CONVERGING AND DIVERGING REGIONS IN THE EU: IMPLICATIONS FOR REGIONAL POLICY

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Abstract:

This paper investigates the extent of regional cohesion amongst European regions; an issue of emerging importance in the fast growing literature on regional economics. This paper aims to shed some further light on the question of regional cohesion by taking into account the impact of the existing technological gaps across regions. Regional cohesion is examined in terms of labour productivity for the NUTS-2 regions of the EU-27 during the time period 1995-2006. The results suggest the existence of two separate groups or clubs. The first includes regions from advanced northern European countries, while the members in the second club are mainly found in the new member-states and in southern European countries, putting the issue of European regional policy into a fresh premise. To be more specific, the results have important implications for the (re) direction of regional policy in Europe towards a new set of objectives and instruments.

Key words: Regional Cohesion, Technological Gap, Regional Policy
JEL: C21; O18; R11

1. Introduction

The debate on regional convergence has bred, and continues to do so, dozens of empirical studies (e.g. Button and Pentecost, 1995; Neven and Gouyette, 1995; Martin, 2001; Funke and Niebuhr, 2005). In this fast growing literature technological progress has been acknowledged to be of critical importance in promoting regional convergence. Nevertheless, the impact of the adoption of technology has received surprisingly little attention thus far. Indeed, Bernard and Jones (1996) claim that empirical studies on convergence have over-emphasised the role of capital accumulation in generating convergence at the expense of the diffusion of technology. It is the intention of this paper to develop and apply a model that incorporates technology. To complete this introduction, mention must be made to the context upon which the empirical analysis will be conducted. In this paper we will use the NUTS-2 regions of the EU as a sort of laboratory for the analysis of regional convergence. The paper is organised in five sections. The first section introduces the theoretical framework. Data related issues are overviewed in Section 3, and the models are submitted to the usual econometric tests yielding the main findings in section 4. In the concluding section we offer a possible explanation for the results we obtain and suggest that might afford an interesting policy conclusion.

2. Regional Convergence and Technology Adoption

It is possible to identify two sources of technological change. The first is a process of intentional creation of technology; an autonomous process that takes place exclusively within the 'borders' of a region. Acknowledging the idea that regions are, by definition, open economies technology is also affected by technological improvements that take place in other regions. This process is usually termed as *technology adoption* and constitutes the second source of technological change. Alternatively, this source refers to the part of technology that is generated from *interaction* between spatial units. An essential assumption for the purpose of this paper is that technology adoption is related to the size of the 'technological gap'[1]. This can be defined as the difference between an exogenously determined best-practice frontier (x), and the prevailing level of technology in a region (a_i), i.e. $b_i = a_i - x_i$; a measure which can be conceived as an approximation of 'technological proximity'. Thus, technology in a region ($\dot{a}_i$) grows as follows:

$$\dot{a}_i = \tilde{\theta}_i + \xi b_i \tag{1}$$

In equation (1) $\tilde{\theta}_i$ denotes the autonomous part of technology growth, i.e. technology created within a region. The ability of a region to implement technological innovations is represented by the parameter ξ, which reflects the opportunities for technological catch-up. Given that $b_i = a_i - x_i$, then the technological distances between a leading and a follower region, are given by: $b_l = a_l - x$ and $b_f = a_f - x$, respectively or $\dot{a}_l = \tilde{\theta}_l + \xi b_l$ and $\dot{a}_f = \tilde{\theta}_f + \xi b_f$. The growth rate for the technology gap between the two regions ($\dot{b}_{lf}$) is therefore:

$$\dot{b}_{lf} = \dot{a}_l - \dot{a}_f = \left(\tilde{\theta}_l - \tilde{\theta}_f\right) + \xi\left(b_l - b_f\right) \tag{2}$$

Defining $b_{lf} = b_f - b_l$ and $\tilde{\theta}_{lf} = \left(\tilde{\theta}_l - \tilde{\theta}_f\right)$, equation (2) can be written as follows:

$$\dot{b}_{lf} = \tilde{\theta}_{lf} - \xi b_{lf} \tag{3}$$

Assuming that ξ is a decreasing function of the *initial* technological gap in a region, i.e. $\xi_i = f\left(b_{lf_{i,0}}\right)$ with $f' < 0$, then a relatively high initial level of technological gap implies that the prevailing conditions are not favourable for technology adoption and, consequently, the distance from the technological leader increases through time. Conversely, a relatively low level of the initial technological gap can be taken as an indication that conditions allow adoption of technological innovations, reflected in a relatively high value of ξ. Obviously, regional disparities in the absorptive parameters generate a strong tendency for regional per-capita output to diverge.

It becomes of crucial importance, therefore, to determine the dynamic path of convergence that this model implies. This can be shown using an example in which the economy is divided into three regions, one 'leader' (l), which is at the technological frontier $(b_l = a_l - x = 0)$, and two followers ($i = 1, 2$). Assume that $\tilde{\theta}_{lf_1} - \tilde{\theta}_{lf_2} = 0$ and $b_{lf_{1,0}} - b_{lf_{2,0}} > 0$, which implies that $\xi_1 - \xi_2 < 0$. If this difference remains unchanged over a given period of time, then a catch-up, in terms of technology, between region 1 and 2 is not feasible. Stated in alternative terms, if $\left(\Delta\xi_{1,2}\right)_t \to \infty$, then $\left(\Delta b_{lf_{1,2}}\right)_t \to \infty$, as $t \to \infty$ and the two regions move towards different directions (Figure 1). Only regions with low technology gaps are likely to converge towards a steady-state equilibrium growth path, as represented by the growth rate of the leading region. Regions with relatively large technology gaps may fall progressively behind. It seems thus legitimate to ask, if there is a way for the 'technologically poor' regions to catch-up with the 'technologically rich' regions? In this example a catch-up is feasible only if region 1, viz. the 'technologically poor' region, improves its adoptive ability, i.e. if the value of ξ increases through time, from ξ_1 to ξ_1', as shown in Figure 2. Provided that $\left(\Delta\xi_{1,2}\right)_t \to 0$, then gradually

[1] See Alexiadis (2010) for further elaboration of this argument.

$\left(\Delta b_{lf_{1,2}}\right)_t \to 0$, allowing region 1 to catch-up with the 'technologically rich' region 2. The conclusion to drawn is that a pattern of club-convergence is the most probable outcome, if the adoptive parameters differ across regions. Movements towards overall convergence occur only as regions become similar in terms of their adoptive abilities.

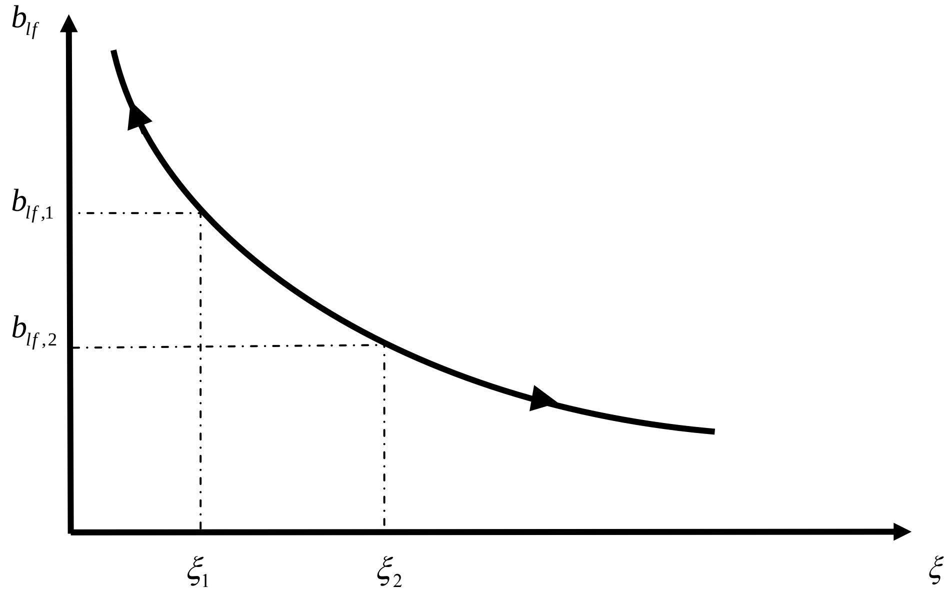

Figure 1: Diverging regions

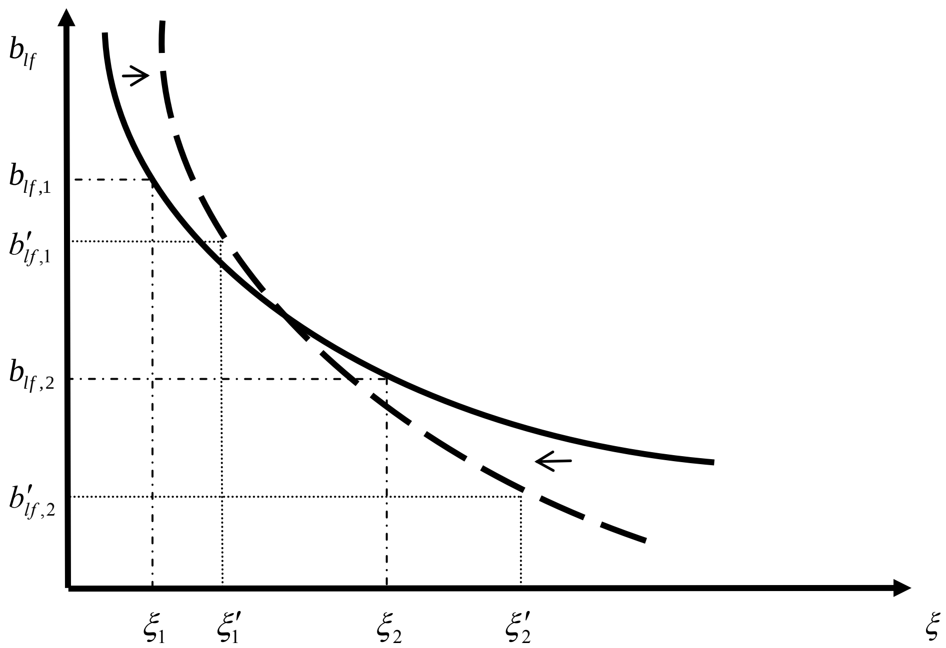

Figure 2: Converging regions

Overall, this model suggests that convergence towards the leading region(s) is feasible only for regions with sufficient absorptive capacity. There is the distinct possibility that only regions with low technology gaps are able to converge towards a steady-state equilibrium growth path, relative to the growth rate of the leading region. Regions with large technology gaps may fall progressively behind.

3. Econometric Specification

The empirical literature on regional convergence (e.g. Barro and Sala-i-Martin, 1992) makes extensive use of two alternative tests for convergence, namely absolute and conditional convergence:

$$g_i = a + b_1 y_{i,0} + \varepsilon_i \tag{4}$$

$$g_i = a + b_1 y_{i,0} + b_{\mathbf{X_i}} \mathbf{X_i} + \varepsilon_i \tag{5}$$

where y_i typically represents per-capita output, or output per-worker, of the i[th] region (in logarithm form), $g_i = (y_{i,T} - y_{i,0})$ is the growth rate over the time interval $(0,T)$, and ε_i is the error-term, which follows a normal distribution while the rate of convergence (β) is calculated as $\beta = -\frac{\ln(b_1+1)}{T}$, where T is the number of years in the period. Absolute (unconditional) convergence is signalised by $b_1 < 0$. On the other hand, conditional convergence is based upon the argument that different regional characteristics will lead to different steady-states. Conditional convergence requires that $b_1 < 0$ and $b_{\mathbf{X_i}} \neq 0$. Consider two groups of regions, let $i = k,l$, that differ not only in terms of initial labour productivity, i.e. $\mathbf{\Delta y_{kl,0}} \equiv y_{k,0} - y_{l,0} \neq 0$, but also in terms of their structural characteristics, i.e. $\mathbf{\Delta X_{kl}} \equiv \mathbf{X}_k - \mathbf{X}_l \neq 0$. Assume that $\mathbf{\Delta y_{kl,0}} > 0$ and $\mathbf{\Delta X_{kl}} > 0$. An implication of this assumption is that a superior (inferior) regional infrastructure, approximated in terms of a high (low) $\mathbf{X_i}$, is associated with a high (low) level of initial level of labour productivity. Absolute convergence amongst these groups is possible if $g_{k,T} - g_{l,T} < 0$. However, given that $\mathbf{\Delta X_{kl}} > 0$, a relatively slow process of convergence is expected. It follows, therefore, that a test for conditional convergence is more suitable for the empirical application of the model developed in Section 2, with variable(s) representing technology the principal focus, which is what the remaining paragraphs of this section will be dealing with.

Technical change, leading to regional productivity growth, originates either from within the region, namely indigenous innovation (IC_i), or from other regions, i.e. technological spillovers from adopting innovations created elsewhere (ADP_i). In the former case, technical change may be approximated in several ways[2]. Nevertheless, in this paper we use the percentage of workers employed in the science and technology sectors of each region[3]. The second source of technical growth, namely the ability of a region to adopt technological innovations, is approximated as the percentage of total employment in technologically dynamic sectors:

$$ADP_{i,t} = \frac{\sum_{\rho=1}^{\kappa} \eta_{i,t}^{\rho}}{\sum_{j=1}^{m} L_{i,t}^{j}}, \ \rho \subset j \tag{6}$$

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[2] Pigliaru (2003), for example, uses the 'propensity to innovate', which can be measured in terms of the number of patents per-capita in each region. Empirical applications of this measure in the case of EU regions can be found in Alexiadis (2010b), Alexiadis and Korres (2010).

[3] This corresponds to 'Human Resources in Science and Technology' (HRST) database of EUROSTAT, which includes persons who have completed a tertiary education in a field of science or technology and/or are employed in science and technology.

where $\eta_{i,t}^{\rho}$ refers to personnel employed in high-tech manufacturing and knowledge-intensive high-technology services ($\rho = 1, \ldots, \kappa$), while $L_{i,t}^{j}$ is the employment in all the sectors ($j = 1, \ldots, m$).

Equation (6), represents the level of technological development, but also, indicates a capacity for technology adoption, since these are taken to apply high technology. However, the potential for such technology diffusion increases as the technological gap increases, defined as the distance between a region's technological level and that of the most advanced technological region with the highest percentage of employment in high-tech manufacturing and knowledge-intensive high-technology services[4]. Consequently, in this context a variable that approximates the technological gap for region *i* at time *t* can be defined as follows:

$$TG_{i,t} = \left(\frac{ADP_{L,t}}{ADP_{i,t}} \right) \tag{7}$$

Expressing equation (7) in logarithmic terms yields:

$$TG_{i,t} = \ln ADP_{L,t} - \ln ADP_{i,t} . \tag{8}$$

Embodied in this variable is the idea of both a gap and the capacity to adopt technological innovations. As shown by the model in Section II, the presence of a technological gap alone is not sufficient to promote significant technology diffusion. There has to be an appropriate level of capability to adopt technology. Thus, the bigger the gap the greater the potential for technology adoption, but the lower the capacity to actually achieve this[5]. To explain the impact of technology adoption a model is set up of conditional convergence. This takes the usual Barro and Sala-i-Martin (1992) form, but includes two additional explanatory variables. Therefore, a model of 'technologically-conditioned' convergence can be structured as follows:

$$g_i = a + b_1 y_{i,0} + b_2 IC_{i,0} + b_3 TG_{i,0} + \varepsilon_i \tag{9}$$

The time dimension of variables describing technology should refer to the initial point in time for the period of study. From an econometric point of view, inclusion of technological variables measured at the initial time helps to avoid the problem of endogeneity. Moreover, Pigliaru (2003) claims that models which include measures of technology require data on total factor productivity. In the absence of such data, econometric estimation requires that the variables related to technology ought to be included in initial values.

Equation (9), thus, incorporates the potential impact of both internally generated technological change and technology adoption upon a region's growth. Broadly speaking, it is anticipated that $b_2 > 0$, since regions with high initial levels of patents per capita are normally associated with high levels of growth and vice versa. However, it is not automatically the case that this condition promotes convergence. In other words, this view accepts the argument that if low productivity regions have a high initial level of intentional technology creation, then this will have positive impacts on convergence, by enhancing their growth rates. On the other hand, if such regions have a low propensity to innovate, then no significant impacts on growth are anticipated and, hence, it may be difficult to converge with technologically advanced regions. The latter case is the more likely.

In the case of the $TG_{i,0}$ variable, this variable reflects two distinct features, namely the level of 'technological distance' from the leading region and the degree to which existing (initial)

[4] This is the region 'Berkshire, Bucks and Oxfordshire' in the UK.

[5] See also Alexiadis and Tomkins (2008).

conditions in a region allow adoption of technology. The approach adopted here is based on the contention that a high initial technological gap combined with a high rate of growth may indicate, ceteris paribus, that less advanced regions are able to adopt technology, which is transformed into high growth rates and, subsequently, convergence with the technologically regions. It may be argued, therefore, that the condition $b_3 > 0$ promotes convergence. On the other hand, a high initial value for $TG_{i,0}$ may indicate that although there is significant potential for technology adoption, initial infrastructure conditions are not appropriate to technology adoption and, therefore, there are no significant impacts on growth. In other words, if the latter effect dominates then $b_3 < 0$, and convergence between technologically lagging and technologically advanced regions is severely constrained. This brings the notion of club-convergence into consideration.

4. Econometric Estimation and Discussion

In this paper we exploit data on Gross Value Added (GVA) per-worker since this measure is a major component of differences in the economic performance of regions and a direct outcome of the various factors that determine regional 'competitiveness' (Martin, 2001). The European Statistical Office (EUROSTAT) is the main source for data used in this paper. Regional GVA data and all the structural data stem from this source. The regional groupings used in this paper are those delineated by EUROSTAT and refer to 267 NUTS-2 regions. The EU uses NUTS-2 regions as 'targets' for convergence and are defined as the 'geographical level at which the persistence or disappearance of unacceptable inequalities should be measured' (Boldrin and Canova, 2001, p. 212). Despite considerable objections for the use of NUTS-2 regions as the appropriate level at which convergence should be measured, the NUTS-2 regions are sufficient small to capture sub-national variations (Fischer and Stirböck, 2006). The time period for the analysis extends from 1995 to 2006, which might be considered as rather short. However, Durlauf and Quah (1999) point out that 'convergence-regressions' are valid for shorter time periods, since they are based on an approximation around the 'steady-state' and are supposed to capture the dynamics toward the 'steady-state'.

The dynamics of regional growth for Europe between 1995 and 2006 are summarised in Figure 3, which shows a scatterplot of the average annual growth rate against the initial level of GVA per-worker. Alternatively, Figure 3 indicates the potential or otherwise for β-convergence. Even a cursory analysis of the EU27 data suggests that the inverse relationship between growth rate and initial level of labour productivity is not so obvious. Figure 3 indicates that this relationship is more probable to occur among regions that exceed a certain level of initial labour productivity. The presence or absence of β-convergence, however, cannot be confirmed by visual inspection alone. Therefore, the cross-section test, based on estimation of equation (4) for the 267 NUTS2 regions, is applied to the period 1995-2006. Furthermore, the conventional test of regional absolute convergence is modified to include the hypothesis of 'technologically-conditioned' convergence. The relevant results are set out in Table 1 and show the convergence coefficient to be negative and significant at the 95%, implying a positive value for the rate of convergence (β), although in a relatively small range, estimated to be 0.65% per annum.

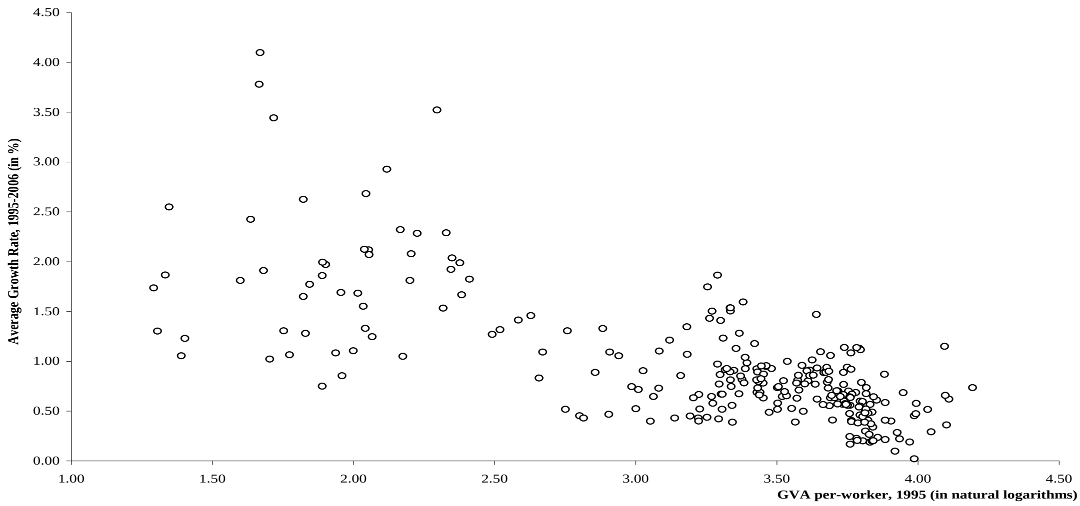

Figure 3: Absolute Convergence, GVA per-worker, EU NUTS-2 Regions, 1995-2006

Table 1: Regional Convergence, GVA per-worker, EU regions: 1995-2006

	Eq. (4)	Eq. (9)
Depended Variable: g_i , n = 267 NUTS-2 Regions, Ordinary Least squares		
a	0.5714**	0.6144**
b_1	-0.0747**	-0.0824**
b_2		0.0016
b_3		-0.0191*
Implied β	0.0065**	0.0072**
LIK	147.552	148.711
AIC	-291.104	-289.422
SBC	-283.929	-275.073

Notes: ** indicates statistical significance at 95% level of confidence, * 90% level. AIC, SBC and LIK denote the *Akaike*, the *Schwartz-Bayesian* information criteria and Log-Likelihood, respectively.

These cross-section tests provide some, albeit, very limited evidence that the NUTS2 regions of EU-27 are in the process of absolute β-convergence with low productivity regions growing faster than high productivity areas. But given the extremely slow convergence rate estimated[6], it would take a very long time for all prefectures to reach a common level of productivity, as predicted by the absolute convergence model. A positive coefficient is estimated for the variable describing technology creation. As argued in Section 3, a positive value of b_2 does not necessarily promote convergence as such, since regions with relatively high initial level of innovation exhibit relatively higher rates of growth. The variable $TG_{i,0}$ is statistically significant and negative in sign. A high technological gap does not necessarily imply that technologically lagging regions will be able to adopt technology - a large gap may constitute an obstacle to convergence. This proposition is supported by the empirical analysis which suggests that, on average, regions with high technological gaps at the start of the period grow slower than regions with low gaps, ceteris paribus. But what can this possibly mean? Clearly, a high initial

[6] This slow process of regional convergence can, possibly, be explained by the low degree of labour mobility that characterises the European regions, due to linguistic and cultural barriers. As Boldrin and Canova (2001, p. 243) state 'while capital is moving around Europe, labour is definitely not'. Obstfeld and Peri (1998) report that labour mobility in Germany, Italy and the UK over the period 1970-1995 was only about one-third of the US level.

technological gap is a factor that helps to sustain initial differences across regions, constraining any possibilities for overall convergence. If technologically backward regions of the EU were successful in adopting technology, then the estimated coefficient b_3 would be positive. Since $b_2 < 0$ this indicates that infrastructure conditions in regions with high technological gaps are inhibiting this process of technology adoption. It follows, therefore, that adoption of technology, although it might be the best 'vehicle' for lagging regions to converge with leading regions, nevertheless, this is a process which might be difficult for lagging regions, especially during the early stages of development when conditions are least supportive. Although the concept of conditional convergence implies a slower rate of convergence (Barro and Sala-i-Martin, 1992), nevertheless introducing the technological variable increases the estimated rate of convergence (0.72%).

The superiority of the model described by equation (9) is supported by both the criteria for model selection applied here, namely the *Akaike* (AIC) and the *Schwartz-Bayesian* (SBC) information criteria.[7] Further support is also provided by the value of the Log-likelihood (LIK), which increases, as anticipated, with the introduction of the technological variables. Overall, these results suggest a significant technological dimension in the process of European regional convergence. However, the relatively low rates of convergence imply the existence of a cumulative mechanism. There seems to be a certain 'threshold' level of technology and regions below that level are not able to assimilate technological innovation in an efficient way. In order to further corroborate this argument the empirical analysis is extended by estimating a model that incorporates the possibility of 'convergence in groups'; the so-called 'club-convergence' model.

There are several different approaches for identifying convergence clubs. Economic theory, however, offers little guidance in detecting both the number and composition of such clubs within a given cross-section of regional economies, as Corrado et al. (2005) claim. As a result, choosing a methodology that is appropriate or suitable in the present context is not necessarily a straightforward task, particularly when data is limited.

Nevertheless, existing methodologies can be classified into two broad categories, namely methods that are based on time-series data and those that rely on cross-section data. However, a potential pitfall in these methodologies is that they rely exclusively upon a single variable, namely GVA per-worker, which may be unsatisfactory in terms of policy implications. From a policy perspective, identification of convergence clubs alone is not enough, since successful implementation of economic policies at the regional level requires information on the specific factors that determine the pattern of regional growth. Thus, for example, Corrado et al. (2005) develop an approach that identifies both the number and the composition of convergence clubs using pair-wise stationarity tests on time-series data, but for a variety of conditioning variables. Using these variables, Corrado et al. (2005) test for regional convergence clusters across the EU regions against a number of hypothetical, a priori determined clusters. However, an application of this methodology across all the regions of the 27 countries of the EU is entirely feasible, since it requires an extensive time-series data for variables such as R&D labour and so forth; a requirement that it is difficult to fulfil, especially for the new member-states.

Using cross-section methodologies, on the other hand, can overcome the problem of small data sets for particular conditional variables. Durlauf and Johnson (1995), for example, apply a 'tree-regression' method using cross-section data sets. Here, a conditional convergence equation is estimated for the entire data set and then the same equation is estimated excluding those

[7] As a rule of thumb, the best fitting model is the one that yields the minimum values for the AIC or the SBC criterion.

economies that do not fulfil certain criteria, defined ex-ante[8]. However, application of such a methodology seems to be biased in identifying a predetermined convergence club. Moreover, applying a 'tree-regression' method in a regional context[9] fails to take into account the spatial dimension of the growth and convergence process (Fischer and Stirböck, 2006).

Apart from the above methodologies, there are two cross-section approaches to convergence club detection, found in Baumol and Wolff (1988) and Chatterji (1992). The latter defines convergence in terms of the narrowing of gaps between a leading region and other regions. Such an approach does not seem entirely appropriate in the case of EU-27, as the group of leading regions is an exceptional case. Thus, a predominant focus on gaps compared to the leading region reveals very little about underlying growth and convergence trends across the remaining regions.

Fischer and Stirböck (2006) propose a methodology that overcomes several of the shortcomings of the previous methodologies and involves two broad stages. In a first stage "spatial regimes in the data in the sense that groups (clubs) obey distinct growth regressions" (p. 695) are identified. The hypothesis of β-convergence within the clubs in conjunction with spatial dependence is then examined in a second stage. It is possible, however, to introduce these considerations in the Baumol and Wolff's framework (1988). The reason is that in this methodology a bias from a leading region, although still present to some degree, is much reduced, and can be systematically investigated. More importantly, perhaps, the logic and structure of the model is such that additional variables, which represent initial conditions, can be accommodated, with a view to improving the explanation of growth patterns.

Subsequent empirical analysis is, therefore, based upon application of Baumol and Wolff's (1988) specification. Furthermore, using the Baumol and Wolff (1988) specification it is possible to distinguish between different clubs due to dissimilarities in the rate of β-convergence, which is an essential feature in the clubs identified using the methodology by Fischer and Stirböck (2006)

Baumol and Wolff's model[10] is defined by the following equation:

$$g_i = a + b_1 y_{i,0} + b_2 y_{i,0}^2 + \varepsilon_i \tag{10}$$

A pattern of club convergence is established if $b_1 > 0$ and $b_2 < 0$. Members of a convergence club are identified as those economies which exhibit an inverse relation between the growth rate and initial level of GVA per-worker and exceed a threshold value of initial GVA per-worker, which is calculated as: $y^* = \frac{-b_1}{2b_2}$. Estimating, therefore, equation (10) using cross-section data for the 268 NUTS-2 regions of the EU-27 gives the results in Table 2.

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[8] According to this methodology the existing observations are ordered in increasing order based on a control variable and then the sample split that minimises the residual variance is identified. To that aim, Durlauf and Johnson (1995) propose two methods. The first identifies the number of splitting in an arbitrary way, based exclusively on one variable (usually per-capita income). The second implements a branching approach. Initially, the entire sample is divided into two sub-samples based on the variable that produces the best fir and this procedure is repeated for each of the resulting sub-samples, until the degrees of freedom become too small or the split into sub-samples becomes insignificant.

[9] The reader interest in these issues can, for instance, refer to the contributions Fagerberg and Verspagen (1996) and Siano and D'Uva (2006).

[10] Alexiadis (2010a) applies this method in the case of the Greek regions.

Table 2: Convergence Clubs: Baumol and Wolff's (1988) specification, 1995-2006

OLS, Estimated equation: $g_i = a + b_1 y_{i,0} + b_2 y_{i,0}^2$ Sample: 268 EU-27 NUTS-2 regions					
a	b_1	b_2	R^2 [ser]	Implied y^*	
0.0057	0.3233**	-0.0704**	0.17261 [0.1361]	2.2926**	
LIK	155.034	AIC	-304.068	SBC	-293.306

Notes: ** indicates statistical significance at 95% level of confidence [ser] denotes the standard error of the regression. AIC, SBC and LIK denote the *Akaike*, the *Schwartz-Bayesian* information criteria and Log-likelihood, respectively.

The SBC criterion indicates a very marginal preference for the convergence club model. The outcome is also consistent with the presence of a convergence club, in that the estimated coefficients are as expected. As can be seen from Table 2, the coefficient b_1 is positive while the coefficient b_2 is negative. In order to identify convergence club members the threshold value of initial GVA per-worker (y^*) is determined using equation (10), which is statistically significant at 95% level of confidence. At this point the conclusion that the simple model of club convergence provides a better explanation of the data than the simple absolute convergence model is tentative. The overall fit remains poor, and the power to discriminate between those regions which exhibit β-convergence, and those which do not, must be therefore be viewed with caution.

According to Baumol and Wolff's (1988) specification of convergence club, the property of β-convergence is apparent for the regions with an initial level of GVA per-worker in excess of the estimated threshold value of initial labour productivity. According to the implied threshold value, over the period 1995-2006, all but 43 NUTS-2 regions can be identified as exhibiting the property of β-convergence. Figure 4 and Table 3 point in the direction of the existence of convergence clubs among the European regions.

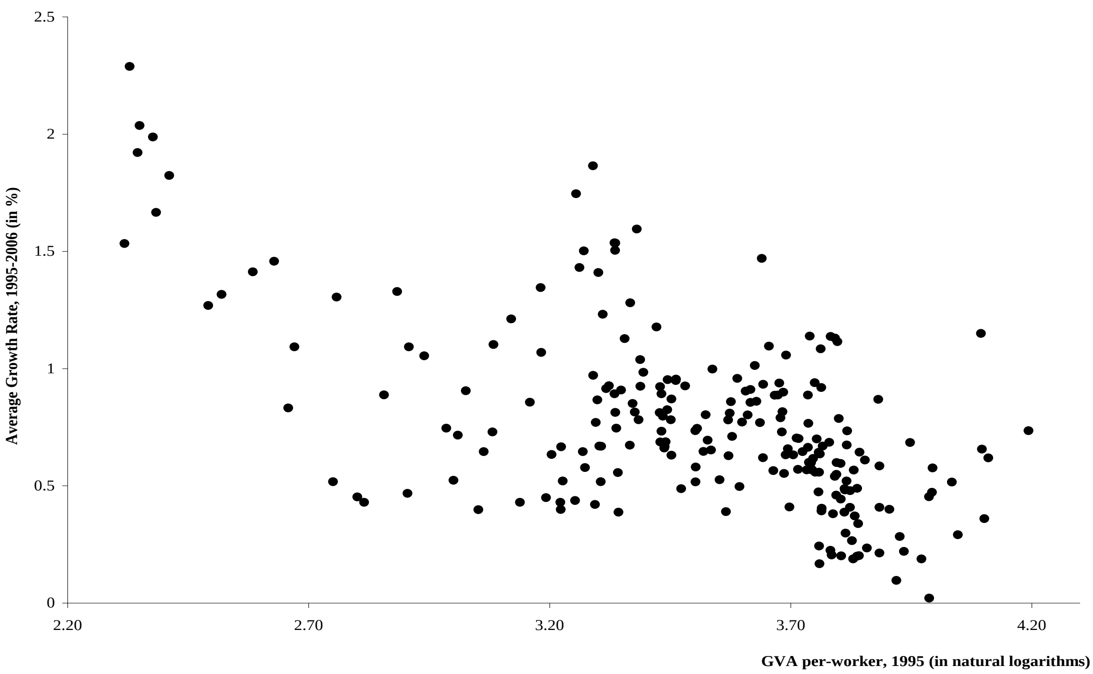

Figure 4: β-convergence amongst the convergence club

Table 3: β-convergence in the converging and diverging club

OLS, Estimated equation: $g_i = a + by_{i,0}$, Sample: 226 NUTS-2 regions		
a	*b*	Implied β
0.7444**	-0.1238**	1.102**
OLS, Estimated equation: $g_i = a + by_{i,0}$, Sample: 42 NUTS-2 regions		
a	*b*	Implied β
-0.0871**	0.2766**	-2.035**

Notes: ** indicates statistical significance at 95% level of confidence while * indicates significance at 90% level.

The regions included in the club converge at an average rate equal to 1.1% per annum. An opposite picture is revealed for the regions excluded from the convergence club (Figure 5). Given that the estimated value of the *b* coefficient is positive (Table 3), these regions exhibit *diverging* tendencies, at an average rate about 2% per annum.

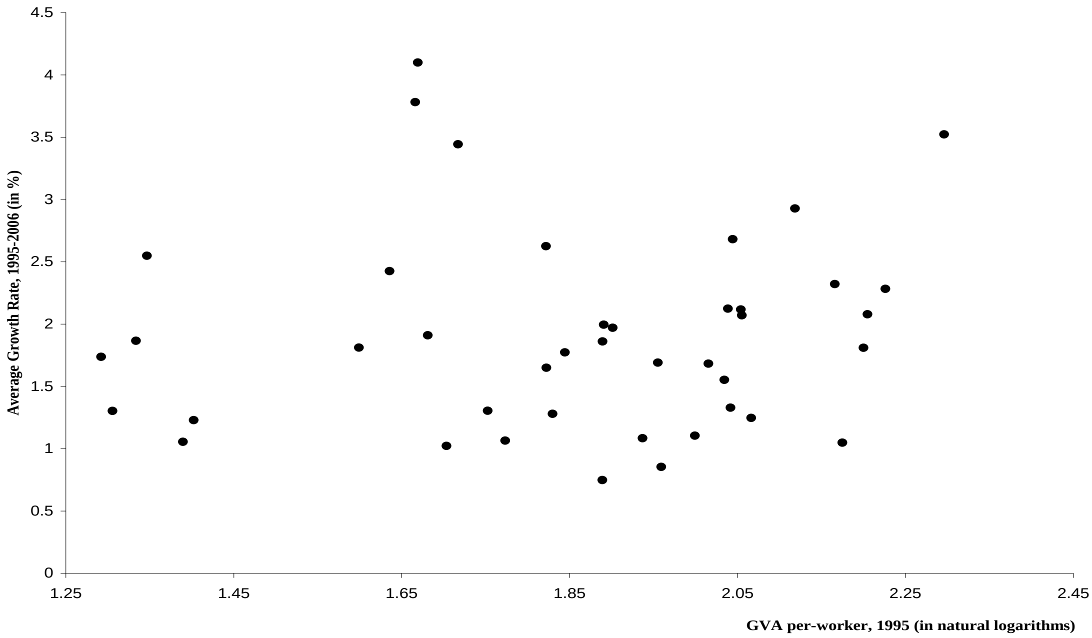

Figure 5: Diverging regions

Of particular importance, from a policy point of view is the impact of the technological variables. Thus, introducing these variables in a club-convergence context yields the following regression equation:

$$\mathbf{g_i} = a + b_1 y_{i,0} + b_2 y_{i,0}^2 + b_3 \ln IC_{i,0} + b_4 \ln TG_{i,0} \qquad (11)$$

The obtained results are reported on Table 4.

Table 4: Club Convergence and Technology

Depended Variable: g_i, n = 267 NUTS-2 Regions, OLS	
a	-0.0221
b_1	0.4472**
b_2	-0.0919**
b_3	-0.0123
b_4	-0.0427**
Implied y^*	2.43**
LIK	159.566
AIC	-309.133
SBC	-291.197

Notes: ** indicates statistical significance at 95% level of confidence, * 90% level. AIC, SBC and LIK denote the *Akaike*, the *Schwartz-Bayesian* information criteria and Log-Likelihood, respectively.

Overall, the extended model confirms, yet again, the existence of the convergence club across the NUTS-2 regions of the EU-27. The coefficients b_1 and b_2 have the appropriate signs but individually highly significant coefficients (at 95% level). This outcome is perhaps not unexpected in that convergence is now conditional upon initial structural characteristics. The threshold value of GVA per-worker (y^*), which is a combination of the two estimated coefficients, is found to be statistically significant, however. Turning to the impact of the other explanatory variables, only the technology gap variable yields a statistically significant coefficient at the 95% level. The innovation variable ($IC_{i,0}$) indicates a negative relationship with growth for the overall period, which can be interpreted as a source of convergence, in the sense that benefits from a high initial technological level have already taken place. As a result, regions with high initial $IC_{i,0}$ grow slowly, which can create a catch-up potential. However, the negative and significant value for b_4 suggests that, in the long-run, regions with high technological gaps at the start of the period grow slower than regions with low gaps, ceteris paribus. Bearing in mind that a high initial technological gap may also signify inappropriate conditions for technology adoption, then a large gap may not promote convergence. Since $b_4 < 0$ in all the equations above this suggests that for technologically poor regions this problem exists. Alternatively, $b_4 < 0$ indicates that regions with high technological gaps do not have the potential to adopt technology. This constitutes a substantial barrier to the diffusion of technology across the regions of the EU-27. The empirical findings reported in this section enhance the argument put forward by Fisher and Stirböck (2006) that "technology does not instantaneously flow across regions and countries in Europe" (pp. 710-711).

Accordingly, it may be adequate, but with much caution, to associate the poor convergence performance of the diverging group with a series of structural elements that characterise the regions in this group. Although it is beyond the scope of this paper to go into detail, nevertheless it is worth mentioning that the list of these elements includes the usual suspects such as science, technology and conditions related to the structure of the economy. More specifically, in 2005 the R&D intensity, measured in terms of R&D expenditure as a percentage of GDP[11], in these regions was less than 0.5%. There are two exceptions; a region in Poland

[11] A level of R&D intensity above 3% in the EU as whole to reach by 2010 is set by the Barcelona Council in 2002 and maintained in the Europe 2020 strategy. Nevertheless, only 10% of the EU regions were able to reach this target, located in the advanced EU-12 Member-States (UK, Germany and France).

(Mazowieckie) and the capital-region of Romania (Bucuresti-Ilfov). The R&D intensity in these two regions is about 1%. It is important to note that a comparison of GDP per-capita in these regions between the three-year periods 1998-2000 and 2005-2007 indicates that were able to pass the 75% threshold set by EU, which is a key criterion for being eligible to support from the Structural Funds. Contrary, the GDP per-capita in the remaining regions in the diverging group is still below the threshold. A similar situation with respect the distribution of patents applications to the European patent office (EPO) appears among the regions of the diverging group (less than 5 patents per million inhabitants). In 2006 the 'Human resources in science and technology' (HRST) in this group was less than 35%. An exemption is the Romanian region of Bucuresti-Ilfov with a percentage above 40%. It should be noted, however, that there is a tendency for HRST to concentrate in or around capital cities, especially in countries with a low overall proportion of HRST. An average share of high-tech sectors in total employment was less than 4% in the diverging group. For the central region a percentage above 5% is reported. A similar share can be found in four regions in the diverging group; three Hungarian regions, Nyugat-Dunántúl, Közép-Dunántúl and Közép-Magyarország, and one Slovakian, Bratislavský Kraj. It is worth to note that the three Hungarian regions are located in close geographical proximity while the regions Bratislavský Kraj and Nyugat-Dunántúl are close to the Austrian borders. Agriculture plays an important role in the economy of the diverging regions, if one considers the fact that this sector contributes about 3-6% in their GDP and in several cases, mainly in Romania and Bulgaria, over 6%. The percentage of rural population in these regions is in the range between 20% and 50%, with several regions above 50%. Furthermore, the regions in the diverging group exhibit a low degree of business concentration, with the anticipating exception of Bucuresti-Ilfov.

Figure 6 shows the spatial distribution of the convergence-club member regions. The convergence club includes, almost exclusively, regions from the 'old' and 'advanced' members-states of the European Union (EU-15). Such an outcome is in accordance with the view put forward by Dunford and Smith (2000), which highlight a significant '*development divide*' between the EU-15 and the East Central Europe. Indeed, according to the threshold value of the initial level of labour productivity, implied by the Baumol and Wolff's (1988) specification of convergence club, very few regions form the new member-states are included in the converging group. Most of these regions are located in Czech Republic; a relatively advanced economy of the East Central Europe. Conversely, the diverging areas are found in relatively backward Eastern European countries, such as Slovakia, Hungary, Poland, Romania and Bulgaria. The results reported insofar, clearly, indicate that the wide economic disparities between the regions of the EU-15 and the regions in the East Central Europe is a factor that constraints any possibilities for overall convergence across the EU-27.

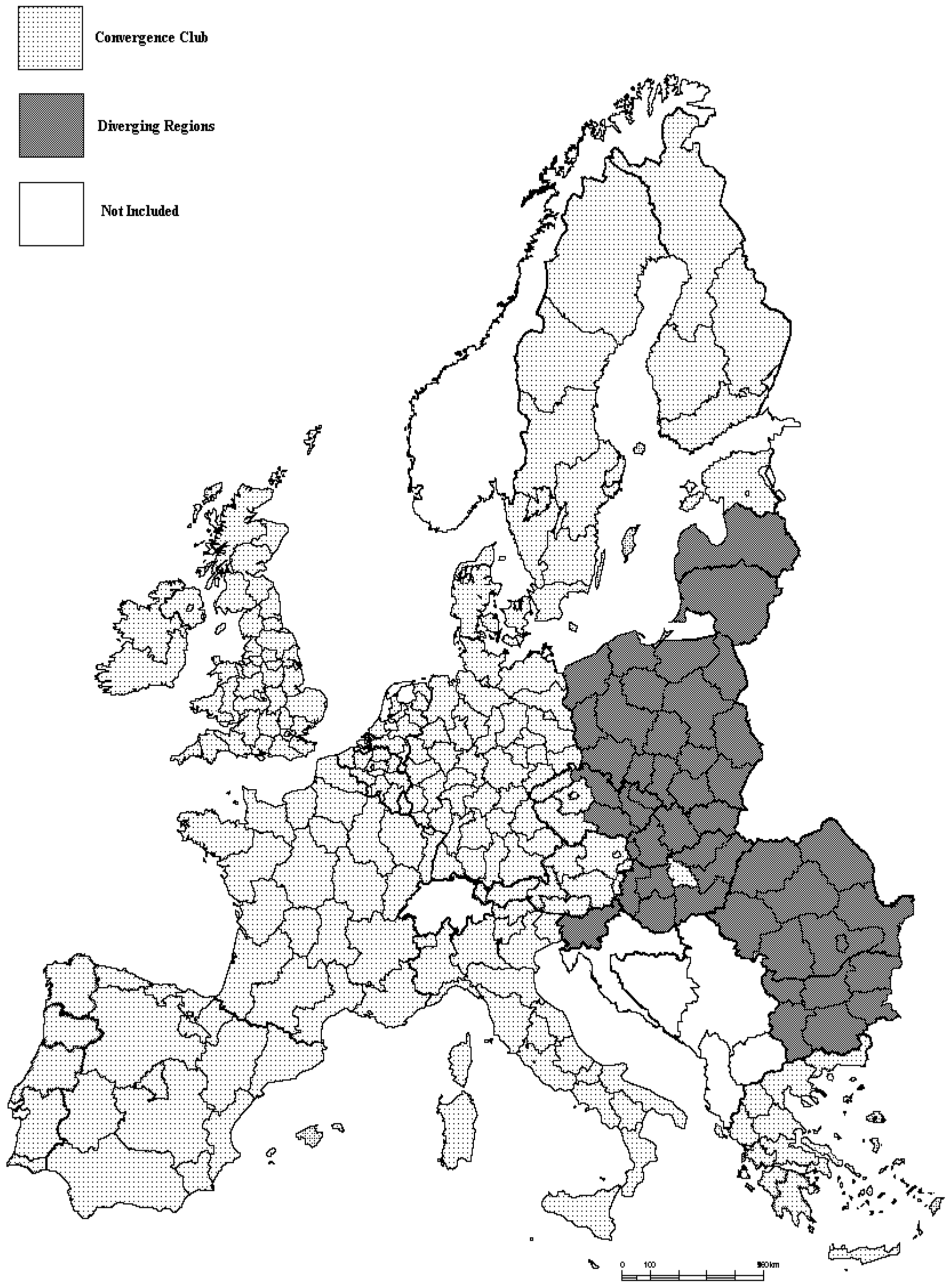

Figure 6: Converging and Diverging clubs

5. Conclusion

It is beyond argument that, although an increasing number of empirical studies have paid attention to issues of economic convergence in the EU, the impact of technology adoption in regional convergence has so far received more limited attention. We have attempted in this paper to address this issue by developing a model of regional convergence that puts primary focus upon the infrastructure conditions in a region. As in any modelling situation, we cannot know for certain whether a lack of correspondence between our theoretical presuppositions and the available empirical evidence is the result of falsify of our target theory or the approximations and omissions that we employed in specifying the empirical model. Nevertheless, estimating this model using data for the 267 NUTS-2 regions of the EU-27 over the period 1995-2006 yields some interesting results. To be more concrete, it is established that the NUTS-2 regions of EU-27 exhibit a very slow tendency towards overall convergence in terms of labour productivity. In this context, club-convergence seems to be a more probable outcome across the regions of an enlarged Europe. The evidence reported in this paper seems to confirm this hypothesis. More than ever, policy makers in the EU need independent and encompassing studies like this which can provide critical new information about regional convergence. Nevertheless, the important point to grasp, from a policy perspective, is that a primary aim of regional economic policy in an enlarged Europe should be the promotion of high-technology activities, and R&D, including universities, scientific and research institutions. Moreover, in order to enhance regional growth and convergence, policy should seek to reorient these activities. High-technological and knowledge-creating activities should be directed, if possible, at regions with unfavorable infrastructure conditions, as to stimulate the production structure in those regions towards activities that implement high technology.

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