# Spatial heterogeneity in economic growth of European regions

Paolo Postiglione[1], M.Simona Andreano[2], Roberto Benedetti[3]

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**Abstract** This paper describes a new technique for the identification of convergence clubs in a cross-section of regions, using geographical estimation through an adaptive algorithm. The approach extends a procedure originally proposed in the field of image denoising analysis based on the assumption of local homogeneity of the signal and is applied here on 187 European NUT2 regions. Our results highlight the presence of five different clubs with different growth paths within each subgroup.

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[1] Paolo Postiglione, University of Chieti-Pescara, postigli@unich.it
[2] M. Simona Andreano, Universitas Mercatorum, s.andreano@unimercatorum.it
[3] Roberto Benedetti, University of Chieti-Pescara, benedett@unich.it

## 1. Introduction

The convergence of national economies has usually been investigated by regressing growth rates of real Gross Domestic Product (GDP) on its initial levels, eventually after correcting for some exogenous variables. A negative regression coefficient is interpreted as evidence of convergence, as it implies that countries with low per-capita initial GDP are growing faster than those with high initial per-capita GDP. There exists an extensive empirical literature (Mankiw et al. 1992; Barro and Sala-i-Martin, 1995; Canova and Marcet, 1995) on conditional convergence and why some countries grow faster than others. The idea of club convergence is based instead on models that yield multiple equilibria, suggesting that economic convergence could be achieved if we consider groups of countries, within which we observe convergence, but that do not converge to each other (Galor 1996).

The issue of convergence clubs requires the application of non-standard econometric techniques that allows to divide the whole sample into smaller groups. Durlauf and Johnson (1995), Feve and LePen (2000), and Ramajo et al. (2008), Postiglione et al. (2010, 2013) are only some examples of evidence that there are multiple poles of attraction in the growth process.

In the present paper we apply a new technique to identify multiple growth regimes, based on the presence of heterogeneity as a criterion to divide the sample of observations (regions) into smaller homogenous groups (clubs): the Adaptive Geographically Weighted Regression (AGWR) method. The AGWR algorithm extends a procedure originally applied in the image segmentation (Polzehl and Spolkoiny, 2003a; 2003b). The original method is modified here by introducing the geographical weighted regression (GWR) in an adaptive procedure and by generalizing the function *f* with the general regression model.

The rest of the paper is organized as follows. Section 2 briefly reviews the economic model and presents the main details of the proposed AWGR procedure. Section 3 uses this technique to identify multiple growth regimes in European regions (NUTS2) and summarizes the empirical results.

## 2. The economic model and the AWGR procedure

In this paper we use the conditional $\beta$-convergence approach to measure economic convergence derived from the neoclassical Solow growth theory. Conditional convergence is estimated on the basis of a multivariate regression analysis where per capita GDP growth rate is measured with respect to the natural logarithm of the initial level of per capita GDP and a set of other explanatory variables.

In our application we consider the conditional $\beta$-convergence model assumed by Mankiw et al. (1992) expressed in the unrestricted form as

$$r_i = \alpha + \beta q_i + \pi_1 s_i + \pi_2 v_i + \pi_3 h_i + \varepsilon_i \qquad i = 1,2,\ldots,n \tag{3}$$

where $r_i = \ln(y_{it} / y_{i0})$ is the average growth rate of GDP per-worker across the time period under investigation, with $y_{it}$ and $y_{i0}$ denoting, respectively, the final and the initial level of GDP per-worker, $q_i = \ln(y_{i0})$, $s_i$ is the natural logarithm of saving rate, $v_i = \ln(x_i + n_i + \delta_i)$, with $n_i$ given by the population growth, $h_i$ is the natural logarithm of a measure of human capital (see section 4) and $\varepsilon_i$ is the error term, which is assumed to be normally distributed, $\varepsilon_i \propto N(0,\sigma_\varepsilon^2)$. The conditional $\beta$-convergence hypothesis is verified if $\beta<0$ is statistically significant.

The assumption of spatial independence seems inadequate, because regional observations are likely to exhibit positive spatial dependence (Anselin, 1988). For this reason, we include spatial effects in the model (1), and express it as a Spatial Durbin Model (SDM). This is our objective function *f* used in the AGWR.

The identification of multiple regimes is substantially equivalent to partitioning an area into groups of geographical zones not necessarily conterminous that have homogenous growth path. The Adaptive Geographically Weighted Regression (AGWR) algorithm solves this problem in an iterative way.

Standard GWR extends traditional regression by allowing local rather than global parameters to be estimated and each observation is weighted in accordance with its proximity to location *i*. The vector estimate is $\hat{\theta}(i) = (\mathbf{X}^t\mathbf{G}(i)\mathbf{X})^{-1}\mathbf{X}^t\mathbf{G}(i)\mathbf{y}$, where $\hat{\theta}(i)$ are the locally stationary parameters, $\mathbf{G}(i)$ is an $n \times n$ weighting diagonal matrix, $\mathbf{X}$ the explanatory variables and $\mathbf{y}$ the dependent variable. As evidenced by Fotheringham et al. (2012), observed data that are contiguous to region *i* have more influence in the estimation of the local coefficients than data located farther from it. To overcome the problem of overparameterization, we express the weights $g_{ij}$ as a Kernel function $K_s$ of $d_{ij}$, the distance between the regions *i* and *j*. The initialization step in our AGWR algorithm is therefore standard GWR. Then at each next iteration *k* the statistics $K^k{}_s$, $K^k{}_T$ are computed, where $K_s^k = e^{-\lambda d_{ij}/k}$, $K_T^k = e^{-\mu T_{ij}^k}$ and

$$T_{ij}^k = \left(\hat{\theta}^{k-1}(i) - \hat{\theta}^{k-1}(j)\right)\Sigma^{-1}\left(\hat{\theta}^{k-1}(i) - \hat{\theta}^{k-1}(j)\right)^t \tag{2}$$

with $\lambda$ and $\mu$ some parameters defined empirically by data-driven simulations. If the statistics $T^k_{ij}$ is large, then the two regions $i$ and $j$ are classified in different groups. The weights $g_{ij}^k$ at iteration $k$ are calculated as

$$g_{ij}^k = K_s(d_{ij}^k) \cdot K_T(T_{ij}^k) = \left(e^{-\lambda d_{ij}/k}\right) \cdot \left(e^{-\mu T_{ij}^k}\right) \tag{3}$$

A convex combination of current and previous weights determines the new weights $\dot{g}_{ij}^k$ that represent the diagonal elements of $\mathbf{G}^k(i)$. If $\max\left|\dot{g}_{ij}^{k-1} - \dot{g}_{ij}^k\right| < \varepsilon, \forall i, j$ with $\varepsilon$ a fixed small value, the procedure is stopped. Then the current weights are used to estimate the final model. Otherwise the new matrix $\mathbf{G}^k(i)$ is used to estimate the model with GWR and the algorithm continues until the stop rule is valid.

## 3. Empirical results

The data used in our empirical analysis are 187 NUTS2 regions, spanning the period 1981-2009, of 12 countries (Austria, Belgium, Finland, France, Germany, Greece, Italy, Portugal, Spain, Sweden, the Netherlands, and the United Kingdom). The saving rate $\delta$ is measured as the average of the investments in percentage of GDP over the period 1981 to 2009. The dependent variable is the natural logarithm of per-worker GDP growth rate (i.e., $r_i$) and the conditioning variables are: the natural logarithm of the initial level of per-worker GDP (i.e., $q_i$), the saving rate ($s$), the population growth ($n$), the level of technology growth rate ($x$), the depreciation rate of capital ($\delta$) and the human capital ($h$), referring to MRW framework. The saving rate $s$ is measured as the average of the investments in percentage of GDP over the period 1981 to 2009. The human capital ($h$) is the adult literacy rates defined as the fraction of population on age 25-64 that has the highest education level (ISCED level 3-4). The spatial weight matrix **W** is defined in terms of normalized distance from the five nearest neighbour's regions.

In the estimated global SDM the presence of spatial effects is confirmed and is highlighted by a significant spatial parameters $\rho = 0.6102$ and by the Moran's $I$ test ($I = 0.4014$). Moreover, the spatial lagged variables in the SDM are significant. However the model shows a slow speed of convergence and an unsatisfactory value of $R^2$. Economic convergence in the whole sample could not hold or be weak because countries belonging to different regimes. Therefore we use the AGWR algorithm to identify multiple regimes and to improve our estimated model.

We first need to choice the tuning parameters $\lambda$ and $\mu$, through data-driven simulations in a grid of [0.1;0.5] and the best SDM is chosen on the basis of some summary statistics: min and max number of regions belongings the clubs, number of observation left out to ensure the estimation, $R^2$ and AIC. The final choice is the combination $\lambda = 0.2$ and $\mu = 0.3$.

Figure 1 shows the clubs identified by AGWR. The AGWR procedure highlights the presence of five different clubs, with different behaviors. The slow convergence determined previously in the whole sample hid in fact different regimes speed and the goodness-of fit is significantly increased.

Heterogeneity across clubs holds for the simple and spatial lagged variables. Our empirical evidence suggests the presence of substantial heterogeneity of growth patterns over the identified clubs, supporting the hypothesis of convergence clubs, and shows the presence of spatial diffusion effects in its determination. Furthermore, we observe significant spatial interaction between regions belonging the same club, confirming the presence of spatial externalities and global technological interdependence.

**Figure 1:** *The identified clubs for* $\lambda$ *= 0.2,* $\mu$ *=0.3*

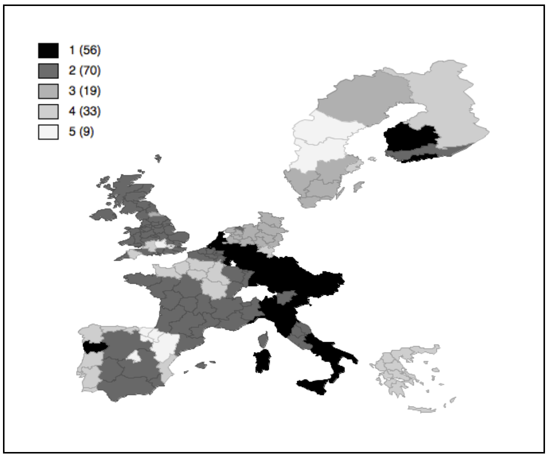


Table 1 - Estimates for SDM on the identified clubs

| | Club 1 | Club 2 | Club 3 | Club 4 | Club 5 |
|---|---|---|---|---|---|
| (Intercept) | 0.0143 | 0.0411* | 0.0708 | 0.0277 | -8.5551*** |
| Per-worker GDP ($q$) | -0.0187*** | -0.0143*** | -0.0253*** | -0.0095*** | 0.1509*** |
| $v=\ln(n+x+\delta)$ | 0.0005 | 0.0015** | 0.0007 | -0.0043*** | 0.0648*** |
| Saving rate ($s$) | -0.0043 | -0.0034# | -0.0155 | -0.0011 | 0.0521** |
| Human capital ($h$) | -0.0006 | 0.0018** | 0.0007 | 0.0001 | -0.0975** |
| W Per-worker GDP (W$q$) | 0.0192*** | 0.0109*** | 0.0269 | 0.0068 | 0.6819*** |
| W$v$ | 0.0014 | -0.0021* | -0.0070 | 0.0016 | 0.1693** |
| W Saving rate (W$s$) | 0.0122# | 0.0022 | 0.0662# | -0.0034 | 0.0573 |
| W Human capital (W$h$) | -0.0003 | -0.0022 | -0.0003 | 0.0034 | -0.6131** |
| $\rho$ | 0.4568*** | | | | |

Significance codes: 0.001 = ***, 0.01 = **, 0.05= *, 0.10 = #

## References


Anselin, L. 1988, *Spatial econometrics: Methods and Models*. Dordrecht, Kluwer Academic Publishers.

Barro, R.J., Sala-i-Martin, X. 1995. *Economic Growth Theory*. Mc Graw-Hill: Boston.

Canova, F. and A. Marcet (1995) The Poor Stay Poor: Non-Convergence Across Countries and Regions. Working paper CEPR 1215.

Durlauf, S. and P.A. Johnson (1995) Multiple Regimes and Cross-Country Behaviour. *Journal of Applied. Econometrics* 10, 365–384.

Feve, P. and Y. LePen Y (2000) On modeling convergence clubs. *Applied Economics Letters* 7, 311–314.

Fotheringham, A.S., Brunsdon, C., Charlton, M.: Geographically weighted regression: the analysis of spatially varying relationships. Wiley, Chichester (2012).

Galor, O. (1996) Convergence? Inference from Theoretical Models. *Economic Journal* 106, 1056–1069.

LeSage, J., Pace, K.: Introduction to spatial econometrics. CRC press (2009).

Mankiw, N.G., D. Romer and D.N. Weil (1992) A contribution to the empirics of economic growth. *Quarterly Journal of Economics* 7, 407–437.

Polzehl, J. and V. Spokoiny (2003a) Image denoising: pointwise adaptive approach. *Annals of Statistics* 31, 30–57.

Polzehl, J. and V. Spokoiny (2003b) Varying coefficient regression modeling. Berlin, WIAS, Preprint 818.

Postiglione, P., R. Benedetti and G. Lafratta (2010) A regression tree algorithm for the identification of convergence clubs. *Computational Statistics & Data Analysis* 54, 2776–2785.

Postiglione, P., M.S. Andreano and R. Benedetti (2013) Using Constrained Optimization for the Identification of Convergence Clubs. *Computational Economics* 42, 151–174.

Ramajo, J., M.A. Màrquez, G. Hewings and M.M. Salinas (2008) Spatial heterogeneity and interregional spillovers in the European Union: Do cohesion policies encourage convergence across regions? *European Economic Review* 52, 551–567.