A Spatially-Filtered Mixture of β-Convergence Regressions for European Regions, 1980-2002[♦]

Michele Battisti[♣] and Gianfranco Di Vaio[♣]

Abstract Assessing regional growth and convergence across Europe is a matter of primary relevance. Empirical models that not account for structural heterogeneities and spatial effects may face serious misspecification problems. In this work, a mixture regression approach is applied to the β-convergence model, in order to produce an endogenous selection of regional growth patterns. A priori choices, as North-South or centre-periphery divisions, are avoided. In addition to this, we deal with the spatial dependence existing in the data, applying a local filter to the data. The results indicate that spatial effects matter, and either *absolute*, *conditional*, or *club* convergence, if extended to the whole sample, might be assumptions too much restrictive. Excluding a small number of regions that behave as outliers, only few regions show an appreciable rate of convergence. The majority of data exhibits slow convergence, or no convergence at all. In addition, a dualistic phenomenon seems to be present inside some States, reinforcing the "diverging-convergence" paradox.

Keywords regional growth, convergence patterns, mixture regression, spatial effects
JEL Classifications C21, O40, R11

1. Introduction

Assessing regional convergence across Europe, in terms of per capita income or product, is a relevant matter, not only to verify what the growth theories predict, but also to evaluate the effectiveness of the Cohesion Policies. The expectations of New Entrants, indeed, require feasible answers from the policy makers. After the recent enlargement, economic disparities underwent a dramatic increase. The ten richest Union's regions have a GDP per head equal to 189% of the EU-25 average, whilst the ten poorest ones have the same indicator equal only to 36%. In the New Member States, 90% of total population lives in regions with a level of per

[♦] A previous version of the paper has been presented at the International Workshop on Spatial Econometrics and Statistics, May 25 – 27, 2006, Rome, Italy. We wish to thank all the participants for their useful comments. We acknowledge Rolf Turner and two anonymous referees for technical advice.
[♣] Dipartimento di Scienze Economiche e Aziendali, LUISS Guido Carli, Viale Pola 12, 00198 – Rome (IT). Corresponding author: gdivaio@luiss.it.

capita income below 75% of the Community average, that is the admissibility threshold to receive the Objective 1 Structural Funds (Commission of the European Communities, 2005).

During the last few years, an intense debate had occurred on the topics of European integration, regional growth and convergence, and Cohesion Policies (see, for a review, Funck and Pizzati, 2003). From one side, the EC stresses the integration's gains and the positive role of the regional policies, that sustain the economic growth of the lagging behind regions (European Commission, 2001, 2004). From the other, some scepticism has been shed (Boldrin and Canova, 2001) and, consequently, some questions have been raised. Will EU citizens see their welfare being equalised to Community's averages? Will their standard of living, on the contrary, worse off, being subjected to growing inequalities? Will cohesion policies have a positive impact on growth and convergence? Will those policies, instead, be ineffective, serving mainly as redistributive instruments?

In this work we study the regional convergence process across Europe, paying attention to some relevant issues linked to the empirical analysis. Particularly, we demonstrate as misspecification sources need to be carefully taken into account. The remainder of the paper is structured as follows: section 2 reviews the literature on the European regional convergence and poses the problem of heterogeneity and spatial effects. Section 3 highlights the existence of spatial dependence among EU regions and, at the same time, present the data. Section 4 introduces the proposed methodology. Section 5 shows the results and, finally, some conclusions follow in section 6.

2. The Empirics of regional convergence

Convergence hypotheses across countries or regions have been subjected to several, and often alternative, theoretical interpretations. Following the taxonomy originally proposed by Galor (1996), three different definitions can be distinguished: a) the *unconditional* or *absolute* convergence, meaning that per capita incomes converge to a common level in the long-run, if structural homogeneities are present across the economies and their initial conditions do not matter[1]; b) the *conditional* convergence, meaning that per capita incomes converge to different levels in the long-run, if structural heterogeneities are present across the economies and their initial conditions do not matter; c) the *club* convergence, meaning that per capita

[1] This hypothesis seems to be the one that the EC is interested in, as Quah (1996b, p. 1048, note 4) already pointed out.

incomes converge to different levels in the long-run, if structural heterogeneities are present across the economies and their initial conditions do matter.

Much of the empirical analysis, aimed to test the validity of these hypotheses, has been based on the measure of β-convergence, derived from the neoclassical growth model of Solow-Cass-Koopmans (see Barro and Sala-i-Martin, 2004). As is well known, the measure refers to the tendency for the poor economies to grow faster than the rich ones, i.e. to "catch-up", and it is related to ranking dynamics in the sample distribution (Sala-i-Martin, 1996a). Other measures are often employed, that look at the reduction of the distributional dispersion over time, as the sigma-convergence[2] (Barro and Sala-i-Martin, 1992), or the evolution of the entire distribution, as the transition matrix approach[3] (Quah, 1993a, 1996a). Those concepts, however, are less suited to the questions assessed in this work, as well as to the methodology adopted, so we prefer to focus on β-convergence.

Empirical β-convergence models usually take the form of a cross-country/region growth regression

$$g_i = a - bx_i + u_i, \qquad i = 1,\dots,n, \tag{1}$$

where $g_i = [\ln(y_{i,T}) - \ln(y_{i,0})]/T$ is the average growth rate of the economy i's per capita income between time 0 and T, a is a constant, $b = (1 - e^{-\beta T})/T$ is a convergence coefficient, $x_i = \ln(y_{i,0})$ is the log of the economy i's initial level of per capita income, and $u_i \sim \mathrm{N}(0, \sigma^2)$ is an error term with the usual properties (see Durlauf *et al.*, 2005). A positive value of the parameter β is supportive of convergence, and provides the rate at which the economy approaches the steady-state[4].

Early empirical studies (Barro and Sala-i-Martin, 1991, Sala-i-Martin, 1996b), estimated equation (1) without control variables, basing on two strong homogeneity assumption. Firstly,

---

[2] As random shocks may produce criss-crossing or overshooting effects, β-convergence is a necessary but not sufficient condition for sigma-convergence (see Barro and Sala-i-Martin, 2004).

[3] Some researchers prefer this approach, because it provides a more complete set of information. β-convergence, in fact, suffers from the so-called "Galton's fallacy", so it may be consistent with a stationary distribution over time (Quah, 1993b, Hart, 1995).

[4] Estimates are usually obtained calculating $\hat{b}$ by ordinary least squares (OLS), and re-parameterizing $\hat{\beta} = -\ln(1 - \hat{b}T)/T$. Estimation may also be done with non linear least squares (NLS). The use of one technique instead of another, however, does not lead to appreciable statistical discrepancies (on this point, see Abreu *et al.*, 2005a).

the constant term was thought as inclusive of the technological progress (γ_i), the steady-state value of effective per capita output $(\tilde{y}_i^*)$, and the initial efficiency $(A_{i,0})$, namely

i) $$a = a_i = \gamma_i + (1 - e^{-\beta_i T})/T \cdot \ln(A_{i,0} \cdot \tilde{y}_i^*), \quad \forall i .$$

Secondly, the convergence coefficient was considered constant across the economies, that is

ii) $$b = b_i = (1 - e^{-\beta_i T})/T, \quad \forall i .$$

Equation (1) estimated with assumptions i) and ii), can be seen as a test for type a) convergence, a positive $\hat{\beta}$ implying that poor regions *unconditionally* grow faster than rich ones, at the same rate, toward a unique steady-state independently from the initial conditions. Barro and Sala-i-Martin (1991, p. 154), analysing a sample of 73 Western European regions over the period 1950-1985, found an "empirical regularity that the rate of β convergence is roughly 2 percent a year in a variety of circumstances [...] the half-life of this convergence process is 35 years"[5]. In the last edition of their book, they concluded that "absolute β convergence is the norm for these regional economies" (Barro and Sala-i-Martin, 2004, p. 496).

Tests of *absolute* β-convergence are plausible when the matter of study is convergence *within*-country. In such a case, regional economies share common steady-states, being affected by similar saving rates, preferences, governmental policies, property rights, infrastructures, and so on. For the case of convergence *between*-country, instead, type a) convergence results quite unrealistic, because regions belonging to different countries may not exhibit a common steady-state. As Solow (1999, p. 640) argued, "there is nothing in growth theory to require that the steady-state configuration be given once and for all [...] the steady-state will shift from time to time [and, we say, from space to space] whenever there are major technological revolutions, demographic changes, or variations in the willingness to save and invest".

[5] The so-called half-life condition is given by $e^{-\beta T} = 1/2 \Rightarrow T = \ln(2)/\beta$. If the speed of convergence is equal to 2% per year, it follows that $T \cong 0.69/0.02 \cong 35$, so the economy fills half the gap in about 35 years.

If the determinants of steady-state are not constant across regions, it follows that $a_i \neq a$, $\forall i$, leading assumption i) to fail[6]. Mankiw *et al.* (1992) solved the problem relaxing the assumption i) in two ways. First, in presence of heterogeneity, $\tilde{y}_i^*$ can be included among a set of control variables added to equation (1). Second, if $A_{i,0}$ reflects not only the initial technology, but also resource endowment, climate, institution, and other region-specific factors affecting growth, it may be constituted by a common and a random component, $\ln(A_{i,0}) = \ln(A_0) + e_i$, where A_0 is the common factor and e_i is the specific effect. The error term is now equal to $u_i = (1 - e^{-\beta T})/T \cdot e_i + \varepsilon_i$, $\tilde{y}_i^*$ being independent of the error term. Assumption i) is so replaced by

iii) $$a = a_i = \gamma_i + (1 - e^{-\beta_i T})/T \cdot \ln(A_0), \quad \forall i .$$

Equation (1), with the assumptions ii) and iii), and the inclusion of control variables, implies homogeneity in the convergence parameter, the initial efficiency, and the technological progress. Steady-states determinants, on the contrary, are allowed to be heterogeneous. Estimation can be considered as a test for type b) convergence, with a positive $\hat{\beta}$ meaning that poor regions grow *conditionally* faster than rich ones, at the same rate, toward different steady-states.

Armstrong (1995), testing for *absolute* and *conditional* convergence, either *within* or *between-country*, on a sample of 85 EU regions over the period 1950-1990, found significant discrepancies between the two hypotheses. The rate of *between*-country *absolute* convergence was about 1% per annum, much slower than the 2% found by previous studies. A rate of 2%, in fact, was only found, in the case of *within*-country *conditional* convergence[7], during the Post-war period. The years following the oil crisis, instead, saw a decrease of the annual convergence rates, ranging from 0.8% to 1%.

Convergence tests of type a) and b), however, have been criticized under many respects. From a general cross-country perspective, parameters heterogeneity, outliers, and measurement errors, have been highlighted (Temple, 1998, 2000). Looking at the European

[6] Steady-state variables might be comprised in the error term, $u_i = (1 - e^{-\beta_i T})/T \cdot \ln(\tilde{y}_i^*) + \varepsilon_i$, where ε_i is a random component. However, if that variables were related with initial income levels, and they had an impact on growth, $\tilde{y}_i^*$ would be an omitted variable and the coefficient $\hat{b}$ would be biased (Bernard and Durlauf, 1996; Sala-i-Martin, 2002).

[7] Country-specific dummies are used to control for heterogeneity in steady-states. The common practice to employ dummy variables is due to lack of data at regional level.

regional experience, some researchers (Martin, 1998, Petrakos *et al.*, 2005) addressed that the convergence process does not obey to an homogeneous pattern of growth[8]. In such a case, testing for convergence of type a) or b) would be misleading, if the "true" convergence process saw the regions converging at different rates toward different income levels.

The existence of structural heterogeneities may be compatible, for instance, with the presence of multiple regimes in cross-country growth behaviour identified by Durlauf and Johnson (1995), or with the convergence clubs – the "twin-peaks" – in the world income distribution detected by Quah (1997). On the one hand, country-specific constraints to the adoption of technologies may affect the efficiency of regional economies, producing structural heterogeneities, as verified world-wide by Durlauf *et al.* (2001). In this case, the assumption iii) does not hold, because

iv) $$a \neq a_i = \gamma_i + (1 - e^{-\beta_i T}) / T \cdot \ln(A_0), \qquad \forall i .$$

On the other one, growth models similar to the one developed by Azariadis and Drazen (1990) assume that spillovers due to physical or human capital accumulation cause threshold effects, that produce shifts in the aggregate production function, leading to multiple, locally stable, steady-state equilibria – i.e. to different convergence "clubs" (see Durlauf and Quah, 1999). A threshold value in the income level, $\bar{y}$, implies $\beta_i = \beta_1$, if $y_{i,0} \prec \bar{y}$, and $\beta_i = \beta_2$, otherwise. Assumption ii) needs this way to be replaced by

v) $$b \neq b_i = (1 - e^{-\beta_i T}) / T, \qquad \forall i .$$

If initially poor regions converge toward a lower income level[9], then estimates of the equation (1) with the assumptions iv) and v) can be seen as tests of type c) convergence. A positive $\hat{\beta}$ indicates that the poor regions grow faster than the rich ones, at different rates, towards different steady-states depending on their initial condition.

The existence of *club* convergence across Europe has been recognized by several authors. Early studies imposed exogenous assumptions on the number of clubs, to emphasize geographical and distributional factors, as North-South, centre-periphery, or rich-poor

[8] Convergence *between* States – towards the outside – but not *within* – towards the inside – has been defined as the "diverging-convergence" phenomenon (Labour Asociados, 2003).
[9] Falling into a "poverty trap".

divisions. Neven and Gouyette (1995) split a sample of 142 EU regions, over the period 1980-1989, in a Northern and a Southern club. They found a very low rate of 0.53% *absolute* convergence for the whole sample, and no statistically significant convergence inside each of the two clubs. Only when country-specific effects are controlled for, the rate of convergence assumes significant values, comprised between 1.1% and 1.8%.

Endogenous criteria to detect the presence of clubs, however, should be better considered, instead of exogenous choices that arbitrarily assign the structural heterogeneities to different clubs. Canova (2004), for instance, adopted a predictive density approach to find clubs of convergence in a sample of 144 EU regions, over the period 1980-1992. Avoiding a priori assumptions, he found four homogeneous clubs, with different convergence rates and steady-states values highlighting North-South or poor-rich dimensions, with the initial conditions influencing the probability of belonging to a club.

Furthermore, many authors have argued that, due to geographical spillovers, the distribution of regional per capita income across Europe tends to be influenced by their physical location (Quah, 1996c, López-Bazo *et al.*, 1999, Le Gallo and Ertur, 2003). Ertur *et al.* (2006) treated spatial problems in the context of club convergence. In a sample of 138 EU regions, over the period 1980-1995, they found that per capita income levels were highly spatially correlated. Particularly, an exploratory spatial analysis (ESDA) revealed a division between Northern-rich regions and Southern-poor ones. Assuming the existence of heterogeneity across two different spatial regimes, and taking the spatial autocorrelation into account, they found no convergence in the Northern club, and an annual convergence rate equal to 2.9% in the Southern one.

The procedure followed by Ertur *et al.* (2006) is based on an exogenous assumption that structural parameters are heterogeneous across regions, due to their geographical locations. To our knowledge, a procedure that merge together an endogenous identification of convergence paths and spatial dynamics, is not yet available either in the theoretical or the empirical literature. Towards this direction, we implement a strategy that leads to an endogenous selection of convergence regimes once that spatial dependence effects, have been taken into account. It can be considered as a first step for future research.

3. Spatial dependence across European regions

Spatial dependence, if not properly modelled, leads to serious misspecification problems in linear regressions (Anselin, 1988 and 2001, Anselin and Bera, 1998). In the cross-sectional growth framework, in which the observations are spatially organized, the existence of geographical spillovers may violate the assumption that the error terms from neighbouring regions are independent (Rey and Montouri, 1999). The common practice is to explicitly incorporate in the regression a spatial component, in the form of a spatial error or a spatial lag (Arbia, 2006). Another approach, as we will see later, is to filter out the spatial dependence.

A simple check of spatial dependence, in its weaker version of spatial autocorrelation, can be performed by means of Moran's *I* statistic. As is well known, the statistic can be expressed as

$$I = \frac{n}{q} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} x_i x_j}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j},$$

where w_{ij} is an element of a binary spatial weight matrix $\mathbf{W}$, x_i is a specific variable for observation i, n is the number of observations, q is a scaling factor equalling the sum of all the elements of the matrix. In this paper we use a row-standardized binary matrix, based on the k-nearest neighbouring regions, whose elements are

$$\begin{cases} w_{ij}(k) = 0 \text{ if } i = j \\ w_{ij}(k) = 1 \text{ if } d_{\mathrm{ij}} \le d_i(k) \\ w_{ij}(k) = 0 \text{ if } d_{\mathrm{ij}} > d_i(k) \end{cases}$$

where $d_i(k)$ is a critical cut-off distance, defined for each observation i, ensuring that every single region of the sample has the same number (k) of neighbours.

Abreu *et al.* (2005b) has shown as contiguity-based matrices are the most popular choice in the literature. For the case of European regions, however, those kind of matrices leave the islands unconnected to the continent, so distance-based specifications have been therefore preferred in applied works (Le Gallo and Ertur, 2003, Le Gallo and Dall'Erba, 2006). We chose a specification with k = 20, because it cancels out the spatial autocorrelation in the filtered series[10]. Such specification is also able to link Cyprus with the Greek regions, which in turn are connected to Italy, Ireland with UK, this latter being connected to the continental

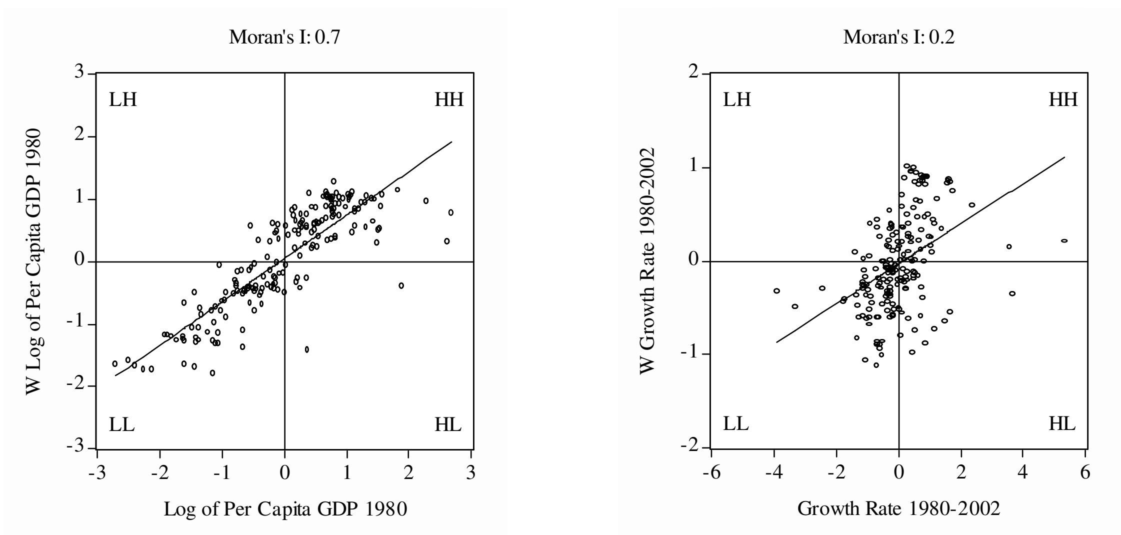
[10] However, other weight matrices, with k=10, 15, produced very similar results in the mixture. See the next section for the filtering procedure.

Europe, Sicily and Sardinia with continental Italy, Corsica with the continental French regions[11].

Data on per capita GDP, expressed in Euros at 1995 prices, are taken from Cambridge Econometrics, *European Regional Database*, 2004. We work with two samples. The larger sample includes 242 NUTS-2 regions from EU-25[12], covering the period 1991-2002, while the smaller one comprises 190 NUTS-2 regions from EU-15, covering the period 1980-2002. Figure 1 shows for the smaller sample standardized scatter-plots based on Moran's *I* of (a) the log of per capita GDP, and (b) the average growth rates of per capita GDP[13]. A highly positive spatial correlation of per capita income levels among the European regions is clearly evident. The majority of the observations falls in the high-high (HH) or in the low-low (LL) quadrant. Rich (poor) regions, indeed, are surrounded by rich (poor) ones. Spatial correlation of growth rates is positive as well, else if in a weaker form. Over the whole period, the spatial dynamic of the growth rates is not able to offset the spatial concentration of the economic activity. At the end of the period, the physical location of income levels is agglomerated as it was at the

Figure 1 Moran scatterplots (standardized) of (**a)** per capita GDP, 1980, (**b)** average growth rate of per capita GDP, 1980-2002. 190 NUTS-2 regions from EU-15

a **b**



Data Source Cambridge Econometrics, *European Regional Database*, 2004

[11] The weight matrix has been obtained using the software package GeoDa (Anselin, 2005).
[12] Inclusive of German Ex-Länder. See Appendix for the list of regions. Longer time series for EU-25 are unavailable.
[13] To save space, we do not show here the figures for the larger sample. The results, however, are very similar.

beginning. Moran' s I of per capita GDP in 2002 equals 0.6, only 1 percentage point lesser than the value it took in 1980.

From the above statistics, we would expect that spatial dependence matter for the study of β-convergence in Europe. As a preliminary analysis we estimate equation (1) for both the samples, by standard OLS, and test the existence of spatial autocorrelation among the regression residuals. We break the EU-15 sample in two sub-periods of the same length, 1980-1991 and 1991-2002. The breakdown is useful at least for two reasons. First, in the Nineties main institutional changes, as the implementation of Cohesion policies and the establishment of the adhesion criteria to EMU, might have had an impact on the convergence process of the EU regions. Second, such breakdown makes possible to compare the smaller sample with the larger one, to see if regions that first joined the Union experienced different convergence patterns. The results are shown in Table 1.

Over the whole period, the convergence coefficient for the EU-15 sample is highly

Table 1 *Absolute* β-convergence. OLS estimates and diagnostics for spatial autocorrelation

		EU-15		**EU-25**
	1980-2002	**1980-1991**	**1991-2002**	**1991-2002**
$\hat{a}$	.076 (.011)	.040 (.016)	.102 (.015)	.093 (.012)
$\hat{b}$	.006 (.001)	.002 (.002)	.009 (.002)	.008 (.001)
Half-life	108 years	310 years	69 years	79 years
R^2	.12	.01	.15	.17
Log-likelihood	686	623	642	700
Obs	190	190	190	242
		Diagnostics for spatial autocorrelation		
Moran's I err-u*	.12 (.00)	.16 (.00)	.17 (.00)	.07 (.00)
Moran's I err-f*	-.03 (.24)	-.01 (.87)	-.02 (.42)	-.02 (.44)

Standard errors within brackets

* P-values within brackets

Data Source Cambridge Econometrics, *European Regional Database*, 2004 significant. Its magnitude, however, is only about one fourth of the "empirical norm" of 2%. Actually, the convergence rate equals about 0,6% per annum, leading to an half-life of 108 years[14]. The poorest regions, this way, are supposed to fill half the gap with the richest ones in more then a century. Looking at the two sub-periods, it clearly appears as the bulk of convergence is given by the Nineties. During the Eighties, the convergence coefficient is very slow and not statistically significant, pointing out a lack of convergence. Enlarging the sample to the EU-25 regions does not change the picture so much, since the convergence decreases only slightly, when compared to the EU-15 sample.

Finally, the bottom part of Table 1 shows the spatial autocorrelation diagnostics. The test is based on Moran's *I* statistic applied to regression residuals. Under some regularity conditions, the distribution of the test corresponds to the standard normal (Anselin, 1988). The results highlight a significant spatial autocorrelation among the residuals[15], for both the samples, either over the whole period or the two sub-periods. Interestingly, during the Nineties, the spatial dependence is higher for the EU-15 regions, meaning that per capita income is less concentrated in the enlarged Europe.

This preliminary spatial analysis demonstrates that spatial phenomena can be relevant for the study of EU regional convergence, and that they should be taken into account in the cross-sectional framework, in order to avoid misspecification problem. A*bsolute β*-convergence, tested by standard OLS with no spatial specification, suffers from many shortcomings that invalidate its capability in explaining the regional growth processes.

4. The spatially-filtered mixture of regressions

Given the spatial influence highlighted in the previous section, our interest here lies in an endogenous determination of heterogeneity in regional convergence patterns, once the spatial dependence in the data has been properly treated. We avoid a priori restrictions, as geographical (North-South or centre-periphery), or exploratory (based upon spatial association indices) divisions. To this aim, we use a spatially-filtered mixture regression approach (for mixture densities, see Titterington *et al.*, 1985, Wedel and Kamakura, 1998,

[14] The result might be not very interesting in terms of policy implications. On how to calculate $\hat{\beta}$ see note 4 in section 2.

[15] The test has been carried out on the residuals of the unfiltered series (err-u), as well as on the filtered series (err-f) obtained with the filtering procedure described in the next section. Once spatial correlation is filtered out from the series, the test become not significant.

MacLachlan and Peel, 2000). Previous attempts to apply mixture densities to convergence analysis are in the works of Paap and Van Djik (1998) and Tsionas (2000). Those studies, however, do not use mixture regression models, do not deal with spatial related questions, and differ under some other aspects from the our.

Let us begin considering the spatial dependence. As we have seen in the previous section, if spatial dependence is present across a sample, OLS estimates are biased or not efficient. In the case of spatial effects influencing the errors in equation (1), statistical inference based on OLS is not reliable, because assumption of errors independence from neighbouring regions may be violated. We treat potential sources of misspecification, in the β-convergence framework, isolating the spatial correlation by means of a local filter[16]. Two filtering procedures have been shown to give the same empirical results in "cleaning up" the spatial effects from geographically organized variables (Getis and Griffith, 2002).

We use the Getis local filter $G_i(d)$ (Getis, 1995) constructed as, for each spatial unit i,

$$G_i(d) = \frac{\sum_{j=1}^{n} w_{ij}(d)x_j}{\sum_{j=1}^{n} x_j}, \qquad i \neq j$$

where x is the original unfiltered variable and w_{ij} is the element of the spatial weight matrix related to the of the j neighbouring regions comprised within the distance threshold d. The filtered variable x^F (where F stands for filtered) can then be obtained as

$$x_i^F = x_i \frac{\left[\sum_{j=1}^{n} w_{ij}(d)\right]}{(n-1)} / G_i(d)\,,$$

while the residual spatial component can be defined as $x^S = x - x^F$ (S stands for the spatial component). Applying this filter to the series makes the OLS estimates consistent. We test

[16] In a previous version of this work we used a global filter obtained by means of a spatial parameter estimated in a spatial error model (see Anselin and Bera, 1998). Results about convergence rates and patterns identification were quite similar, but that procedure is less consolidated in the literature and it causes inference problems in the second step deriving from estimating mixtures of equation with generated regressors (see Pagan, 1984).

different specification of **W** (k = 10, 15, 20) until Moran's I on regression residuals becomes not significant. The specification with k = 20 gives the desired outcome[17].

A similar two step procedure, with a spatial filtering in the first step and a panel regression in the second one, is implemented, for example, by Badinger *et al.* (2004). Our approach has the same first step, where the spatial dependence is "cleaned up", while the second one is based on the application of the mixture regression model to the filtered variables. At the end of the procedure we get a transformed version of the equation (1)

$$g_i^F = a - bx_i^F + u_i \tag{2}$$

whose least squares estimation is consistent[18].

In the second step we employ the mixture regression model to detect the existence of regional convergence patterns. Suppose that the "true" density function of a population is a mixture of more functions, one for each pattern with different parameters, weighted by the probability to belong to a specific pattern. If the population is divided into k groups[19], the number of them being unknown and the probabilities to stay in one of these summing to one for each observation, then, according to the total probability theorem, the conditional distribution function is

$$f(g_i^F \mid \boldsymbol{\theta}) = \sum_{s=1}^{k} \psi_s f_s(g_i^F \mid \boldsymbol{\theta}_s) \tag{3}$$

where g_i^F is the dependent variable, ψ_s is the probability to belong (a priori) to a regime s, with $s = 1,...,k$, and $\boldsymbol{\theta}$ is a vector of parameters. Once ψ_s has been estimated, the posterior probability that observation i comes from s has to be computed by Bayes theorem.

Consider the function of the filtered variable g_i^F as normal. The density function conditional to belong to the regime k is

$$f(g_i^F \mid \mathrm{s} = \mathrm{k}, \boldsymbol{\theta}) = (2\pi\sigma_k^2)^{1/2} e^{-\left[g_i^F - (a_k - b_k x_i^F)\right]^2 / 2\sigma_k^2} . \tag{4}$$

[17] See the row labelled Moran's *I* err-f in Table 1.
[18] We estimate equation (1) without control variables, because we admit heterogeneity in steady-states, allowing for different intercepts across clubs.
[19] We refer to patterns, groups, or regimes without distinction.

In this way, the component represented by $(a_k - b_k x_i^F)$ gives us a linear predictor that replace the population mean of the group. From the Bayes rule, it is straightforward to extract the unconditional probability of g_i^F for $s = k$ as a joint probability, that is the product of conditional probability and the marginal probability of staying in a club. This latter is equal to ψ_k, so that the joint probability is $\psi_k f(g_i^F \mid \mathrm{s} = \mathrm{k}, \boldsymbol{\theta})$. Summing all the values of s gives the unconditional density of g_i^F

$$f(g_i^F, \boldsymbol{\theta}) = \sum_{s=1}^{k} \psi_s (2\pi\sigma_s^2)^{1/2} e^{-\left[g_i^F - (a_s - b_s x_i^F)\right]^2 / 2\sigma_s^2} \ . \tag{5}$$

The vector of parameters $\boldsymbol{\theta}$, that also contains the weights ψ_s, is unknown. A simple way to solve this form of missing data problem is through the Expectation-Maximization (EM) algorithm. The solution is to find an initial value of the parameters, then compute the density for these parameters, and re-compute the final $\boldsymbol{\theta}$, by maximization of the log-likelihood. So the algorithm has two alternated steps: in the first one (expectation) it computes the density function for the chosen parameters, while in the second one (maximization) it derives the estimation of the parameters a_s, b_s, and σ_s^2. In the case of a linear mixture regression, De Sarbo and Cron (1988) show as the second step is equivalent to perform k weighted least squares regressions, where the weights are the roots of the probabilities to belong to a club.

We begin with random starting probabilities, and then we update the probabilities step by step. This strategy could have two types of shortcoming. First, the results might depend on the initial probabilities. Second, the maximization of the log-likelihood could converge in a local optimum. To avoid those problems, and to be reasonably confident that our estimates do not correspond to a local maximum, we run 500 regressions. We choose the highest value of log-likelihood, that also helps to determine the number of the components in the mixture, as we will see below.

Finally, each region is attributed to a regime, if the probability to belong to that regime is higher than the probability to belong to the other ones. A last point refers to inference considerations. Since standard errors in the EM algorithm are not used to iterate (Wedel and Kamakura, 1998), when the algorithm converges to the final value, an estimation of the covariance matrix is given by the Fisher information matrix. For the case of the EM algorithm, Louis (1982) finds this observed information matrix as the difference between two matrices, the total information matrix and the missing information matrix. Turner (2000) shows computational details for mixture regression models[20].

5. Results

This section shows the results obtained with the two-step methodology described above. In the first step, we proceed to filter out the spatial dependence from the variables, while in the second one we run the mixture regression model, searching for potential sources of heterogeneity in convergence patterns. The choice of the mixture's components number is

Table 2 Decision criteria for the mixture's components number

	Log-likelihood	**AIC**	**MAIC**	**BIC**
		EU-15: 1980-2002		
1 Component (OLS)	693	-1380	-1377	-1370
2 Components	730	-1446	-1439	-1423
3 Components	736	-1450	-1439	-1415
		EU-15: 1980-1991		
1 Component (OLS)	629	-1252	-1249	-1243
2 Components	660	-1306	-1299	-1283
3 Components	669	-1316	-1305	-1281
		EU-15: 1991-2002		
1 Component (OLS)	637	-1268	-1265	-1258
2 Components	653	-1293	-1286	-1270
3 Components	657	-1292	-1281	-1256
		EU-25: 1991-2002		
1 Component (OLS)	732	-1458	-1455	-1447
2 Components	750	-1485	-1478	-1461
3 Components	754	-1487	-1476	-1448

Data Source Cambridge Econometrics, *European Regional Database*, 2004

[20] The observed information matrix can be computed as the difference between the total information matrix and the missing information matrix. This matrix is then inverted to extract the square roots of the elements from the main diagonal, in order to obtain the standard errors of the parameters. The matrix dimension is given by the number of parameters minus one, because one of the weights is a linear combination of the other ones.

based upon two complementary criteria. On the one hand, we look at the improvements given by additional components in the loglikelihood, through a set of log-likelihood based tests. On the other one, we consider a meaningful interpretation of the data. The latter criterion regards either the existence of appreciable differences in the significance of the parameters, or the certainty in the regions attribution to specific regimes[21]. The logic of the former criterion is to penalize the increase of the components in the mixture, in order to avoid an excessive – and

Table 3 Spatially-filtered mixtures regressions*

	2 Components		3 Components		
	Regime 1	**Regime 2**	**Regime 1**	**Regime 2**	**Regime 3**
			EU-15: 1980-2002		
$\hat{a}$	.324 (.120)	.062 (.015)	.340 (.120)	.183 (.023)	.037 (.020)
$\hat{b}$	.032 (.013)	.005 (.002)	.034 (.013)	.018 (.002)	.002 (.002)
Half-life (years)	5	131	11	30	339
Weight	12%	88%	12%	22%	66%
			EU-15: 1980-1991		
$\hat{a}$	.267 (.108)	.067 (.021)	.454 (.048)	-.072 (.127)	.075 (.023)
$\hat{b}$	.027 (.012)	.005 (.002)	.047 (.005)	-.010 (.014)	.006 (.003)
Half-life (years)	22	135	10	–	112
Weight	26%	74%	15%	19%	66%
			EU-15: 1991-2002		
$\hat{a}$	-.061 (.145)	.064 (.025)	-.161 (.179)	.255 (.111)	.036 (.030)
$\hat{b}$	-.008 (.015)	.005 (.003)	-.019 (0.02)	.025 (.012)	.002 (.003)
Half-life (years)	–	135	–	24	343
Weight	20%	80%	14%	24%	62%
			EU-25: 1991-2002		
$\hat{a}$	.144 (.063)	.069 (.016)	.222 (.085)	.137 (.032)	.012 (.024)
$\hat{b}$	.013 (.007)	.006 (.002)	.021 (.009)	.012 (.003)	-.000 (.002)
Half-life (years)	49	112	29	54	–
Weight	23%	77%	16%	38%	46%

*Standard errors within brackets
Data Source Cambridge Econometrics, *European Regional Database*, 2004

[21] In some cases the attribution might be less precise (i.e. there are regions with a 100% of probability to stay in a group, and regions that have only the with only 51%). Generally, we find about 90% of regions that are attributed with a high difference with respect to the alternatives.

not useful – number of parameters. The AIC (Akaike Info Criterion) is the less restrictive test, so it generally selects less parsimonious specifications. On the contrary, the BIC (Bayesian Info Criterion) is the most restrictive one. The MAIC (Modified Akaike Info Criterion) falls in the middle (for a detailed description, see Hawkins *et al.*, 2001).

According to the tests reported in Table 2, a specification with only one component is a choice not supported by the data, while a three components specification is the better approximation for all the samples, except for the EU-15, 1991-2002 . Table 3 reports the results obtained by the mixture regression model, applied to the spatially filtered variables. Generally, the two components specification selects a small group of very fast convergence, comprising from 12% to 26% of the data. Such group seems to behave as an "outliers bin", since it collects regions following particular growth experiences[22]. The majority of the regions fall in a regime characterized by a very slow convergence rate, equal to about 0.5% per year. The regime does not manifest substantial differences across samples and periods. The half-lives, in all cases, exceed a century.

The three components specification makes clear as the slow convergence regime is constituted by a smaller group of fast convergence rates, ranging from about 1.2% to 4.7%, and a bigger regime no convergence[23]. This latter comprises one half or two thirds of the regions in the samples, depending on the periods considered. Overall results, interestingly, seems to be in line with recent empirical research on the topic (see Meliciani and Peracchi, 2006).

As a final step, we proceed with a visual inspection of the regions, allocated by the mixture to different regimes (Fig. 2). As illustrative purpose, we show the EU-25 sample. Regions in dark grey compose the faster convergence group, the light grey group is the slower convergence regime, while in the white group are the regions that do not converge. The map depicts the existence of dualistic phenomena in many States. Rich and poor regions in Ireland, UK, France, Germany, Spain, Italy, as well as in many of the New Member States, fall in opposite regimes, that are not converging between themselves. Such phenomena reinforce the paradox of the "diverging-converging" (i.e. convergence between States, but not within).

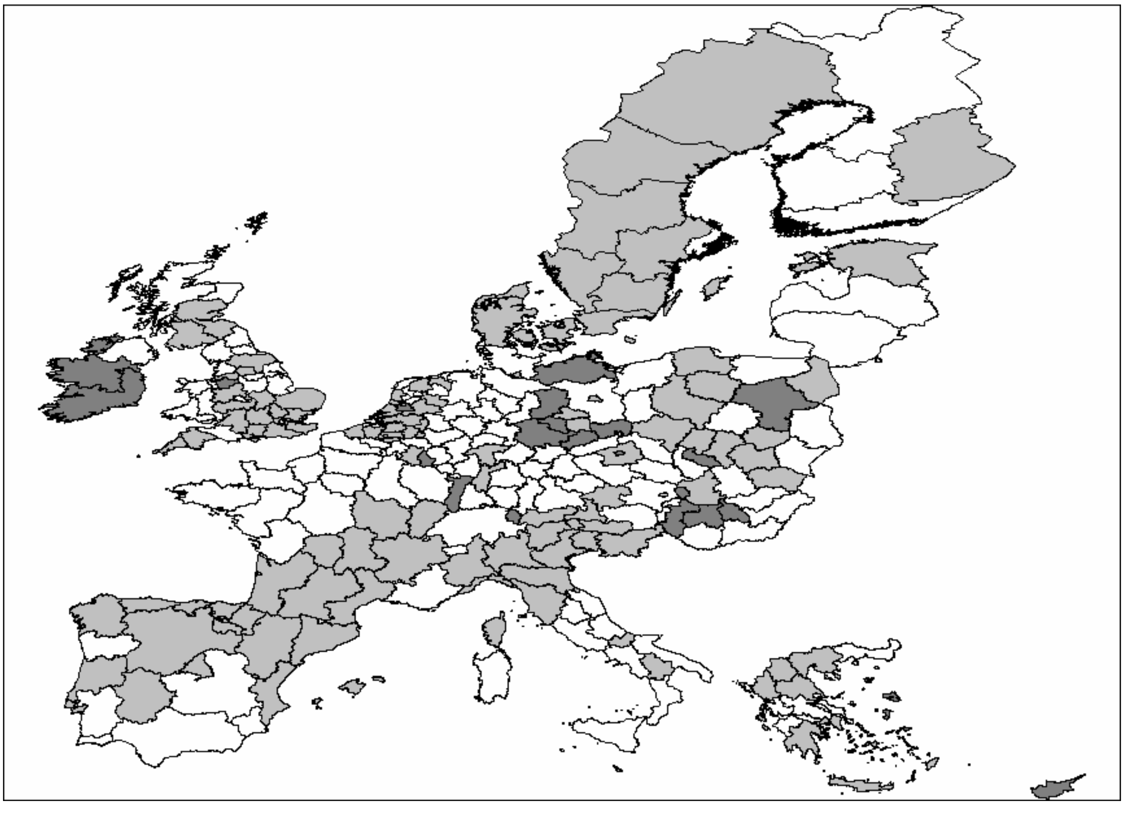
6. Conclusions

[22] During the Nineties the group becomes a divergence regime.
[23] For the case of EU-15, 1980-1991, the convergence rate remains similar to the two components specification, being equal to about 0.6% per year.

In the present work we analysed regional convergence patterns, trying to avoid potential sources of problems due to spatial effects, parameters heterogeneity and outliers. The methodology adopted here shows as either *absolute*, *conditional*, or *club* convergence are not the best hypotheses able to explain regional growth in Europe, over the period 1980-2002. Summarizing, a common specification for the whole sample is a too much restrictive assumption, convergence rates are far away from the "empirical norm" of 2% per year, spatial effects matter, and per capita incomes are geographically concentrated.

Once the data have been spatially filtered, the mixture endogenously identifies multiple growth regimes. In the case of a three components specification, generally one regime behaves as an "outlier bin", one regime manifests a sustained convergence rate, and the last one, collecting the majority of the sample, shows no convergence at all. Many regions, inside either "poor" or "rich" States, fall in the non convergence regime, where agglomeration factors, and increasing returns, might play a role. Such mechanism reinforces the paradox of the so-called "diverging-convergence", that is the convergence between States but not within.

Figure 2 Convergence patterns, EU-25: 1991-2002*



* Dark grey: Fast convergence; Light grey: Slow convergence; White: No convergence

Furthermore, a North-South division does not emerge, but for the Italian case, while a core-periphery dynamic seems more reasonable.

Finally, since the main intent of this work had been to take into account misspecification sources, in the β-convergence framework, policy prescriptions cannot be easily drawn. However, some implications may be discussed. Since convergence rates does not vary so much between the two sub-periods, cohesion policies does not make substantial differences. If something, the Nineties see an expansion of the non convergence area. Looking at the enlarged sample, regions belonging to the New Member States show diversified experiences. To conclude, regional growth dynamics does not seem to have followed, over the period considered, a common pattern towards the convergence of per capita income across Europe.

References

Abreu M, De Groot HLF, Florax RJGM (2005a) A Meta-Analysis of β-Convergence: the Legendary 2% Journal of Economic Surveys 19: 389-420

Abreu M, De Groot HLF, Florax RJGM (2005b) Space and Growth: A survey of Empirical Evidence and Methods. Région et Développement 21: 13-44

Anselin L (1988) Spatial Econometrics: Methods and Models. Kluwer, Dordrecht

Anselin L (2001) Spatial Econometrics. In: Baltagi BH (ed.) A companion to Theoretical Econometrics. Blackwell, Oxford, pp. 310-330

Anselin L (2005) Exploring Spatial Data with GeoDa: A Workbook. Center for Spatial Integrated Social Science, Santa Barbara, CA

Anselin L, Bera AK. 1998. Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics. In: Ullah A, Giles DEA (eds.) Handbook of Applied Economic Statistics. Marcel Dekker, New York, pp. 237-289

Arbia G (2006) Spatial Econometrics: Statistical Foundations and Applications to Regional Convergence. Springer, Berlin

Armstrong HW (1995) Convergence among regions of the European Union, 1950-1990. Papers in Regional Science 74: 143-152

Azariadis C, Drazen A (1990) Threshold Externalities in Economic Development. Quarterly Journal of Economics 105: 501-526

Badinger H, Müller WG, Tondl G (2004) Regional Convergence in the European Union, 1985-1999: A Spatial Dynamic Panel Analysis. Regional Studies 38: 241-253

Barro RJ, Sala-i-Martin X (1991) Convergence across States and Regions. Brookings Papers on Economic Activity 1: 107-182

Barro RJ, Sala-i-Martin X (1992) Convergence. Journal of Political Economy 100: 223-251

Barro RJ, Sala-i-Martin X (2004) Economic Growth (2nd ed.). MIT, Cambridge, MA

Bernard AB, Durlauf SN (1996) Interpreting tests of the convergence hypothesis. Journal of Econometrics 71: 161-173

Boldrin M, Canova F (2001) Inequality and convergence in Europe's regions: reconsidering European regional policies. Economic policy 16: 207-253

Canova F (2004) Testing for Convergence Clubs in Income per Capita: a Predictive Density Approach. International Economic Review 45: 49-77

Commission of the European Communities (2005) Communication from the Commission. Third progress report on cohesion: Towards a new partnership for growth, jobs and cohesion. 17.5.2005 COM(2005) 192 final. Brussels.

De Sarbo WS, Cron WL (1988) A Maximum Likelihood Methodology for Clusterwise Linear Regression. Journal of Classification 5: 249-282

Durlauf SN, Johnson PA (1995) Multiple Regimes and Cross-country Growth Behaviour. Journal of Applied Econometrics 10: 365-384

Durlauf SN, Quah DT (1999) The New Empirics of Economic Growth. In: Taylor JB, Woodford M (eds) Handbook of Macroeconomics (vol. 1). North Holland, Amsterdam, pp. 235-308

Durlauf SN, Kourtellos A, Minkin A (2001) The Local Solow Growth Model. European Economic Review 45: 928-940

Durlauf SN, Johnson PA, Temple JRW (2005) Growth Econometrics. In Durlauf SN, Aghion P (eds.) Handbook of Economic Growth. North Holland, Amsterdam, pp. 555-677.

Ertur C, Le Gallo J, Baumont C (2006) The European Regional Convergence Process, 1980-1995: Do Spatial Regimes and Spatial Dependence Matter?. International Regional Science Review 29: 3-24

European Commission (2001) Unity, solidarity, diversity for Europe, its people and its territory. Second report on economic and social cohesion. Office for Official Publications of the European Communities, Luxembourg

European Commission (2004) A new partnership for cohesion. Convergence competitiveness cooperation. Third report on economic and social cohesion. Office for Official Publications of the European Communities, Luxembourg

Funck B, Pizzati L (eds) (2003) European Integration, Regional Policy, and Growth. World Bank, Washington D.C.

Galor O (1996) Convergence? Inferences from Theoretical Models. Economic Journal 106: 1056-1069

Getis A, (1995) Spatial Filtering in a Regression Framework: Examples Using Data on Urban Crime, Regional Inequality, and Government Expenditures. In: Anselin L, Florax R (eds) New Directions in Spatial Econometrics. Springer-Verlag, Berlin, pp. 172-88

Getis A, Griffith DA (2002) Comparative Spatial Filtering in Regression Analysis. Geographical Analysis 34: 130-140

Hart PE (1995) Galtonian Regression Across Countries and the Convergence of Productivity. Oxford Bulletin of Economics and Statistics 57: 287-293

Hawkins DS, Allen DM, Stromberg AJ (2001) Determining the Number of Components in Mixture of Linear Models. Computational Statistics and Data Analysis 38: 15-48

Labour Asociados (2003) Analysis of the impact of Community Policies on Regional Cohesion. Contract number 2002 CE 16 0 AT 171. European Commission. DG Regional Policy

Le Gallo J, Ertur C (2003) Exploratory Spatial Data Analysis of the Distribution of Regional Per Capita GDP in Europe, 1980-1995. Papers in Regional Science 82: 175-201

Le Gallo J, Dall'erba S (2006) Evaluating the Temporal and Spatial Heterogeneity of the European Convergence Process, 1980-1999. Journal of Regional Science 46: 269-288

López-Bazo E, Vayá E, Mora AJ, Suriñach J (1999) Regional Economic Dynamics and Convergence in the European Union. Annals of Regional Science 33: 343-370.

Louis TA (1982) Finding the Observed Information Matrix When Using the EM Algorithm. Journal of Royal Statistical Society B 44: 226-233

MacLachlan G, Peel D (2000) Finite Mixture Models. John Wiley and Sons, New York

Mankiw NG, Romer D, Weil DN (1992) A contribution to the Empirics of Economic Growth. Quarterly Journal of Economics 107: 407-437

Martin P (1998) Can Regional Policies Affect Growth and Geography in Europe?. World Economy 21: 757-774

Meliciani V, Peracchi F (2006) Convergence in Per-Capita GDP Across European Regions: A Reappraisal. Empirical Economics 31: 549-568.

Neven D, Gouyette C (1995) Regional Convergence in the European Community. Journal of Common Market Studies 33: 47-65

Paap R, van Dijk HK (1998) Distribution and Mobility of Wealth of Nations. European Economic Review 42: 1269-1293

Pagan A (1984) Econometric Issues in the Analysis of Regressions With Generated Regressors. International Economic Review 25: 221-247

Petrakos G, Rodríguez-Pose A, Rovolis A (2005) Growth, Integration, and Regional Disparities in the European Union. Environment and Planning A 37: 1837-1855

Quah DT (1993a) Empirical cross-section dynamics in economic growth. European Economic Review 37: 426-434

Quah DT (1993b) Galton's Fallacy and Tests of the Convergence Hypothesis. Scandinavian Journal of Economics 95: 427-443

Quah DT (1996a) Empirics for economic growth and convergence. European Economic Review 40: 1353-1375

Quah DT (1996b) Twin Peaks: Growth and Convergence in Models of Distribution Dynamics. Economic Journal 106: 1045-1055

Quah DT (1996c) Regional Convergence Clusters across Europe. European Economic Review 40: 951-958

Quah DT (1997) Empirics for Growth and Distribution: Stratification, Polarization, and Convergence Clubs. Journal of Economic Growth 2: 27-59

Rey SJ, Montouri BD (1999) US Regional Income Convergence: A Spatial Econometric Perspective. Regional Studies 33: 143-156

Sala-i-Martin X (1996a) The Classical Approach to Convergence Analysis. Economic Journal 106: 1019-1036

Sala-i-Martin X (1996b) Regional Cohesion: Evidence and Theories of Regional Growth and Convergence. European Economic Review 40: 1325-1352

Sala-i-Martin X (2002) 15 Years of New Growth Economics: What Have We Learnt?. Discussion Paper Series 0102-47. Columbia University, Department of Economics

Solow RM (1999) Neoclassical Growth Theory. In: Taylor JB, Woodford M (eds) Handbook of Macroeconomics (vol. 1). North Holland, Amsterdam, pp. 637-667

Temple JRW (1998) Robustness Tests of the Augmented Solow Model. Journal of Applied Econometrics 13: 361-375

Temple JRW (2000) Growth Regressions and What the Textbooks Don't Tell You. Bulletin of Economic Research 52: 181-205

Titterington DM, Smith AFM, Makov UE (1985) Statistical Analysis of Finite Mixture Distributions. Wiley, Chichester

Tsionas EG (2000) Regional Growth and Convergence: Evidence from the United States. Regional Studies 34: 231-238

Turner RT (2000) Estimating the Propagation Rate of a Viral Infection of Potato Plants via Mixtures of Regressions. Applied Statistics 49: 371-384

Wedel M, Kamakura WA (1998) Market Segmentation: Conceptual and Methodological Foundations. Kluwer, Dordrecht

Appendix: List of regions[24]

AT (9) 1. Burgenland 2. Niederösterreich 3. Wien 4. Kärnten 5. Steiermark 6. Oberösterreich 7. Salzburg 8. Tirol 9. Vorarlberg **BE (11)** 10. Région de Bruxelles-Capitale 11. Antwerpen 12. Limburg 13. Oost-Vlaanderen 14. Vlaams-Brabant 15. West-Vlaanderen 16. Brabant Wallon 17. Hainaut 18. Liège 19. Luxembourg 20. Namur **CY (1)** 21. Kypros / Kibris **CZ (8)** 22. Praha 23. Stredni Cechy 24. Jihozapad 25. Severozapad 26. Severovychod 27. Jihovychod 28. Stredni Morava 29. Moravskoslezsko **DE (40)** 30. Stuttgart 31. Karlsruhe 32. Freiburg 33. Tübingen 34. Oberbayern 35. Niederbayern 36. Oberpfalz 37. Oberfranken 38. Mittelfranken 39. Unterfranken 40. Schwaben 41. Berlin 42. Brandenburg 43. Bremen 44. Hamburg 45. Darmstadt 46. Gießen 47. Kassel 48. Mecklenburg-Vorpommern 49. Braunschweig 50. Hannover 51. Lüneburg 52. Weser-Ems 53. Düsseldorf 54. Köln 55. Münster 56. Detmold 57. Arnsberg 58. Koblenz 59. Trier 60. Rheinhessen-Pfalz 61. Saarland 62. Chemnitz 63. Dresden 64. Leipzig 65. Dessau 66. Halle 67. Magdeburg 68. Schleswig-Holstein 69. Thüringen **DK (1)** 70. Danmark **EE (1)** 71. Eesti **ES (16)** 72. Galicia 73. Principado de Asturias 74. Cantabria 75. País Vasco 76. Comunidad Foral de Navarra 77. La Rioja 78. Aragón 79. Comunidad de Madrid 80. Castilla y León 81. Castilla-La Mancha 82. Extremadura 83. Cataluña 84. Comunidad Valenciana 85. Illes Balears 86. Andalucía 87. Región de Murcia **FI (4)** 88. Itä-Suomi 89. Etelä-Suomi 90. Länsi-Suomi 91. Pohjois-Suomi **FR (22)** 92. Île de France 93. Champagne-Ardenne 94. Picardie 95. Haute-Normandie 96. Centre 97. Basse-Normandie 98. Bourgogne 99. Nord - Pas-de-Calais 100. Lorraine 101. Alsace 102. Franche-Comté 103. Pays de la Loire 104. Bretagne 105. Poitou-Charentes 106. Aquitaine 107. Midi-Pyrénées 108. Limousin 109. Rhône-Alpes 110. Auvergne 111. Languedoc-Roussillon 112. Provence-Alpes-Côte d'Azur 113. Corse **GR (13)** 114. Anatoliki Makedonia, Thraki 115. Kentriki Makedonia 116. Dytiki Makedonia 117. Thessalia 118.

[24] Some regions have been excluded from the original dataset for lack of data, low population or extremely remote location: Departements d'Outre-Mer (FR), Aland (FI), Canarias and Ceuta y Melilla (ES), Acores and Madeira (PT).

Ipeiros 119. Ionia Nisia 120. Dytiki Ellada 121. Sterea Ellada 122. Peloponnisos 123. Attiki 124. Voreio Aigaio 125. Notio Aigaio 126. Kriti **HU (7)** 127. Kozep-Magyarorszag 128. Kozep-Dunantul 129. Nyugat-Dunantul 130. Del-Dunantul 131. Eszak-Magyarorszag 132. Eszak-Alfold 133. Del-Alfold **IE (2)** 134. Border, Midland and Western 135. Southern and Eastern **IT (20)** 136. Piemonte 137. Valle d'Aosta 138. Liguria 139. Lombardia 140. Trentino-Alto Adige 141. Veneto 142. Friuli-Venezia Giulia 143. Emilia-Romagna 144. Toscana 145. Umbria 146. Marche 147. Lazio 148. Abruzzo 149. Molise 150. Campania 151. Puglia 152. Basilicata 153. Calabria 154. Sicilia 155. Sardegna **LT (1)** 156. Lietuva **LU (1)** 157. Luxembourg **LV (1)** 158. Latvija **MT (1)** 159. Malta **NL (12)** 160. Groningen 161. Friesland 162. Drenthe 163. Overijssel 164. Gelderland 165. Flevoland 166. Utrecht 167. Noord-Holland 168. Zuid-Holland 169. Zeeland 170. Noord-Brabant 171. Limburg **PL (16)** 172. Dolnoslaskie 173. Kujawsko-Pomorskie 174. Lubelskie 175. Lubuskie 176. Lodzkie 177. Malopolskie 178. Mazowieckie 179. Opolskie 180. Podkarpackie 181. Podlaskie 182. Pomorskie 183. Slaskie 184. Swietokrzyskie 185. Warminsko-Mazurskie 186. Wielkopolskie 187. Zachodniopomorskie **PT (5)** 188. Norte 189. Algarve 190. Centro 191. Lisboa 192. Alentejo **SE (8)** 193. Stockholm 194. Östra Mellansverige 195. Sydsverige 196. Norra Mellansverige 197. Mellersta Norrland 198. Övre Norrland 199. Småland med öarna 200. Västsverige **SI (1)** 201. Slovenija **SK (4)** 202. Bratislavsky kraj 203. Zapadne Slovensko 204. Stredne Slovensko 205. Vychodne Slovensko **UK (37)** 206. Tees Valley and Durham 207. Northumberland and Tyne and Wear 208. Cumbria 209. Cheshire 210. Greater Manchester 211. Lancashire 212. Merseyside 213. East Riding and North Lincolnshire 214. North Yorkshire 215. South Yorkshire 216. West Yorkshire 217. Derbyshire and Nottinghamshire 218. Leicestershire, Rutland and Northamptonshire 219. Lincolnshire 220. Herefordshire, Worcestershire and Warwickshire 221. Shropshire and Staffordshire 222. West Midlands 223. East Anglia 224. Bedfordshire and Hertfordshire 225. Essex 226. Inner London 227. Outer London 228. Berkshire, Buckinghamshire and Oxfordshire 229. Surrey, East and West Sussex 230. Hampshire and Isle of Wight 231. Kent 232. Gloucestershire, Wiltshire and North Somerset 233. Dorset and Somerset 234. Cornwall and Isles of Scilly 235. Devon 236. West Wales and The Valleys 237. East Wales 238. North Eastern Scotland 239. Eastern Scotland 240. South Western Scotland 241. Highlands and Islands 242. Northern Ireland