extensively the model as:

$$E(Y) = \beta_0 + \beta_1 X + \beta_2 BZ + \beta_3 WX + \rho AR, \tag{15}$$

where, beyond the already defined variables *Y, X* and *BZ*, we find:

a) *WX* which indicates the component obtained by the product Wx, i.e. the spatial effect due to the independent variable *X*;
b) *AR* which indicates the component obtained by the product Wy, i.e. the spatial auto-regressive effect due to the dependent variable Y.

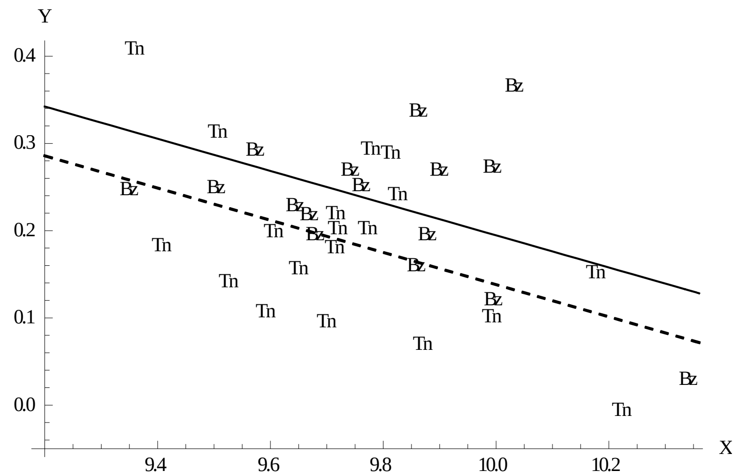

Figure 1. *Y=Log(VA$_{00}$/VA$_{96}$); X=Log(VA$_{96}$). Dashed line*: province of Trento; solid line: province of Bolzano.

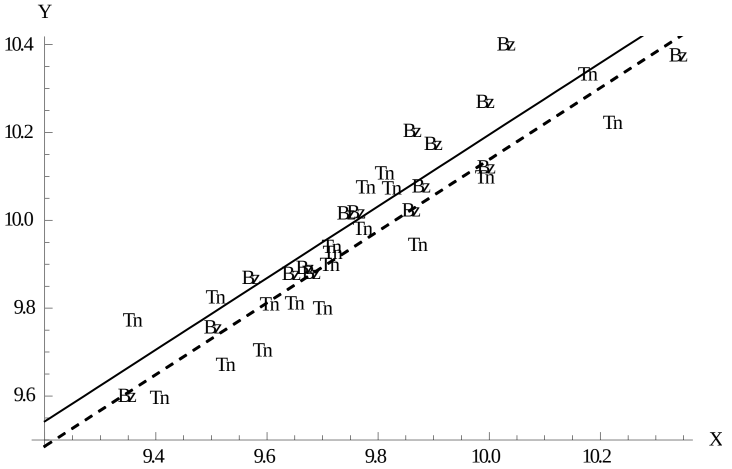

Figure 2. *Y=Log(VA₀₀/VA₉₆)*; *X=Log(VA₉₆)*. *Dashed line*: province of Trento; solid line: province of Bolzano.

In Table 4 one finds the estimates obtained through the ML method of model (15). In the table there are the estimates (Beta), the asymptotic standard error (ASE) from formulas (10) and (11), Wald test statistic and the LRT and their significance levels. The last row of Table 4 reports the LRT to compare models (13) and (15).

Analyze in order the results in Table 4. The effect of β-convergence (β_1) is still significant although with slightly reduced value; the differential between the two provinces has not changed much from model (13) however now the higher variability makes this coefficient insignificant; the spatial effect due to WX is not significant.

Table 4. ML estimates of model (15): coefficients (Beta); asymptotic standard error (ASE), Wald test, LRT. *Y=Log(VA₀₀/VA₉₆)*; *X=Log(VA₉₆) and BZ = 1 if Bolzano, 0 otherwise.*

	Beta	ASE	Wald	Sig.	LRT	Sig.
Costante	-1,575	5,681	-0,277	0,781	0,089	0,764
X	-0,155	0,069	-2,256	0,024	5,479	0,019
BZ	0,054	0,032	1,690	0,091	2,842	0,092
WX	0,347	0,547	0,525	0,525	0,467	0,493
AR	-0,604	0,067	-9,056	0,000	0,624	0,429
$\mathbf{H_0: \beta_3 = \rho = 0}$					1,106	0,293

Note that Wald and LRT test agree on the variables *X*, *BZ* e *WX*. The situation is mixed as far as *AR* is concerned which is significant with the Wald test while it is not with the LRT test. Note also that the LRT for $H_0: \beta_3 = \rho = 0$ is not significant. This test compares models (13) and (15) and the results tells us that the data seem not to support the necessity of using a spatial model.

The presence of contrasting effects in the tests could be due to confusion due to multi-collinearity however the analysis of the *Variance Inflation Factors* (VIF) did not show any problems.

3.2 Analysis of VA 1996-2002

Consider now the series VA per LLS in the period 1996-2002. Define in this case the variables $Y=Log[(VA_{00}-VA_{96})/VA_{96}]$ and $X=Log(VA_{96})$. Note that the logarithm of the relative variation $(Y_{t,i} - Y_{0,i})/Y_{0,i}$ is defined only if the latter is positive, usually this is not a problem if the period considered is large enough. In Table 5 there are the mean values and standard deviation by province.

Table 5. Mean and standard deviation (SD) by province.

	Y=Log[(VA$_{00}$-VA$_{96}$)/VA$_{96}$]			X=Log(VA$_{96}$)		
	TN	BZ	Tot	TN	BZ	Tot
Mean	-1.1986	-0.9429	-1,0817	5.4576	5,7633	5,5973
SD	0.5593	0.3011	0.4715	1.0647	1,0619	1.0592

Consider first of all an analysis through a non-spatial regression model, i.e. we consider a classic approach to β-convergence adapting model (13) to the data. The estimate is obtained by OLS. The Tables 6 and 7 show the traditional output of regression.

The adjusted R^2 value is *0,145* and the F-test of the ANOVA table is significant. Again, the negative coefficient for the independent variable *X*, significantly different from *0*, shows presence of β-convergence effects in the period.

Table 6. OLS estimates for model (13): coefficients (Beta); standard error (SE). *Y=Log[(VA$_{00}$-VA$_{96}$)/VA$_{96}$]*; *X=Log(VA$_{96}$) and BZ = 1 if Bolzano, 0 otherwise.*

	Beta	SE	t-ratio	Sig.
Constant	-0,347	0,402	-0,864	0,394
X	-0,156	0,071	-2,186	0,036
BZ	0,303	0,150	2,029	0,051

Table 7. ANOVA table for model (13). *Y=Log[(VA$_{00}$-VA$_{96}$)/VA$_{96}$]*; *X=Log(VA$_{96}$) and BZ = 1 if Bolzano, 0 otherwise.*

	SS	D$_f$	MS	F	Sig.
Regression	1,476	2	0,738	3,882	0,031
Residual	6,082	32	0,190		
Total	7,558	34			

Figure 3 reports data, by province, and regression lines for model (13).

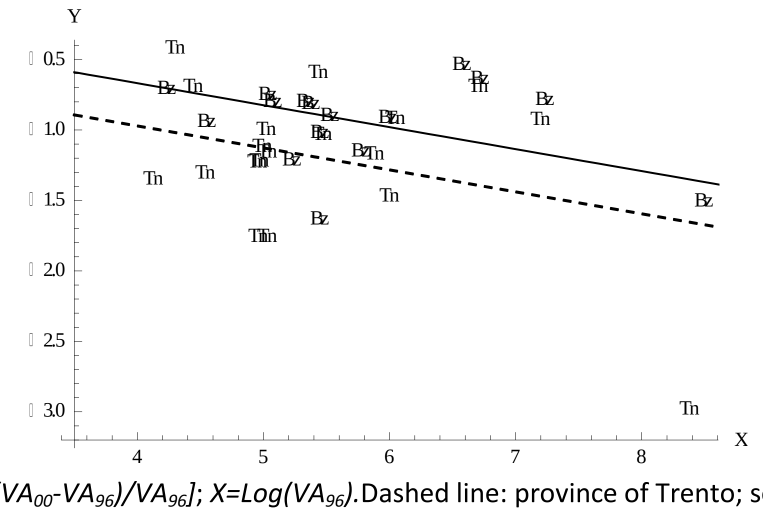

Figure 3. *Y=Log[(VA$_{00}$-VA$_{96}$)/VA$_{96}$]*; *X=Log(VA$_{96}$).* Dashed line: province of Trento; solid line: province of Bolzano.

Similarly to what was done in Section 3.1, we adapt model (15) to the data. In Table 8 there are the results of the estimation procedure by the method of maximum likelihood (ML) of model (15). In the table there are the estimates of the coefficients of equation (15), the asymptotic standard error estimate, obtained from formulas (10) and (11), the Wald test statistic, the LRT and the relative significance levels. The last row of Table 8 shows the LRT of comparison between the spatial and standard regression models.

Table 8. ML estimates of model (15): coefficients (Beta); asymptotic standard error (ASE), Wald test, LRT. *Y=Log[(VA$_{00}$-VA$_{96}$)/VA$_{96}$]*; *X=Log(VA$_{96}$) and BZ = 1 if Bolzano, 0 otherwise.*

	Beta	ASE	Wald	Sig.	LRT	Sig.
Constant	1,064	2,566	0,415	0,678	0,169	0,681
X	-0,172	0,058	-2,947	0,003	7,381	0,006
BZ	0,515	0,125	4,116	0,000	9,404	0,002
WX	-0,679	0,450	-1,509	0,131	1,727	0,189
AR	-2,226	0,059	-37,447	0,000	5,849	0,015
$H_0: \beta_3 = \rho = 0$					6,725	0,009

We analyze the results in Table 8. The effect on β-convergence (coefficient β_1) is significant, with slightly increased value; the differential between the two provinces is greater with respect to the non-spatial model and with lower significance (1%). The spatial effect due to WX is not significantly different from 0 while it is the one related to AR. We note that, unlike the results in Section 3.1, the Wald test and LRT agree on all the variables.

Also note that the LRT for $H_0: \beta_3 = \rho = 0$ has a p-value equal to 0.009 and thus confirms that the data in this case support the model with spatial components.

4. CONCLUSIONS

The analysis supports the hypothesis of a convergence effect at micro-territorial level, i.e. deprived areas tend to grow faster than richer areas. The effect is definitely present, even if the period examined is not very large. If we consider the per capita data, the analysis suggests that the phenomenon is widespread, however with no spatial effects, i.e. it seems that the proximity to the developed areas has not substantially effect on the phenomenon, this may be due to the strong commuting that occurs in many areas of the TAA to major centers. In particular, unlike the results of Bollino and Polinori (2007), that exclude certain cities, the effect of β-convergence is present in a general manner and equal for the two provinces. The introduction of a binary variable for the province of Bolzano indicates the presence of a significant difference between the two provinces; however, interaction effects between province and growth, were not significant.

If we consider the percentage growth in terms of geographical area, the spatial effect becomes significant, the results indicate that the proximity of the fastest growing areas has contagious effect on the growth of nearby areas.

5. REFERENCES

[1]. Anselin L., (1988). *Spatial Econometrics*, Methods and Models. Kluwer Academic, Boston.

[2]. Arbia, G. and Paelinck, J.H.P., (2003). Economic convergence or divergence? Modelling the interregional dynamics of EU regions 1985 – 1999. *Geographical Systems* 5, 1-24.

[3]. Arbia, G. (2005). *Spatial Econometrics*. Springer, Berlino.

[4]. Arbia, G., Piras, G. (2005). Convergence in Per-capita GDP across European Regions using Panel Data Models Extended to Spatial Autocorrelation Effects. *ISAE Working Paper* No. 51. Available at SSRN: http://ssrn.com/abstract=936327.

[5]. Barro R.J. and Sala-i-Martin X., (1995). *Economic Growth*. McGraw-Hill.

[6]. Bollino, C.A., (1998). Econometric interpolation of regional time series. *Statistica Applicata* 10, n°1, 35-52.

[7]. Bollino, C.A., Polinori, P., (2007). Ricostruzione del valore aggiunto su scala comunale e percorsi di crescita a livello micro-territoriale: il caso del''Umbria. *Scienze Regionali* 6, n°2, 35-73.

[8]. Kim, H., Sun, D. and Tsutakawa, R. K., (2001). A bivariate Bayes method for improving the estimates of mortality rates with a twofold conditional autoregressive model. *J. Amer. Statist. Assoc.* 96, no. 456, 1506–1521.

[9]. Leonenko, N.; Taufer, E. (2013). Disaggregation of spatial autoregressive processes. *Spatial Statistics* 3, 1-20.

[10]. Le Sage J., (1999). *Spatial Econometrics: The Web Book of Regional Science*. Regional Research Institute, West Virginia University, Morgantown, WV.

[11]. Mankiw N.G., Romer D. and Weil D., (1992). A contribution to the empirics of economic growth. *Quarterly Journal of Economics* 107, 407-437.

[12]. Peracchi F., Meliciani, L., (2001) Convergence in per capita GDP across European regions, a reappraisal. *Working Paper Università di Tor Vergata*, Roma.

[13]. Sforzi, F., (1997). *I sistemi locali del lavoro 1991*. Istat, Roma.