Technology adoption and club convergence

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Abstract

A model of regional convergence is developed in which the pattern of convergence is attributed to the rate of technological adoption across regions. If absorptive abilities vary across regions, convergence is constrained within a certain group of regions that share common structural characteristics. Whether regions exhibit a pattern of convergence depends on the degree to which infrastructure conditions are appropriate for the adoption of technological improvements. The model is tested using data for the NUTS-2 regions of the EU-27 during the time period 1995-2006. The results suggest that adoption of technology has a significant effect on regional growth patterns in Europe, and hence the analysis has important implications for the direction of regional policy in Europe.

Key words: Convergence-club, Technological Gap, European Regions
JEL classifications: C21, O18, R11, R12

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; Puga, 2002). Although technological progress has been acknowledged, in this literature, to be of paramount importance in promoting convergence across regions, the impact of the adoption of technology has received less attention. 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.

> '[T]o the extent that the adoption and accumulation of technologies is important for convergence, the empirical convergence literature is misguided'. (Bernard and Jones, 1996, p. 1037)

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Some attempts have been made to capture the impact of technology adoption (e.g. de la Fuente, 2000; Rogers, 2004), but this issue remains a fruitful area of research, especially for regional economists, given that the adoption of technology is more clearly manifest across regions and is accelerated by geographical proximity.

It is the intention of this paper to develop and apply a model that incorporates technology adoption in an extensive regional context, namely that of the NUTS-2 regions of the EU, widening thus the range of empirical studies on European regions. This effort is organised as follows. The following section provides an extension to a general model in order to analyse the impact of technological diffusion and adoption in the process of economic growth and convergence. The subsequent section presents the empirical context within which the propositions are tested, considering both the data to be employed and the empirical methodology. The remaining two sections provide a discussion of the results and some concluding remarks.

2. A Model of Regional Convergence with Technology Creation and Adoption

In the standard neoclassical model, a factor that promotes, and accelerates, regional convergence is technological progress. If there is instantaneous diffusion of technology in conjunction with movement of factors of production, then convergence in levels of labour productivity (or in per-capita output) is an inevitable outcome in the neoclassical model. Technological progress is also highlighted by several models within Endogenous Growth Theory and New Economic Geography.[1] According to these models growth, and subsequently any possibilities of convergence/divergence, depend upon the degree to which regions are able to innovate. However, less emphasis is placed upon the process of technology absorption, where the ability of a regional economy to catch-up may substantially depend on its capacity to imitate and adopt innovations developed in more technologically advanced regions.

A process of technology adoption is not a simple and automatic process. Instead, it requires that lagging economies should have the appropriate infrastructure or conditions to absorb technological innovations. Abramovitz (1986) recognises this possibility by arguing as follows:

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[1] Martin (1999), Martin and Sunley (1996, 1998) provide a survey together with a critical assessment of these models.

> 'Countries that are technologically backward have a potentiality for generating growth more rapid than that of more advanced countries, provided their social capabilities are sufficiently developed to permit successful exploitation of technologies already employed by the technological leaders' (p. 225)

In other words, if infrastructure conditions are not 'sufficiently developed' then it cannot be presumed that there is an 'advantage of backwardness' associated with a high technological gap.[2]

Although the importance of technology adoption has been acknowledged, it is frequently the case that, empirically, only specific aspects of the infrastructure conditions are examined within this context. Rogers (2004), Howitt and Mayer-Foulkes (2005), for example, approximate the absorptive ability of an economy in terms of human capital measures. This paper takes a more general approach, addressing the questions of how overall infrastructure conditions affect the absorptive ability of a regional economy, and furthermore, what the implications of a poor infrastructure are for regional convergence.

These issues are investigated by examining a model of regional convergence that encapsulates the role of infrastructure in the absorptive ability of a regional economy. Following de la Fuente (2000) in the first instance, the growth of technology (g_{A_i}) in a region i is assumed to be a function firstly of 'technological capital', through the 'intentional creation of technology', (θ_i) and secondly the opportunities for 'technological catch up', as measured by the gap between the existing level of technology in a region and that of a 'technological best-practice frontier', (b_i). Thus,

$$g_{A_i} = \gamma\theta_i + \varepsilon b_i \text{ with } \gamma, \varepsilon \geq 0 \tag{1}$$

It is anticipated that the ability of a region to produce technological capital will have positive effects on the growth of technology in the region, and secondly, a high technological gap implies opportunities for adopting technological improvements from

[2] Although Gerschenkron (1962) is acknowledged as the initiator of this view, nevertheless, the basis of the argument is based on Veblen (1915).

more advanced regions. In such circumstances, the further away a region's technology is from that of the most advanced region, the faster will be its rate of technological progress. The logic behind this hypothesis is that technology transfer will be relatively cheap for lagging regions, when compared to regions which are already employing the most modern technologies and which cannot therefore simply imitate existing production techniques in order to promote further growth. Specific resources must be allocated to innovation activities, and hence innovation is a much higher cost activity for leading regions. Low technology regions can therefore experience faster growth provided, of course, that they possess the necessary infrastructure to facilitate the adoption of technology from the more technically advanced regions.

Given that θ_i approximates the level of innovation in a region, then the parameter γ measures the productivity of that innovation in augmenting technology whilst ε represents the rate of diffusion of technology and, hence, reflects the opportunities for technological catch-up. The technological distance (b_i) is defined as the difference between a best-practice frontier (x), which is determined exogenously, and the prevailing level of technology in a region, represented by some index a_i, i.e. $b_i = a_i - x$; a measure which can be conceived as an approximation of '*technological proximity*'. Assuming that an economy is divided into two regions, (leader and follower, $i = l, f$), then the technological distances are given by: $b_l = a_l - x$ and $b_f = a_f - x$, respectively. Thus, the growth of technology in the two regions may be represented as follows:

$$\dot{a}_l = \gamma\theta_l + \varepsilon b_l \tag{2}$$

$$\dot{a}_f = \gamma\theta_f + \varepsilon b_f \tag{3}$$

The growth rate for the technology gap between the two regions ($\dot{b}_{lf}$) is therefore:

$$\dot{b}_{lf} = \dot{a}_l - \dot{a}_f = \gamma(\theta_l - \theta_f) + \varepsilon(b_l - b_f) \tag{4}$$

Defining $b_{lf} = b_f - b_l$ and $\theta_{lf} = (\theta_l - \theta_f)$, equation (4) can be written as follows:

$$\dot{b}_{lf} = \gamma\theta_{lf} - \varepsilon b_{lf} \tag{5}$$

An implicit assumption of this model is that all economies are capable of absorbing technology to the same degree (constant ε), so that the higher the technological gap the greater the impact on growth, *ceteris paribus*, and the smaller the growth of any gap with the leading economy.

However, as argued above, large gaps do not necessarily promote convergence in this way because underlying conditions are not favourable for technology adoption. This possibility is currently not reflected in equations (3) and (5) and we therefore extend the analysis to take account of this. Our point of departure is to assume that the rate of diffusion of technology (ε) is a function of the initial technological gap as follows:

$$\varepsilon_i = \frac{\rho}{b_{lf_{i,0}}^{\pi}} \tag{6}$$

where $\rho, \pi > 0$ are parameters.

The parameter ρ can be interpreted as a constant underlying rate of diffusion, which would apply to all regions if there were no infrastructure/ resource constraints upon technological adoption. However, the existence of such constraints causes the actual rate to diverge from ρ, and the higher the technological gap, the slower the rate of technological diffusion (ε). Of critical importance, therefore, is the parameter π, which determines the extent to which the existing gap, and implicitly the existing infrastructure, impacts on the rate of diffusion.

The implications of modelling the rate of diffusion in this way are seen by substituting equation (6) into equation (5) to yield an expression for the rate of change in the technological gap:

$$\dot{b}_{lf} = \gamma\theta_{lf} - \rho b_{lf}^{(1-\pi)} \tag{7}$$

In equilibrium, the rate of change in the gap $\dot{b}_{lf} = 0$ so that:

$$\gamma\theta_{lf} = \rho b_{lf}^{(1-\pi)} \tag{8}$$

which gives an equilibrium value for the technological gap:

$$b_{lf}^{*} = \left(\frac{\gamma}{\rho}\theta_{lf}\right)^{\frac{1}{1-\pi}} \tag{9}$$

It is interesting to consider the implications for a regional economy when its gap with the leading economy is not at this equilibrium level. The outcome turns upon the value of the parameter π. If $\pi = 0$, then according to equation (6) $\varepsilon_i = \rho$ and the diffusion of technology occurs at a constant autonomous rate equal to ρ implying a linear process of convergence, while if $\pi = 1$ the size of the gap becomes irrelevant in the process of technological diffusion. Two distinct patterns of convergence arise, however, when $\pi < 1$ and when $\pi > 1$.

Figure 1 portrays the pattern of convergence implied by $\pi < 1$.

As illustrated in Figure 1, the process of convergence is a non-linear one. When the gap between leader and follower is below b_{lf}^*, the dynamics of the system cause the gap to grow towards its steady-state value, since the rate of innovation investment outweighs the effect of technology diffusion and, hence, $\dot{b}_{lf_i} > 0 \; \forall i \in [0 \;\; b_{lf}^*]$. Conversely, when the gap is greater than b_{lf}^*, there is movement towards equilibrium since $\dot{b}_{lf}$ is negative, i.e. $\dot{b}_{lf_i} < 0 \; \forall i \in [b_{lf}^* \;\; \infty]$. Assuming, further, that the leading region maintains its leading position over a given time period, then economies with a large technology gap, i.e. above b_{lf}^*, converge towards equilibrium but at slower rates compared to those regions where the gap is below b_{lf}^*. Thus, when $\pi < 1$ convergence towards a single equilibrium is possible but regions with unfavourable infrastructure conditions reflected in a large technological gap move towards equilibrium at a slower pace.

In circumstances where $\pi > 1$, then convergence towards a unique equilibrium for all but the leading region is no longer the case, and b_{lf}^* represents a threshold value now. In this case technology diffusion is represented by a convex function implying that following regions converge towards different equilibria, depending upon their starting point.

As Figure 2 shows, economies on either side of the threshold b_{lf}^* move in different directions. This pattern of convergence and divergence can be illustrated using a simple example. Consider an economy divided into three regions, one leader (l) and two followers, i.e. $(i = 1, 2)$. Assuming that the leading region is at the technological frontier

$(b_l = a_l - x = 0)$ so that steady-state equilibrium is, therefore, approximated by the leading region, then convergence with the leading region requires that the gap at a terminal time (T) should be zero, i.e. $b_{lf,T} = 0$. However, as Figure 2 indicates, a zero gap with the leader is not feasible, since by definition the curve $\rho b_{lf}^{(-\pi)}$ is asymptotic to the axis of the graph. Hence, a more realistic condition would be that the technological gap tends towards zero over a given time period, i.e. $b_{lf,T-0} \to 0$. For simplicity assume that $\theta_1 = \theta_2$, so that $\theta_{lf_1} = \theta_{lf_2}$ and that $\gamma_1 = \gamma_2$. It is also assumed that ρ is the same for both regions. If the initial technological gap differs between these regions $(b_{lf_1} < b_{lf}^* < b_{lf_2})$, then region 1 is able to close the technological gap with the leader, approaching zero asymptotically. Despite a lower rate of innovation compared to the leader, this region is able to adopt technology from the leading region and it is this latter effect which dominates. However, region 2, with a high gap and poor infrastructure conditions exhibits too slow a rate of technology absorption and, as a result, the gap with the leader increases over time. Convergence, therefore, is a property apparent only for region 1 and the leading region. These regions form an exclusive convergence-club which, more generally, would include any region with a technological gap in the range $(0, b_{lf}^*]$, for which $\dot{b}_{lf_i} < 0$. Thus, the technological advantages of particular regions would accumulate and militate against convergence for all. In this context, b_{lf}^* does not represent an equilibrium, but rather a threshold, which distinguishes between converging and non-converging regions.

These assumptions impose a non-linear process of technological diffusion (i.e. $\pi > 1$) that depends on infrastructure conditions as embodied in the size of the gap at a point in time. To be more precise, if the adoption of technology is related in a particular way to the size of the initial technological gap and associated infrastructure conditions, then two groups of regions can emerge; one which is a convergence club while a second group that does not exhibit an 'equilibrium'. Whether a region belongs to the convergence club depends on its capacity to adopt technology, and this capacity declines the higher the initial technology gap.

In the preceding example it was assumed that $\widetilde{\theta}_{lf_1} = \widetilde{\theta}_{lf_2}$. A more complicated picture arises if this assumption is relaxed, i.e. when $\widetilde{\theta}_{lf_1} \neq \widetilde{\theta}_{lf_2}$ [3].

Figure 4 shows a situation where $\widetilde{\theta}_{lf_1} < \widetilde{\theta}_{lf_2}$. Point B represents the critical threshold for region 2, showing that a large technological differential requires a high rate of technology absorption in order to prevent the region moving further away from the leading region in terms of overall technology growth. On the other hand, point A is the threshold for region 1, which has a lower technology differential compared to the leader. As a result, the rate of technology absorption that is required to prevent region 1 from following a divergent path, is lower compared to that of region 2. A diverging path for region 1 corresponds to movements to the right of point A. Hence, by imposing different abilities to create and absorb technology, two thresholds exist, one that corresponds to b_{lf_1}, with low $\widetilde{\theta}_{lf}$ and another to b_{lf_2}, with high $\widetilde{\theta}_{lf}$.

To summarise, the non-linear process of technological diffusion outlined above provides a link between the rate of technology adoption and the size of the technological gap in a region. Two distinct cases are identified depending on the value of the parameter π. If $\pi < 1$, then the model predicts a constant equilibrium gap between following regions and the leading region, with different equilibrium positions possible dependent upon whether θ_{lf} is the same or different across regions or, more generally, whether regions share the same characteristics. The pattern of convergence implied by $\pi > 1$ is, however, the most interesting. Here, two outcomes are possible, even when all regions share the same characteristics. The important condition is the size of the technological gap compared to the leader, and whether this is above or below a key threshold value. It is this characteristic that distinguishes whether a region follows a convergent path as a member

[3] Such a situation might also occur if region 1 develops a 'technology-producing' sector in a subsequent time period (t_1) due to the combined effect of a relatively low initial technological gap and high absorptive ability. In particular, assume that $b_{lf_1,t_0} > b_{lf_1,t_1}$, which signifies that conditions in region 1 are favourable as to allow adoption of technology, that leads to $\theta_{lf_1,t_0} > \theta_{lf_1,t_1}$. If this sequence continues, providing of course that the adoptive ability of this region remains, at least, the same in future periods, then convergence towards the leader is feasible. Thus, we may express this process as: $b_{lf_1,t_n} \to 0$ and $\theta_{lf_1,t_n} \to 0$, as $n \to 0$.

of a convergence club, or whether the path is a divergent one.[4] A further complication is introduced if regions also differ with respect to their structural characteristics (in terms of θ_{lf} or the values of parameters ρ and γ, for example). Then the membership of the convergence-club is more complex to establish, but fundamentally there is still one convergence-club, which is most likely to include regions with structural characteristics similar to the leader.

Overall, the 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. The Empirical Context

The NUTS-2 regions of the European Union provide the context for an assessment of the role of the technology gap in growth and convergence. Prior to a discussion of the measurement of the technology gap variable, and the data, we provide a brief overview of the methodology and empirical models to be employed.

The empirical literature on regional convergence (e.g. Martin, 2001; Barro and Sala-i-Martin, 1992) makes extensive use of two alternative tests for convergence, namely absolute and conditional convergence:

$$g_i = a + b_1 y_{i,0} + \varepsilon_i \qquad (10)$$

$$g_i = a + b_1 y_{i,0} + b_{\mathbf{X}_i} \mathbf{X_i} + \varepsilon_i \qquad (11)$$

where y_i typically represents per-capita output, or output per worker, of the i[th] economy (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.

[4] This outcome is in accordance with a fast growing literature on club convergence (e.g. Galor, 1996, Galor and Tsiddon, 1997; Corrado, et al., 2004; Martin and Sunley, 2006). Our view on club convergence implies that this pattern might be permanent unless lagging regions improve their abilities to absorb technology.

Absolute or strong convergence occurs if $b_1 < 0$ while the speed at which regions move towards the same steady-state level of per-capita output, or productivity, is calculated as $\beta = \ln(b_1 + 1) - T$. Conditional convergence requires that $b_1 < 0$ and $b_{\mathbf{X}_i} \neq 0$. If different economies have different characteristics, captured by the vector ($\mathbf{X_i}$) in equation (11), then convergence is conditional on these, giving rise to different steady states. 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.

As it stands, this approach neglects spatial factors. The location of a region within a system of regional economies is a unique characteristic, and in the same way as other structural characteristics, has the potential to impact on growth. The economic inter-dependence of regions is partly a function of spatial inter-dependence. The processes underlying regional convergence depend upon the relative extent of mechanisms such as factor mobility, price flexibility and knowledge or technology spillovers. Where such mechanisms exist, they are likely to be enhanced, rather than reduced, by spatial proximity, and in the light of recent literature it may be argued that any empirical test for regional convergence is misspecified if the spatial dimension is ignored (Rey and Montouri, 1999; Fingelton, 2001; Rey and Janikas, 2005).

Following Rey and Montouri (1999) spatial dependence can be incorporated into convergence analysis through three models, namely the spatial-error, the spatial-lag and the spatial cross-regressive models. The spatial-error model assumes that any effects from spatial interaction are captured in the error-term, abandoning the usual assumption of independent-error terms. This is not implausible given the fact that regions are typically very open economies exhibiting a high degree of interaction with their neighbours. In the case of the convergence model of equation (10) above, this leads to the following estimating equation:

$$\mathbf{g_i} = a + b\mathbf{y}_{\mathbf{i,0}} + (\mathbf{I} - \zeta\mathbf{W})^{-1} u_t \qquad (12)$$

where $\mathbf{W}$ is the $n \times n$ matrix of distance weights representing the spatial links between regions. The elements of $\mathbf{W}$ may be devised as follows:

$$w_{ij} = \frac{1/d_{ij}}{\sum_j 1/d_{ij}} \tag{13}$$

Here, d_{ij} denotes the distance between two regions i and j. The denominator is the sum of the (inverse) distances from all regions surrounding region i, within a selected boundary. Equation (13) implies that interaction effects decay as the distance from one area to another increases.

In this model regions are a linked network in that the effects of a random shock on the growth rate of any one region will disperse beyond that region's boundaries, impacting upon growth in surrounding regions and beyond. Such spillover effects will ripple throughout the national economy, their size and distribution determined by the elements of the spatial transformation matrix $(\mathbf{I}-\zeta\mathbf{W})^{-1}$.

An alternative approach to spatial interaction, following Rey and Montouri (1999), is to introduce the spatial weights matrix directly, either via regional growth rates to produce the spatial lag model (equation 14) or via initial levels of output per capita/worker to generate the spatial cross-regressive model (equation 15):

$$\mathbf{g_i} = a + b\mathbf{y_{i,0}} + \rho(\mathbf{Wg_i}) + \varepsilon_i \tag{14}$$

$$\mathbf{g_i} = a + b\mathbf{y_{i,0}} + c(\mathbf{Wy_{i,0}}) + \varepsilon_i \tag{15}$$

The conditional convergence model can be similarly amended to take account of spatial interaction.

An interesting issue that emerges from the discussion of the three spatial econometric models regards the sign of the spatial coefficients ζ , ρ and c. Although in the empirical literature this is not often of specific concern, both positive and negative spillover effects are possible. More specifically, if growth in one region is enhanced by proximity to another successful region then a positive sign is expected for the coefficients. On the other hand, a negative sign may be considered as an indication that successful regions are growing at the expense of surrounding regions. However, the outcome is ultimately an empirical issue, and dependent upon particular circumstances.

Although it is important to take account of spatial interaction in the analysis, it is not the primary focus of this paper. Our main purpose is to investigate the influence of technology, and particularly the technology gap, in promoting growth and generating potential for convergence. We turn our attention, therefore, to the question of appropriate measurement of the relevant technology variables. Technical change in a region occurs as a result of indigenous innovation or via the adoption of innovations from other regions. In the former case, technical change may be approximated by the 'propensity to innovate' ($PI_{i,t}$), as proposed by Pigliaru (2003), and can be measured in terms of the number of patents per-capita in each region.

It is more difficult to measure the ability of regions to adopt technology. A number of approaches have been adopted, such as in Peri and Urban (2006) for example, where technology adoption is approximated in terms of spillovers from foreign direct investment[5]. Other approaches put emphasis on the role of dynamic, advanced technology sectors in driving the diffusion process, and measure this by the share of a region's resources found in such sectors.[6] This is the methodology adopted here, although modified to also incorporate the concept of a technology gap. The first step is to identify technically dynamic sectors, which are perceived to be the most receptive to innovation and its subsequent utilisation. A region's level of technological development is then measured as the percentage of total employment in technologically dynamic sectors. More formally, at time t:

$$ADP_{i,t} = \frac{\sum_{j=1}^{m} \eta_{i,t}^{j}}{L_{i,t}} \quad (16)$$

where $\eta_{i,t}^{j}$ refers to personnel employed in 'high-tech' manufacturing and knowledge-intensive high-technology services ($j = 1 \ldots m$) and $L_{i,t}$ is the total employment in region i. The technology gap is then defined as the distance between a region's technology level and that of the most advanced region, which has the highest percentage of employment in 'high-tech' sectors.

[5] Bode (2004) develops a model that distinguishes between spillovers from abroad and local spillovers.

[6] Alderman (2004) uses a similar approach in identifying sectors that are able to adopt technological innovations, although in a context other than of regional convergence.

$$TG_{i,t} = \ln ADP_{L,t} - \ln ADP_{i,t} \,. \tag{17}$$

This variable is used to approximate a region's capacity to adopt technological innovations. The further away a region's technology is from that of the most advanced region, the greater the potential for technological progress, but the weaker the capacity to implement technical change, as argued in Section 2.

A (non-spatial) conditional convergence model which incorporates indigenous innovation capacity and adoption capabilities would therefore appear as follows:

$$g_i = a + b_1 y_{i,0} + b_2 PI_{i,0} + b_3 TG_{i,0} + \varepsilon_i \tag{18}$$

Introducing spatial terms to this conditional convergence model yields the following set of three equations:

$$\mathbf{g_i} = a + b_1 \mathbf{y_{i,0}} + b_2 PI_{i,0} + b_3 TG_{i,0} + \left(\mathbf{I} - \zeta \mathbf{W}\right)^{-1} u_i \tag{19}$$

$$\mathbf{g_i} = a + b_1 \mathbf{y_{i,0}} + b_2 PI_{i,0} + b_3 TG_{i,0} + \rho\left(\mathbf{W}\mathbf{g_i}\right) + \varepsilon_i \tag{20}$$

$$\mathbf{g_i} = a + b_1 \mathbf{y_{i,0}} + b_2 PI_{i,0} + b_3 TG_{i,0} + c\left(\mathbf{W}\mathbf{y_{i,0}}\right) + \varepsilon_i \tag{21}$$

It is important to note at this point that the technology variables are measured at time $t = 0$, that is to say, at their initial values for the period of analysis. There are three reasons for adopting such an approach, the first being that current regional growth performance is the outcome of past efforts to enhance technology levels. A second reason for using initial values is to reflect the hypothesis presented in Section 2, that initial conditions 'lock' regions into a particular position or pattern of growth. As previously demonstrated, a divergent growth path can emerge when a region's initial technology gap lies above a particular threshold. Finally, from an econometric point of view, inclusion of variables dated at the start of the period of analysis helps to avoid the problem of endogeneity.[7]

Equations (18) to (21) thus incorporate the potential impact on a region's growth of both internally generated technological change and technology adoption. The expectation is that the propensity to innovate will have a positive effect on growth ($b_2 > 0$) although this

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[7] 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 as initial values.

does not automatically promote convergence. If lagging regions have a low initial propensity to innovate, then no significant impacts on growth are anticipated and convergence with technologically advanced regions is unlikely from this direction. On the other hand, a value of $b_2 < 0$ signifies a convergence effect, in the sense that the 'propensity to innovate' in lagging regions is transformed into relatively higher growth rates.

In the case of the technology gap variable ($TG_{i,0}$), the impact on growth may be either positive or negative since there are two factors working in opposite directions, namely the technological distance from the leading region, representing the potential for growth, and the degree to which existing (initial) conditions in a region facilitate adoption of technology. If the first effect predominates, then the coefficient will be positive ($b_3 > 0$). If the latter effect dominates then the coefficient will be negative ($b_3 < 0$), and convergence between technologically lagging and technologically advanced regions is severely constrained, as suggested by the model in Section 2.

4. Empirical Application

Having outlined the empirical context in terms of the methodology and variables to be employed, the next step forward is to apply these to an investigation of the pattern of regional growth in Europe. The spatial units used in this paper are those delineated by EUROSTAT and refer to 267 NUTS-2 regions of 27 member countries in the EU. The EU uses NUTS-2 regions as 'targets' for convergence, 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 to the use of NUTS-2 regions as the appropriate spatial level for the assessment of convergence, they are nevertheless sufficiently small to be able to capture sub-national variations (Fischer and Stirböck, 2006).

The growth of regional economies is measured using data on Gross Value-Added (GVA) per worker since this measure is a major component of differences in the economic performance of regions and is a direct outcome of the various factors that determine regional competitiveness (Martin, 2001). The time period for the analysis extends from 1995 to 2006. This might be considered as rather short but Islam (1995), and 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.

All results are presented in Table 1, and include the simple absolute convergence model (10) and the conditional convergence model (18). The inclusion of spatial interaction yields a further six equations (12), (14), (15) and (19), (20), (21).

In the case of the spatial-error models, estimation is carried out by the maximum likelihood (ML) method, as OLS may result in problems of bias. The presence of spatial interaction in the error-term leads to the following non-spherical covariance matrix (Rey and Montouri, 1999, p. 149):

$$E[\varepsilon_t \varepsilon_t'] = (\mathbf{I} - \zeta \mathbf{W})^{-1} \sigma^2 \mathbf{I} (\mathbf{I} - \zeta \mathbf{W})^{-1'} \quad (22)$$

The presence of non-spherical errors results in unbiased OLS estimators but biased estimations of a parameter's variance. Thus, all inferences based on that model are invalid. Hence, the recommended estimation method is through maximum likelihood (Anselin, 1988). The spatial-lag model is also estimated by the ML method since the OLS estimators are inconsistent due to the simultaneity introduced through the spatial dimension. In contrast, the spatial cross-regressive model treats the spatial variable as exogenous and, hence, estimation is possible through the OLS method.

Considering first the case of simple absolute convergence, this is typically associated with an inverse relationship between growth and some initial level of output per-worker. Thus, poor regions grow faster than rich regions. In the context of the EU regions between 1995 and 2006, the potential for absolute convergence is suggested by Figure 4, which shows a scatterplot of the average annual growth rate against the initial level of labour productivity. This is confirmed by the estimation of equation (10). As shown in Table 1, there is a statistically significant inverse relationship between growth over the time period, and the level of GVA per-worker at the start of the period. Nevertheless, the rate of convergence of labour productivity is a slow one, estimated to be 0.65% per annum.

When spatial interaction is included (equations 12, 14 and 15), the rate of convergence ranges from 0.64% to 0.71% per annum. In all cases, the spatial coefficient is statistically significant and positive and in two out of three cases the underlying rate of convergence is higher than in the non-spatial model, showing that spatial interaction plays a positive role in the convergence process. The superiority of the spatial models is supported by both the criteria for model selection applied here, namely the *Akaike* (AIC) and the *Schwartz-Bayesian* (SBC) information criteria.[8] Further support is also provided by the value of the Log-likelihood (LIK), which increases, as anticipated, with the introduction of spatial interaction. Overall, these results suggest a significant spatial dimension in the process of European regional convergence.

Turning to the role of technology in growth and convergence, the estimation of equation (18) shows provides some interesting results. The convergence coefficient is significantly negative and the rate of convergence is now estimated as 0.23% per annum. The coefficient on the propensity to innovate is negative, suggesting that regions with a high propensity to innovate, normally high productivity regions, grow slower than technologically lagging regions. This might act as source of convergence, provided that the poor regions are able to absorb technology. However, this does not seem to the case. A negative sign is also estimated for the variable representing technology adoption. The existence of a high technology gap and associated low capability for technology adoption is thus inhibiting growth and convergence.

The spatial versions of the model, represented by equations (19), (20) and (21), again show statistically significant spatial effects and confirm the impact of spatial interaction between regions upon regional growth patterns. Overall, the spatial equations would also appear to provide a better fit to the data. In particular, according to the both the AIC and SBC criteria and the LIK statistic, the spatial-error model of equation (19) is to be preferred.

Focusing on this spatial error model, Table 1 shows that the propensity to innovate variable is again negatively related to growth over the period. While this can be conceived

[8] As a rule of thumb, the best fitting model is the one that yields the minimum values for the AIC or the SBC criterion. The SBC test has superior properties and is asymptotically consistent, whereas the AIC is biased towards selecting an overparameterized model.

as a convergence effect, nevertheless the impact of the technology adoption variable works in the opposite direction. On average, regions with high technological gaps at the start of the period grow slower than regions with low gaps, *ceteris paribus*. Thus, a 1% increase in the measure of capacity to adopt technology adoption leads to a 5% fall in growth over the period. Comparing equation (19) with equation (12) shows that the underlying rate of convergence is lower when the impact of technology factors is made explicit (0.71% compared to 0.33%).

In summary, the evidence presented here clearly supports the arguments previously put forward, that technology adoption is a route by which lagging regions might be able to converge with leading regions, but that this is a process which is likely to be difficult, especially during the early stages of development when conditions in the lagging regions are least supportive. Thus, a high technology gap presents an obstacle to convergence because of the implied poor infrastructure and weak adoptive capacity. These factors work to sustain initial differences across regions, and suggest the possibility of *club convergence* towards different equilibria following the predictions of the model examined in Section 3.

In order to encapsulate this possbility, equation (19) is extended as follows:

$$\mathbf{g_i} = a + b_1\mathbf{y_{i,0}} + b_2 PI_{i,0} + b_3 TG_{i,0} + (I - \zeta\mathbf{W})^{-1} u_i \qquad (23)$$

According to Baumol and Wolff (1988), a convergence-club is apparent when $b_1 > 0$ and $b_2 < 0$. Club-membership is determined by a threshold level of y_i, given by the unique maximum of equation (23): $y^* = \frac{-b_1}{2b_2}$. The essence of equation (23) can be summarised quite simply: only those economies with $y_{i,0} - y^* > 0$ belong to the convergence-club, in the sense that their growth rates are inversely related to initial labour productivity in

Essentially, equation (23) is a parametric method to detect convergence-clubs, and it might be argued that is inferior to other methods proposed in the literature.[9] Nevertheless, using such a method as a first step in a research project is more comprehensible, and it

[9] For a more detailed review see Durlauf et al. (2005).

allows the inclusion of variables that might account for a pattern of club-convergence. It is thus possible to identify the appropriate areas for intervention if the aim of regional policy is to achieve overall convergence across regions.

The obtained econometric results in Table 2 confirm the pattern of club convergence. The convergence-club includes, almost exclusively, regions from EU-15 and only two regions from new member-states. The diverging regions are all located around the 'edge' of the EU, as shown in Figure 5.

VI. Conclusions

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 the question of whether regions with a high technology gap are able to take advantage of this potential for faster growth, using data for the 267 NUTS-2 regions of the EU-27 over the period 1995-2006. The results suggest that the NUTS-2 regions of EU-27 exhibit some underlying tendency towards convergence in terms of labour productivity, but an important conclusion which emerges is that the regions exhibit slower convergence after conditioning for technological differences across regions. While the 'technological gap' approach predicts, in principle, that the higher the technological distance from the leader, the greater the incentive to adopt technology, the results in this paper imply that not all the lagging regions of the EU are able to reap the 'benefits of backwardness'. This inability can be attributed, perhaps, to inappropriate infrastructure conditions prevailing in lagging regions, which prevent or constrain convergence with the more technologically advanced regions. Convergence, where possible, is not towards a single equilibrium but towards different equilibria, creating thus a pattern of club convergence. Catch-up to the leading regions is feasible only amongst those regions whose conditions are similar or close to those of the technologically advanced regions.

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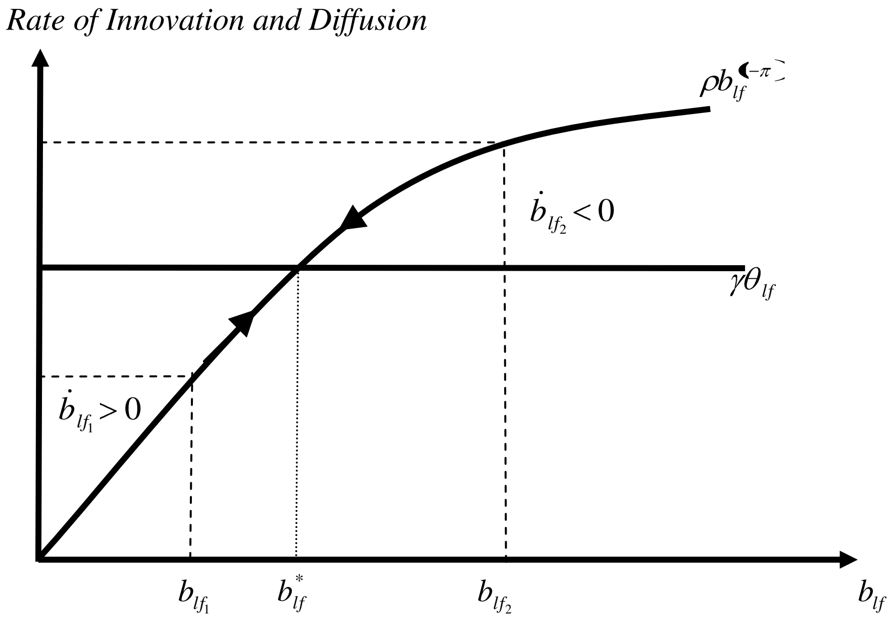

Figure 1. Convergence towards a single equilibrium when $\pi < 1$

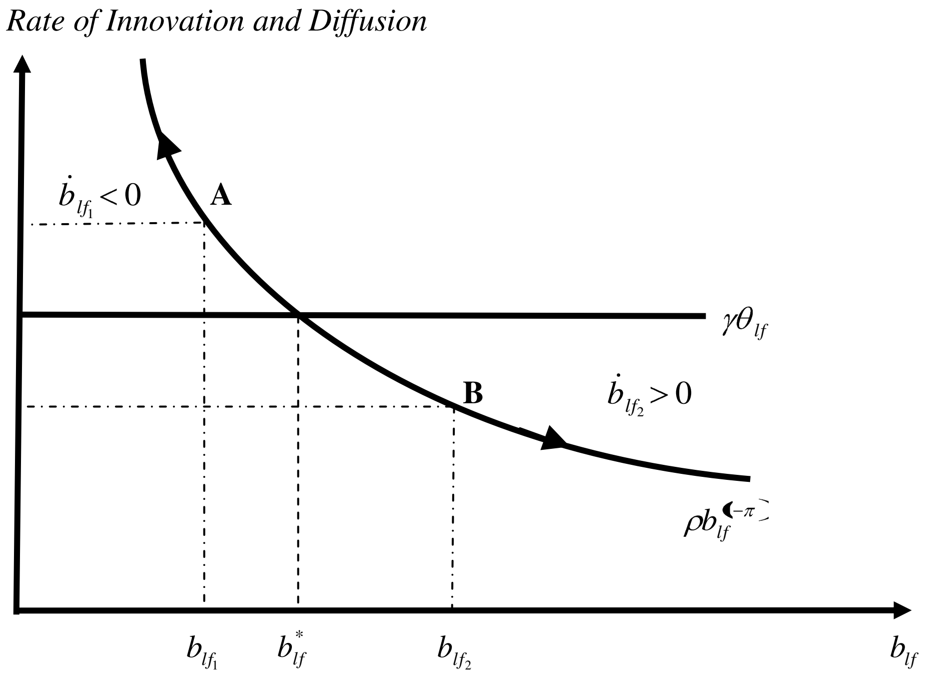

Figure 2. Convergence towards different equilibria when $\pi > 1$

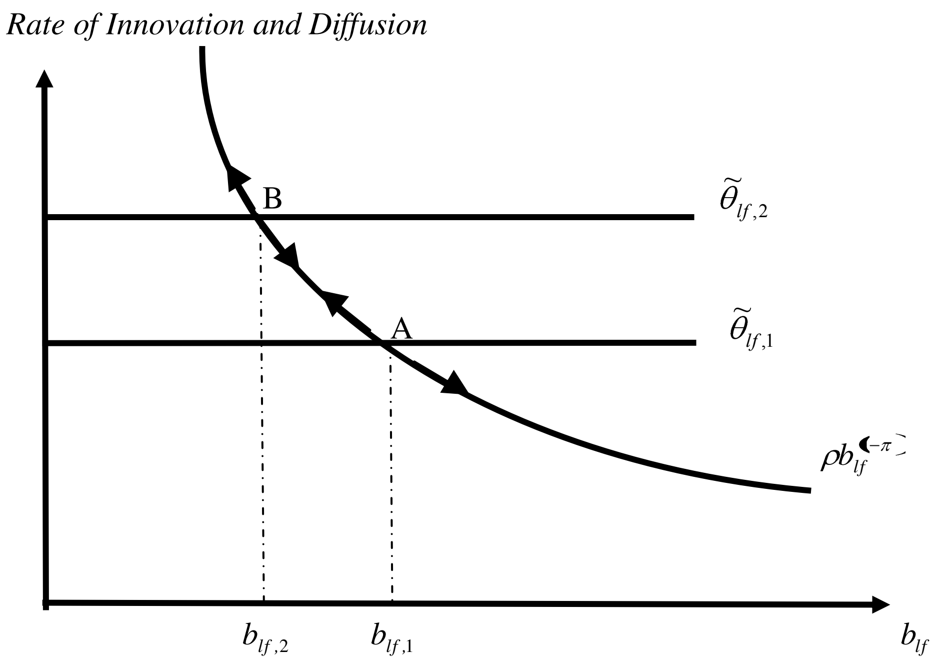

Figure 3. Club Convergence when $\pi > 1$ and $\widetilde{\theta}_{lf_1} \neq \widetilde{\theta}_{lf_2}$

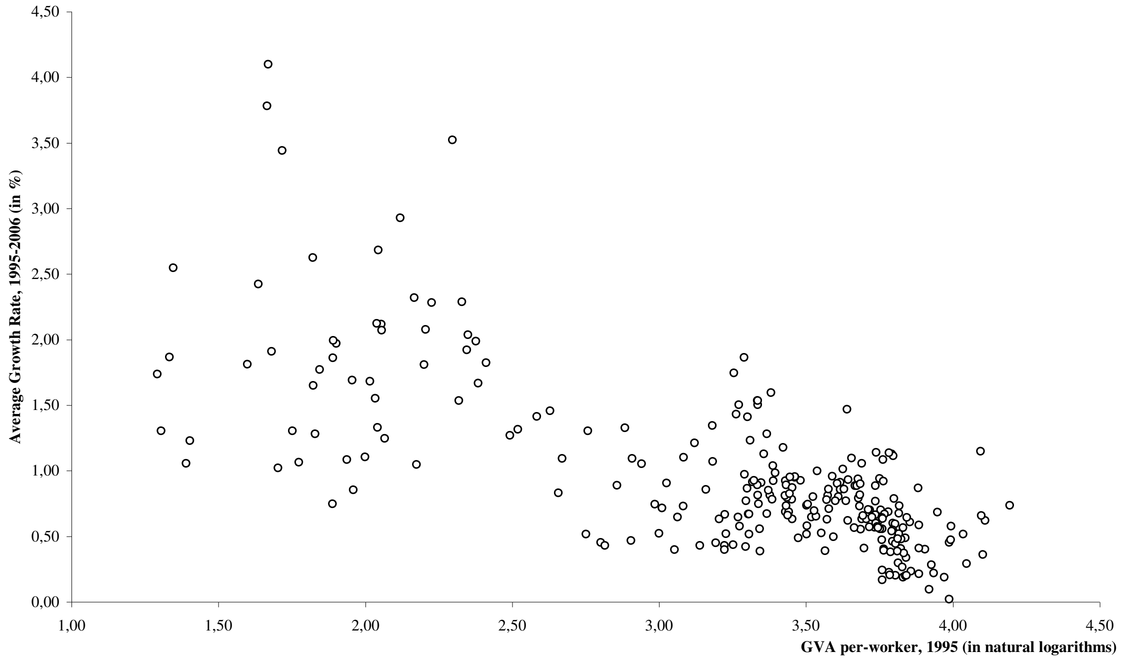

Figure 4. Absolute convergence, GVA per-worker, EU-27 NUTS-2 Regions, 1995-2006

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

	Equation (10)	Equation (18)	Equation (12)	Equation (14)	Equation (15)	Equation (19)	Equation (20)	Equation (21)
Depended Variable: g_i, n = 267 NUTS-2 Regions								
a	0.5714**	0.6191**	0.5985**	0.5482**	0.5743**	0.6828*	0.5465**	0.6409**
b_1	-0.0747**	-0.0279*	-0.0819*	-0.0770	-0.0741**	-0.0361**	-0.0187	-0.0300**
b_2		-0.0401**				-0.0382**	-0.0428	-0.0399**
b_3		-0.0631**				-0.0504**	-0.0531*	-0.0714**
ζ			0.7506**			0.6667**		
ρ				0.1148			0.1490	
c					0.5979**			0.8671**
Implied β	0.0065**	0.0023**	0.0071**	0.0068	0.0064**	0.0033**	0.0015	0.0025**
LIK	147.552	163.971	270.2628	270.1091	164.9574	272.2321	271.3244	185.1642
AIC	-291.104	-319.943	-534.5256	-530.2182	-323.9148	-538.4643	-532.2182	-360.3280
SBC	-283.929	-305.594	-523.7639	-512.2820	-313.1531	-527.7026	-514.7127	-342.3918

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

Table 2. Club Convergence Spatial error specification

Depended Variable: g_i, n = 267 NUTS-2 Regions	
a	0.1081**
b_1	0.3001**
b_2	-0.706**
b_3	-0.0353*
ζ	-0.0502**
Implied y^*	2.607

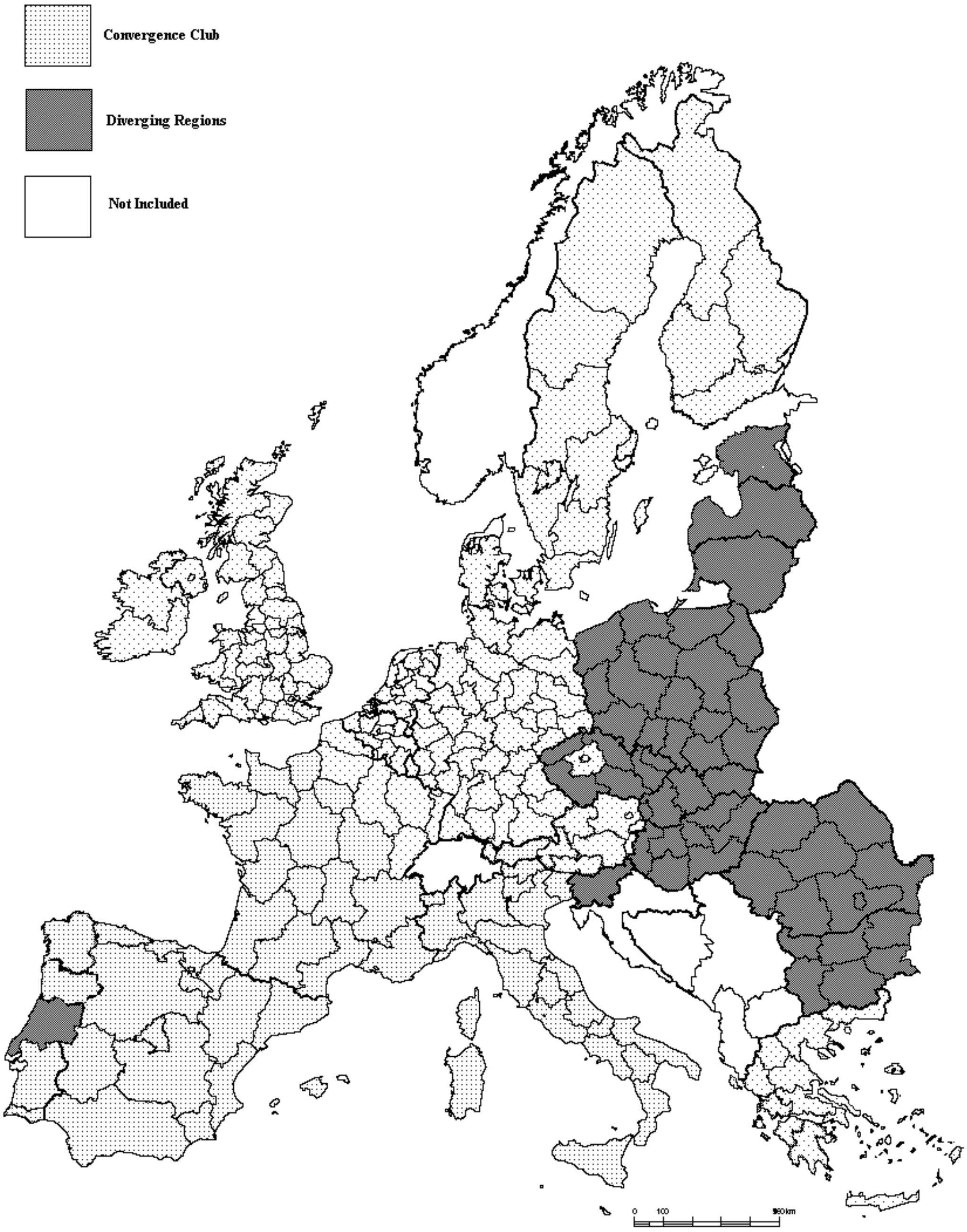

Figure 5: Convergence Club across the regions of Europe