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Abstract
This paper investigates the extent of convergence amongst the 51 prefectures of Greece during the time period 1970-2000. The main objectives are to discover whether there is a convergence club amongst the regions, to establish whether there is a spatial pattern to club membership, and to assess the impact of agglomeration effects and regional capacities to innovate or adopt technology. The results suggest that there is a significant spatial dimension to regional growth and that members of the convergence club are in close spatial proximity. Technology spillovers are also significant in providing an explanation of regional growth patterns.

Key words: Convergence Clubs, Technological Gap, Spatial Econometrics, Greek Regions
JEL: C21; O18; R11; R12

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The Extent of Regional Convergence in Greece: The Role of Geography and Technology

S. Alexiadis & J. Tomkins

1. Introduction

Amongst the many studies of national and regional economic convergence (Beine and Hecq, 1998; Soukiazis and Castro, 2005; Martin, 2001; Tsionas and Christopoulos, 2003; Mauro, 2004, for example), some have drawn attention to a phenomenon known as club convergence (for example, Chatterji and Dewhurst, 1996; Alexiadis and Tomkins, 2004; Corrado, Martin and Weeks, 2005). This concept was originally introduced by Baumol (1986) to allow for the possibility that only a subset within a grouping of national economies might exhibit convergence properties. As Baumol and Wolff (1988, p. 1159) subsequently noted, however, "*just how countries achieve membership in the convergence club, and on what basis they are sometimes ejected*" is a difficult question to answer. The mechanisms underlying convergent growth paths are complex and hinge upon a variety of factors such as the extent of factor mobility, price and wage flexibility and the diffusion of technology and innovation.

Studies of regional, as opposed to national, economies frequently seek explanations for convergence that also incorporate a spatial dimension[1]. Although trade and migration are acknowledged as two of the most common factors that determine regional convergence, nevertheless, it is argued that spatial proximity facilitates and enhances a wider range of regional interactions, which includes knowledge exchange and technology diffusion/adoption, and these have significant potential to impact upon convergence

(Maurseth, 2001; Lopez-Bazo, Vaya and Artis, 2004; Funke and Niebuhr, 2005, for example). However, as Bernard and Jones (1996) point out, empirical studies have not considered the role of technological adoption to the same extent as that of capital accumulation. Furthermore, as acknowledged by Abramovitz (1986), technological progress is driven not only by indigenous innovation but also by the process of technology absorption, and thus the ability of a regional economy to 'catch-up' may substantially depend on its capacity to imitate and adopt innovations developed in neighbouring regions. Despite rapid developments in information and communication technology, distance continues to present a source of friction within and between economies, raising costs and thereby generating barriers to economic, social and cultural exchange. Thus, the interplay between the relative proximity of regions, shared characteristics such as a common national currency, and the 'openness' of regional economies compared to national economies, leads to the general expectation that convergence mechanisms will operate more forcefully in a regional context.

Set within this context, the purposes of this paper are twofold: firstly, to address the issue of club convergence by testing for its presence amongst the regions of Greece, and secondly, to do so in a way which explores the potential contribution of spatial characteristics combined with innovation and technology adoption. Previous empirical studies on regional convergence in Greece suggest either that convergence is weak or virtually non-existent, or that regions are polarised into two distinct groups comprising rich and poor regions (Siriopoulos and Asteriou, 1998; Tsionas, 2002). However, such contributions have not considered the impact of spatial factors and technology within a club convergence framework.

The remainder of this paper is therefore organised as follows. The following section outlines the concepts of absolute, conditional and club convergence, and introduces the spatial model which will be used to investigate spatial interaction and regional club convergence. A brief discussion of how technology and spatial effects are incorporated into the analysis concludes this section. Section three introduces the empirical context and provides a discussion of the specific variables used in the empirical analysis, the results of which are considered in the remaining sections.

2. The Framework

A widely used approach to the study of regional convergence is to test for the existence of β-convergence. Absolute β-convergence occurs when there is a negative relationship between growth rates over a given time period and initial levels of per capita output, and may be examined, following Baumol (1986), by estimating the following relationship:

$$\boldsymbol{g}_i = \boldsymbol{a} + \boldsymbol{b}\boldsymbol{y}_{i,0} + \boldsymbol{\varepsilon}_i \tag{1}$$

where $\boldsymbol{y}_i$ represents per capita output of the i^{th} economy (in logarithm form), $\boldsymbol{g}_i = (\boldsymbol{y}_{i,T} - \boldsymbol{y}_{i,0})$ is the growth rate over the time interval $(\mathbf{0},\boldsymbol{T})$, and $\boldsymbol{\varepsilon}_i$ is the error term, which follows a normal distribution. If economies with higher initial levels of per capita output grow more slowly, then the convergence coefficient $\boldsymbol{b}$ will have a negative sign. This can be used to provide an estimate of $\boldsymbol{\beta} = \frac{\ln(\boldsymbol{b}+\mathbf{1})}{-\boldsymbol{T}}$ which is the speed of convergence towards the steady-state level of per capita output. This approach, however, rests on the assumption that all economies are converging to the same steady-state (Sala-i-Martin, 1996)[2].

The concept of conditional convergence, on the other hand, has developed in recognition of the potential for different steady-states, dependent upon the differing structural characteristics ($\mathbf{X_i}$) of individual economies. The inclusion of the vector $\mathbf{X_i}$ in equation (1) above leads to the identification of conditional convergence, when $\boldsymbol{b < 0}$ and $\boldsymbol{c \neq 0}$ in equation (2) below:

$$\boldsymbol{g_i = a + by_{i,0} + cX_{i,0} + \varepsilon_i} \tag{2}$$

Club convergence

A convergence club is said to exist if the property of convergence is restricted to a sub-set of economies which are part of a larger system. Within the club, however, convergence may be defined in an absolute or conditional sense. Although different authors suggest different approaches[3], a simple test for the existence of club convergence is outlined by Baumol and Wolff (1988) and involves estimation of the following equation:

$$\boldsymbol{g_i = a + b_1 y_{i,0} + b_2 y_{i,0}^2 + \varepsilon_i} \tag{3}$$

In brief, this technique suggests the presence of a convergence club when the estimates of $\boldsymbol{b_1}$ and $\boldsymbol{b_2}$ are positive and negative respectively, with membership of the club determined by a threshold level of output per capita, given by the unique maximum of equation (3): $\boldsymbol{y^* = \frac{-b_1}{2b_2}}$. Thus, only those economies with an initial level of per capita output in excess of this threshold belong to the convergence club, in the sense that their growth rates are inversely related to initial output per capita.

A conditional club convergence model, which incorporates differences in the structural characteristics of regions, is represented as follows:

$$\boldsymbol{g_i = a + b_1 y_{i,0} + b_2 y_{i,0}^2 + b_3 X_{i,0} + \varepsilon_i} \tag{4}$$

Club convergence, conditional upon differences in initial structural characteristics, requires that $\boldsymbol{b_1 > 0}$, $\boldsymbol{b_2 < 0}$ and $\boldsymbol{b_3 \neq 0}$.

Regional Convergence and Spatial Interaction

The preceding discussion has considered, albeit briefly, the specification of a test for club convergence which can incorporate the impact of initial structural characteristics and which has general applicability to both national and regional economies. For the regional context, however, it is also possible to extend the approach to take account of the role of spatial proximity in the convergence process, and hence to assess whether convergence club members are geographically clustered. Indeed, in the light of recent literature it may be argued that any empirical test for regional convergence is mis-specified if the spatial dimension is ignored (Rey and Montouri, 1999; Lall and Yilmaz, 2001), the presumption being that the extent of regional interactions, such as technology spillovers, are significantly dependent upon the location of regions relative to each other.

According to Rey and Montouri (1999) the potential for spatial interaction can be incorporated within convergence analysis by means of the spatial-error, spatial-lag and spatial cross-regressive models. Considering first of all the spatial-error model, the key feature is that spatial interaction occurs through the error terms of the equations above, and hence the usual assumption of independent error terms is not sustainable. Following Rey and Montouri (1999), the error term incorporating spatial dependence is shown as follows:

$$\boldsymbol{\varepsilon}_i = \boldsymbol{\zeta}\mathbf{W}\boldsymbol{\varepsilon}_i + \boldsymbol{u}_i = (\mathbf{I} - \boldsymbol{\zeta}\mathbf{W})^{-1}\boldsymbol{u}_i \qquad (5)$$

where $\boldsymbol{\zeta}$ is the spatial error coefficient and $\boldsymbol{u}_i$ is a new independent error-term with $\boldsymbol{u} \sim \boldsymbol{N}(\mathbf{0}, \boldsymbol{\sigma}^2\mathbf{I})$. Inter-regional spatial dependence is generated by means of the spatial-weights matrix, $\mathbf{W}$, the elements of which ($\boldsymbol{w}$) may be devised in various ways. For example, a common practice is to allow these weights to take the value of 1 if a region is contiguous to another and 0 otherwise (a first order continuity matrix). Alternatively, the spatial weights may be continuous variables (Cliff and Ord, 1981), constructed so as to produce declining weights as distance between regions increases. Thus:

$$\boldsymbol{w}_{ij} = \frac{\mathbf{1}/\boldsymbol{d}_{ij}}{\sum_j \mathbf{1}/\boldsymbol{d}_{ij}} \tag{6}$$

where $\boldsymbol{d}_{ij}$ denotes the distance between two regions *i* and *j*, as measured by the distance between the major urban centres where the majority of economic activities are located. The denominator is the sum of the (inverse) distances from all regions surrounding region *i*.

To introduce spatial interaction into the club convergence framework, equation (5) is substituted into equation (3):

$$\boldsymbol{g}_i = \boldsymbol{a} + \boldsymbol{b}_1 \boldsymbol{y}_{i,0} + \boldsymbol{b}_2 \boldsymbol{y}_{i,0}^2 + (\mathbf{I} - \zeta\mathbf{W})^{-1} \boldsymbol{u}_i \tag{7}$$

to produce a linked network of regions in which 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 effectively ripple throughout the network, their size and distribution determined by the elements of the spatial transformation matrix. It is still the case, however, that convergence is associated with a negative relationship between growth and initial per capita output levels, and that converging regions are moving towards the same steady state.

The alternative approaches to spatial dependence involve the introduction of a spatial lag on growth rates or initial per capita output. Adopting the former strategy in the club convergence framework produces the spatial lag model:

$$\boldsymbol{g}_i = \boldsymbol{a} + \boldsymbol{b}_1 \boldsymbol{y}_{i,0} + \boldsymbol{b}_2 \boldsymbol{y}_{i,0}^2 + \boldsymbol{\rho}(\mathbf{W}\boldsymbol{g}_i) + \boldsymbol{\varepsilon}_i \tag{8}$$

where $\boldsymbol{\rho}$ is an autoregressive parameter, and $\boldsymbol{\varepsilon}_i$ is once again $\mathrm{N}(0,\sigma^2\mathrm{I})$. A region's growth is thus directly linked to growth in surrounding regions, with the relative extent of these linkages again determined by the spatial weights matrix[4]. The third and final model, referred to as the spatial cross-regressive model, introduces spatially lagged levels of initial output per capita, as follows:

$$\boldsymbol{g}_i = \boldsymbol{a} + \boldsymbol{b}_1 \boldsymbol{y}_{i,0} + \boldsymbol{b}_2 \boldsymbol{y}_{i,0}^2 + \boldsymbol{c}(\mathbf{W}\boldsymbol{y}_{i,0}) + \boldsymbol{\varepsilon}_i \tag{9}$$

Localisation and urbanisation effects

The models represented by equations (7), (8) and (9) above provide a framework for assessing the extent of inter-regional spatial dependence, and are based on the assumption that the extent of such dependence decays as distances increase and barriers to regional interaction strengthen accordingly. A second aspect of spatial analysis is to consider also *intra*-regional externalities; that is to say, the effects of 'agglomeration' upon regional growth.

It is widely recognised that the spatial concentration of economic activity can generate a range of externalities to local firms, although they remain 'internal' to the region. Some of these effects can be negative in impact, for example, the costs of congestion or localised pollution, but other externalities are beneficial, leading to enhanced competitiveness of firms and regions (Henderson, 1997). Such external benefits of spatial concentration are typically separated into two categories; firstly, ‘urbanisation’ effects associated with the agglomeration of diverse economic activities within an area, and secondly, ‘localisation’ economies arising from a clustering of similar economic activities.

In the latter case, the impact of spatial concentration combined with specialisation leads not only to economies of scale in production (internal to the firm), but also to external economies such as in the areas of knowledge accumulation and exchange (Glaeser, Kallal, Scheinkman and Schleifer, 1992). Likewise, strong forward and backward linkages, access to specialised skills in local labour markets, and the movement of specialised labour between firms are also positive by-products of spatial proximity.

The existence of urbanisation economies, on the other hand, depends more upon the expanded market opportunities and infrastructure which a large urban population can support. In these circumstances, cost advantages flow from access to large local markets, a wide range of suppliers, specialised support services, improved transport infrastructure, a broader spectrum of skills and a more highly educated and diverse labour force. Likewise, a concentration of innovative firms, albeit across a range of different industries, promotes regional competitiveness through knowledge accumulation and the diffusion of innovation within the region. However, it is also possible that the negative externalities of urbanisation and agglomeration may partially offset the positive, and in some instances may even predominate. A growth in demand for local infrastructure, resources and public services can lead to rising factor prices, congestion, and a deteriorating environment, and eventually may result in a decline in the overall competitiveness of urban areas.

However, the important point in the present context is that if there are significant regional agglomeration economies, where the benefits of specialisation, concentration and diversity outweigh the costs, then this is not compatible with convergence occurring across all regions. The presence of such agglomeration economies is more consistent with divergent growth trends, or with limited convergence between some, rather than all, regions.

Technological innovation

The final step in developing the analytical framework is to take account of the specific role of technology within a spatial club convergence framework, and to do so, the sources of regional technical change are separated into two broad categories.

The first source, internally generated technical change, is the outcome of regional research and development (R&D) activities, patent applications and associated investment expenditures. Furthermore, any subsequent diffusion of knowledge and innovation throughout the region is potentially a highly significant component in the operation of *intra*-regional spatial externalities. If these impacts are large, then the economic performance of regions containing major urban areas endowed with significant R&D resources and/or specialising in particular industries could persistently outstrip that of other regions that are less well-endowed in these respects. In other words, the technological advantages of particular regions would accumulate and militate against convergence.

The second source of technical change arises from a region's capacity to take advantage of external innovation, that is to say, to benefit from technology spillovers. From an *inter*-regional perspective, such technology diffusion is a major component of the regional convergence process, as noted earlier in the paper. The technology gap perspective suggests that the further away a region's technology is from that of the most advanced region, the faster will be its rate of technological progress (Fagerberg, 1987; Gomulka, 1990). 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. Plummer and Taylor (2001a, 2001b), for instance, place emphasis on the presence of dynamic, advanced technological sectors in a region to drive the technology diffusion process.

In summary, this section has provided a framework for the examination of club convergence that not only takes account of spatial dependence between regions, but also the potential impact of innovation and agglomeration. The following section provides a discussion of the empirical context and the specific variables used in the analysis, prior to the presentation and discussion of the results.

3. The Empirical Context

The empirical analysis is set in the context of the 51 prefectures of Greece[5] during the period 1970 to 2000. Throughout these three decades the distribution of economic activity between the regions has remained extremely unbalanced. Approximately half of all industrial activity and almost 40% of the population are located in just two leading regions - Attiki in the South (R_9), containing the capital city of Athens, and Thessaloniki in the North ($R_{2.2}$). In 1970, for example, Attiki alone accounted for 42% of national output, followed some way behind by the second leading region with 8.6% of total output.

Increasing concern for regional inequalities within Greece led to the implementation of active regional policies from the 1980s onwards, with government intervention taking various forms, mainly tax and financial incentives or direct subsidies to firms and industries to stimulate migration towards lagging regions. Several manufacturing industries, for example, moved their plants from Attiki (R_9) towards Viotia ($R_{8.4}$) and Korinthia ($R_{10.1}$) with the headquarters of these industries remaining in the leading region. A similar movement of manufacturing plants also took place from the leading northern region of Thessaloniki ($R_{2.2}$) towards adjacent regions. Although the effectiveness of such regional policies has been questioned, there was some improvement in the economic position of the less favourable areas of Greece (Argyris, 1986). Over the period 1970-2000, for example, the gap between the richest region of Attiki (R_9) and the poorest region Evritania ($R_{8.2}$) has narrowed at a rate of 0.2% per annum. Nevertheless, by 2000 the relative domination of the two leading areas still remained; Attiki contributing 38.5% of national output and Thessaloniki a further 9.9%.

The extent to which convergence has taken place across the 51 regions over the thirty year period is assessed in this paper in terms of regional gross value added (GVA) per worker, which is a measure of regional productivity and competitiveness. Data prior to 1970 are not entirely reliable since they are not published from any official source and refer to regional divisions other than those that used by the National Statistical Agency of Greece. GVA data are converted to constant (1970) prices using deflators provided by the National Statistical Agency of Greece. Preliminary analysis of this data shown in Figure 1 indicates a complex relationship between growth rates and initial levels of GVA per worker, with some suggestion of β-convergence occurring for a subset of regions, rather than for all regions.

Spatial weights

The spatial interaction models (equations 7, 8 and 9) require construction of a spatial weights matrix such that the weights decline as distance between regions increases. Our approach, based on equation (6), is to set the numerator as the distance between the principal city in a region and the principal city of the neighbouring region with the highest GVA per worker. This choice is based on the assumption that spillover effects are dominated by leading areas, and that such effects are most likely to diffuse towards the nearby locations.

Technology and Agglomeration

Finally, we turn to measurement of the explanatory variables designed to capture a region's propensity to innovate, the capacity to adopt technologies developed elsewhere, and the potential impact of localisation and urbanisation economies. Measurement is based, in essence, on the distribution of employment at two-digit sector level, data for which are published annually by the National Statistical Agency of Greece for the 51 regions. All such data relate to the starting point of the time period (1970), so that growth between 1970 and 2000 is explained in terms of initial conditions, which according to Henderson (1997) captures the contribution of the 'history' of a given location to its growth.

In empirical studies (for example, Piergiovanni and Santarelli, 2001), patent applications and patent citations[6] are often used to provide estimates of the degree of innovative activity, although an alternative approach outlined by Pigliaru (2003) suggests a broader measure of a region's propensity to innovate, measured by the share of a region's resources allocated to research and development (R&D). In the absence of suitable data on patents at the required level of disaggregation, we measure a region's innovation potential by reference to employment in the R&D sector, following to some extent the approach of Pigliaru (2003). The labour resources allocated to research and development are used to approximate a region's propensity to innovate. Thus, the variable (***PRIN***) is measured by the percentage of the regional labour force that is found in the R&D sector (SIC-code 73) reflecting the relative concentration of innovation activity. Although this approach is by no means ideal, since some R&D activity will also take place within other industrial sectors, we nevertheless believe it to be an appropriate indicator of innovation potential.

Figure 2 presents the regional pattern of R&D employment shares for 1970. Overall, the regions of Greece are characterised by very low levels of R&D employment concentration, with the majority not exceeding 0.2% and the highest concentrations observed in the two leading regions of Attiki and Thessaloniki (0.46% and 0.43% respectively). This is not unexpected given that Greece has been found to have the lowest level of R&D activity in the EU, prior to 2004 enlargement (Korres and Rigas, 2002).

In order to measure a region's capacity to adopt new technologies, we utilise the approach of Plummer and Taylor (2001a, 2001b). In the first instance, this involves identifying technically dynamic sectors, perceived to be the most receptive to innovation and its utilisation. Plummer and Taylor (2001a, 2001b) select five such industrial sectors: pharmaceutical and veterinary, aircraft manufacturing, photographic, professional and scientific equipment, data-processing services and, finally, research and scientific institutions. In the case of Greece, however, straightforward adoption of the same sectors is not possible. There is no aircraft manufacturing in Greece, while research and scientific institutions are included in the R&D

sector, which has already been used to approximate the propensity to innovate. In these circumstances, therefore, we focus on four sectors that match most closely the sectors identified above, that is: chemicals and allied products, office equipment and machinery, scientific equipment production and information and data processing[7]. A region's level of technological development is thus measured as the percentage of its total labour force employed in these four sectors. The final step in measuring the propensity for technology diffusion is to calculate the technology gap (***TG***), constructed as the difference in technology levels between the leading region of Attiki and all other regions[8].

Figure 3 shows the relative importance of these technologically advanced sectors to the regions of Greece in 1970. The two leading regions have the highest concentrations (7.6% and 5.4%), with the other regions which also exhibit relatively higher concentrations clustered around these leading regions. Low concentrations are located mainly in the more peripheral parts of the mainland, or in the island regions.

Localisation and urbanisation economies

The remaining two variables require measurement of the extent of regional specialisation and regional diversity. In the first case, the degree to which a region specialises in one particular industry is approximated by the use of a concentration measure. In the present context we base our concentration measure (***LOC***) on the distribution of employment across industry sectors (Henderson, 1997) and produce a set of localisation coefficients in the form of sectoral employment shares using data for all sectors in a region. The highest localisation coefficient is selected for each region to indicate the extent to which the region specialises in one particular type of activity. Regions with high localisation values are located in the north and island areas of Greece while central regions, and areas around the two leading regions, do not appear to be highly specialised suggesting that low productivity areas are more likely to exhibit a higher degree of specialisation.

Finally, the extent of a region's economic diversity (***DVR***) is measured by means of a Hirschman-Herfindahl index (hereafter **HH**), as follows[9]:

$$\boldsymbol{DVR_i = \sum_{s \neq k,l} (\varpi_{s,i})^2} \qquad (10)$$

where $\boldsymbol{\varpi_s^i}$ is the employment share of each sector $\boldsymbol{s}$ in region $\boldsymbol{i}$. In this analysis, the particular sector in which a region specialises (***l***) is excluded from the calculations, as are the sectors used to approximate innovation potential and technology diffusion (***k***). The logic of this approach is to produce a measure of diversity in the economic environment that surrounds and interacts with the key sectors identified above. Not surprisingly, the highest levels of diversity are associated with the two leading regions, whilst the most northerly areas and island regions exhibit the least diversity in 1970.

4. Empirical Analysis

As a first step in the process of investigating club convergence in the regions of Greece we examine the data for evidence of absolute β-convergence, using OLS to estimate equation (1). The results, presented in Table 1, show the convergence coefficient ($\boldsymbol{b}$) to be negative and statistically significant, thus indicating the presence of absolute convergence over the period 1970 to 2000[10]. The rate of convergence is, however, relatively low, at 0.24% per annum and the regression on which this estimate is based exhibits low 'goodness of fit' overall.

The second step is to test for club convergence, that is to say, whether convergence exists for a sub-group of regions. The results from estimation of equation (3) are also shown in Table 1. The outcome is consistent with the presence of a sub-group of regions demonstrating convergence properties in that the estimated coefficients are as expected; $\boldsymbol{b_1}$ is positive and $\boldsymbol{b_2}$ is negative, although the former coefficient is not significant. Nevertheless, we make use of the estimated equation to determine the members of the convergence club, by calculating the threshold point ($\boldsymbol{y}^*$) at which a negative relationship between growth and initial GVA per worker begins to emerge. On this basis, all but six regions are identified as exhibiting β-convergence properties ($R_{8.2}$, $R_{6.2}$, $R_{4.3}$, $R_{3.4}$, $R_{6.4}$, and $R_{11.3}$), where three of these exceptional cases are island regions and a further two are located in the Northwest border region.

At this point it is difficult to conclude that the simple model of club convergence provides a far better explanation of the data than the simple absolute convergence model. 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.

In seeking to overcome these deficiencies, the final and main stage in the empirical analysis is to extend the convergence club model of equation (3) by investigating three forms of spatial dependence and by taking account, in each case, of the potential impact of localisation and urbanisation economies, innovation propensity and technology diffusion. All variables are measured at the starting point of the time period under investigation. Thus we have three estimating equations as follows:

$$\boldsymbol{g_i = a + b_1 y_{i,0} + b_2 y_{i,0}^2 + b_3 PRIN_{i,0} + b_4 TG_{i,0} + b_5 LOC_{i,0} + b_6 DVR_{i,0}} + (\mathbf{I} - \zeta \mathbf{W})^{-1} \boldsymbol{u_i} \quad (11)$$

$$\boldsymbol{g_i = a + b_1 y_{i,0} + b_2 y_{i,0}^2 + b_3 PRIN_{i,0} + b_4 TG_{i,0} + b_5 LOC_{i,0} + b_6 DVR_{i,0}} + \rho(\mathbf{W}\boldsymbol{g_i}) + \boldsymbol{\varepsilon_i} \quad (12)$$

$$\boldsymbol{g_i = a + b_1 y_{i,0} + b_2 y_{i,0}^2 + b_3 PRIN_{i,0} + b_4 TG_{i,0} + b_5 LOC_{i,0} + b_6 DVR_{i,0} + c\left(\mathrm{W} y_{i,0}\right) + \varepsilon_i} \quad (13)$$

A potential problem for equations (11), (12) and (13) is that of endogeneity of the explanatory variables (i.e. ***PRIN***, ***TG***, ***LOC*** and ***DVR***). This, however, is overcome by the fact that these variables are dated at the initial time (1970) so that it is the impact of these initial conditions upon future growth performance that is being tested. Estimation of the spatial-error and spatial-lag models (equations 11 and 12) is carried out by the maximum likelihood method, since in the former case, OLS may result in problems of bias[11] and in the latter case OLS estimators are inconsistent because of the endogeneity introduced by the inclusion of spatially lagged growth. In contrast, the spatial lag variable in the cross-regressive model (equation 13) is exogenous and estimation using OLS is appropriate (Anselin, 1988).

Table 2 presents the results of estimating the spatial models above, and also shows the non-spatial model for purposes of comparison. For all models, the coefficients $\boldsymbol{b_1}$ and $\boldsymbol{b_2}$ have the appropriate signs to signal the presence of a convergence club but only in the spatial-error model (equation 11) are the results significant at the 95% confidence level. The threshold value ($\boldsymbol{y^*}$), which is used to identify the members of a convergence club, and which is a combination of the two estimated coefficients, is also found to be statistically significant at 95% confidence level.

Turning to the impact of the technology variables, the outcome for both is consistent with prior expectations; propensity to innovate (***PRIN***), as measured by the percentage of employment in the R&D sector at the start of the period, exhibits the anticipated positive relationship to growth, as does the technology gap variable (***TG***), suggesting that regions with higher technology gaps will grow more quickly. However, it is only in the context of the spatial-error model that both results are statistically significant.

The evidence in Table 2 does not support the operation of agglomeration economies arising from specialisation. The localisation variable is insignificant and hence localisation economies, as measured by the variable (***LOC***), do not contribute to an explanation of the regional pattern of growth. In the case of agglomeration economies arising from economic diversity; the coefficient b_6 on the ***DVR*** variable is positive and statistically significant at 95% level, for the spatial-error model only. Thus, higher diversity in economic activity at the start of the time period is associated with lower growth rates over the thirty years.

Finally, if we are to select from the three models in terms of their ability to capture spatial interaction, then it is apparent from Table 2 that only the spatial error model (11) produces a significant outcome; the spatial lags attached to growth and income are both insignificant. Also, the spatial-error model yields the lowest Schwartz-Bayesian criterion value (SBC), and the highest values for the Log-Likelihood statistic (LIK) and Lagrange-Multiplier (LM)[12]. Overall, the extended club convergence model, which incorporates spatial interaction through the disturbance term, provides a better explanation of the pattern of regional growth than the alternatives investigated, including the non-spatial model.

Convergence club Membership

Identification of the convergence club members, that is to say those regions exhibiting the property of β-convergence, is therefore based upon the spatial error model and its associated threshold level for GVA per worker ($\boldsymbol{y}^{*}$ = 8.014). Using this criterion, the convergence club is seen to include 17 regions whose initial level of GVA per worker exceeds the threshold value and whose average growth rate over the period 1970-2000 is 0.8%, compared to 1.2% for the group of 51 regions as a whole.

Figure 4 shows the location of the convergence club members. Spatial connectivity between the converging regions is clearly evident with the majority of the converging regions clustered around a central axis extending from north to south. More specifically, there is a clustering around the four leading-regions of Greece; which are Attiki (R_9) and Achaia ($R_{7.2}$) in the south, Thessaloniki ($R_{2.2}$) in the North and Larissa ($R_{5.1}$) in the central area.

The majority of the more peripheral border and island regions are excluded from the convergence club. The one exception is the island region of Heraklion ($R_{13.3}$) which is the most dynamic island region, and whose economy is significantly supported by tourism. It is worthy of note, however, that this region has also benefited from new university and research establishments in the 1980s and 1990s, to complement its successful performance in tourism.

5. Conclusions

This paper extends the analysis of regional economic convergence in Greece by addressing the question of club convergence, whilst at the same time examining the role of spatial interaction, agglomeration, innovation and technology spillovers in explaining regional growth performance. The outcome of the analysis is that convergence is seen to be a property of only a third of all regions in Greece.

In terms of *intra*-regional effects, the propensity to innovate and diversity in the economic environment are both found to be significant factors in the regional growth process. *Inter*-

regional effects are also seen to be important, in that the analysis demonstrates significant spatial dependence in regional growth rates and also provides evidence in support of the technology diffusion process. Evidence of the importance of *inter*-regional spillover effects is also to be found in the fact that there are clear spatial links between the members of the convergence club.

Finally, whilst the model presented in this paper is tested only in the context of Greek regions, it is sufficiently flexible to be applied to other regional contexts, and, dependent upon data availability, to incorporate different factors that shape the pattern of club convergence.

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Appendix: NUTS-3 Regions of Greece

$R_{1.1}$	Evros	$R_{5.1}$	Larissa	$R_{10.1}$	Korinthia
$R_{1.2}$	Rodopi	$R_{5.2}$	Magnesia	$R_{10.2}$	Argolida
$R_{1.3}$	Xanthi	$R_{5.3}$	Trikala	$R_{10.3}$	Arcadia
$R_{1.4}$	Drama	$R_{5.4}$	Karditsa	$R_{10.4}$	Messinia
$R_{1.5}$	Kavala	$R_{6.1}$	Kerkira	$R_{10.5}$	Lakonia
$R_{2.1}$	Serres	$R_{6.2}$	Lefkada	$R_{11.1}$	Lesvos
$R_{2.2}$	Thessaloniki	$R_{6.3}$	Kefalonia	$R_{11.2}$	Chios
$R_{2.3}$	Chalkidiki	$R_{6.4}$	Zakinthos	$R_{11.3}$	Samos
$R_{2.4}$	Kilkis	$R_{7.1}$	Aitoloacarnania	$R_{12.1}$	Kiklades
$R_{2.5}$	Pella	$R_{7.2}$	Achaia	$R_{12.2}$	Dodecanisa
$R_{2.6}$	Hmathia	$R_{7.3}$	Ilea	$R_{13.1}$	Hania
$R_{2.7}$	Pieria	$R_{8.1}$	Fthiotida	$R_{13.2}$	Rethimno
$R_{3.1}$	Florina	$R_{8.2}$	Evritania	$R_{13.3}$	Heraklion
$R_{3.2}$	Kozani	$R_{8.3}$	Fokida	$R_{13.4}$	Lasithi
$R_{3.3}$	Kastoria	$R_{8.4}$	Viotia		
$R_{3.4}$	Grevena	$R_{8.5}$	Evia		
$R_{4.1}$	Ioannina	R_{9}	Attiki		
$R_{4.2}$	Arta				
$R_{4.3}$	Thesprotia				
$R_{4.4}$	Preveza				

Table 1: Absolute and Club Convergence

Absolute Convergence Model (1) $g_i = a + by_{i,0}$

A	b	R^2 [ser]	F [prob]	Implied β	Log-likelihood
0.9224**	-0.0717**	0.1397	7.9535	0.0024**	19.7350
(4.6457)	(-2.8202)	[0.1676]	[0.007]	(2.7165)	

Club convergence Model (3) $g_i = a + b_1 y_{i,0} + b_2 y_{i,0}^2$

A	b_1	b_2	R^2 [ser]	F [prob]	Implied y^*	Log-likelihood
-0.5438	0.2860	-0.0215*	0.1905	5.6464	6.6580**	21.2873
(-0.6273)	(1.3782)	(-1.7357)	[0.1643]	[0.006]	(5.9384)	

Notes:
Figures in brackets are t-ratios. ** indicates statistical significance at 95% level of confidence, * 90% level. [ser] denotes the standard error of the regression. Column *F* gives the F-Statistic and the probability [prob] for the overall significance of the regression.

Table 2: Extended Convergence Club Models

Non Spatial Specification $g_i = a + b_1 y_{i,0} + b_2 y_{i,0}^2 + b_3 PRIN_{i,0} + b_4 TG_{i,0} + b_5 LOC_{i,0} + b_6 DVR_{i,0}$

a	b_1	b_2	b_3	b_4	b_5	b_6		Implied y^*
1.1497	0.17790	-0.01301	0.03714	0.04044*	-0.06283	0.36555*		6.8346**
(0.7036)	(0.6722)	(-0.8219)	(1.2090)	(1.7035)	(-0.9408)	(1.7096)		(3.0669)
AIC	18.7574	SBC	11.9960	LIK	25.7574			

Spatial-Error Model (11) $g_i = a + b_1 y_{i,0} + b_2 y_{i,0}^2 + b_3 PRIN_{i,0} + b_4 TG_{i,0} + b_5 LOC_{i,0} + b_6 DVR_{i,0} + (\mathrm{I} - \zeta \mathrm{W})^{-1} u_i$

a	b_1	b_2	b_3	b_4	b_5	b_6	ζ	Implied y^*
0.02870	0.49067**	-0.0306**	0.0545**	0.04688**	0.00090	0.48650**	19.6136**	8.0141**
(0.0309)	(4.0560)	(-4.4433)	(2.1704)	(2.2856)	(0.0133)	(2.7904)	(2.8419)	(14.6763)
AIC	17.7270	SBC	7.1020	LIK	28.7270	LM	12.8742	

Spatial-Lag Model (12) $g_i = a + b_1 y_{i,0} + b_2 y_{i,0}^2 + b_3 PRIN_{i,0} + b_4 TG_{i,0} + b_5 LOC_{i,0} + b_6 DVR_{i,0} + \rho(\mathrm{W} g_i)$

a	b_1	b_2	b_3	b_4	b_5	b_6	ρ	Implied y^*
0.89166	0.21598	-0.01592	0.04473	0.04258*	-0.06593	0.29180	0.08538	6.7810**
(0.6026)	(0.9114)	(-1.1297)	(1.5188)	(1.7681)	(-1.0565)	(1.4329)	(0.0543)	(3.7041)
AIC	17.8708	SBC	9.1776	LIK	26.8708	LM	11.1139	

Spatial X-Regressive Mod (13) $g_i = a + b_1 y_{i,0} + b_2 y_{i,0}^2 + b_3 PRIN_{i,0} + b_4 TG_{i,0} + b_5 LOC_{i,0} + b_6 DVR_{i,0} + c(\mathrm{W} y_{i,0})$

a	b_1	b_2	b_3	b_4	b_5	b_6	C	Implied $y^{*\,a}$
1.1563	0.17573	-0.01279	0.03660	0.04089	-0.06192	0.36931	-0.00379	
(0.6969)	(0.6462)	(-0.7651)	(1.1003)	(1.5768)	(-0.8786)	(1.5952)	(-0.0454)	
AIC	17.7586	SBC	10.0313	LIK	25.7586	LM	7.8379	

Notes:
Figures in brackets are the t-ratios. ** indicates statistical significance at 95% level of confidence; * 90% level.
[a] The spatial cross-regressive model does not provide a unique threshold value for the determination of a convergence club.

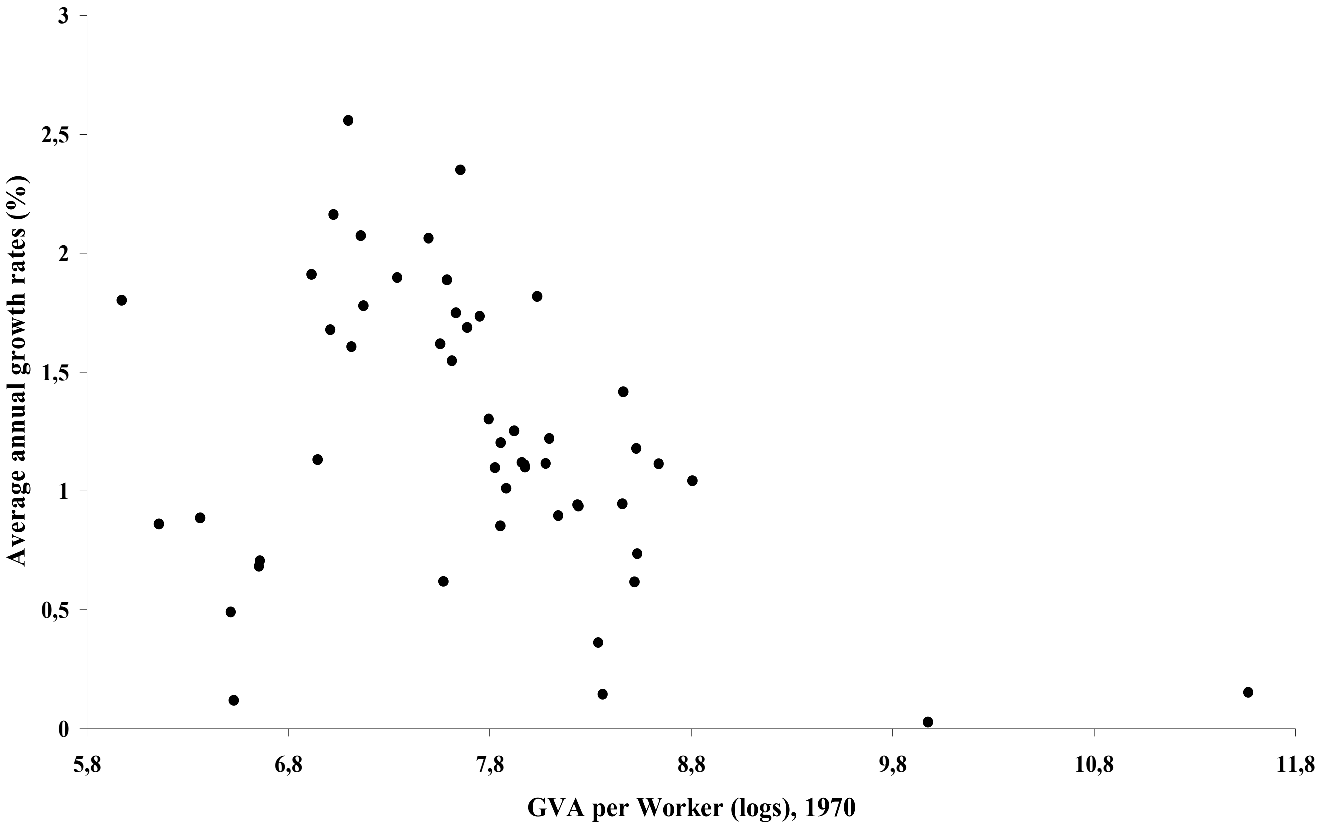

Figure 1: Relationship between growth rates and initial GVA per worker: 51 Greek prefectures, 1970-2000

Figure 2: Employment in the R&D sector as a % of Regional Employment, 1970

Figure 3: Employment in 4 Dynamic Sectors as a % of Regional Employment, 1970

Figure 4: Members of the Convergence Club

[1] See for example Rey and Montouri (1999), Fingleton (2000). For a more detailed review see Abreu, de Groot and Florax (2005).

[2] However, several criticisms have been put forward regarding this model – see, for example, Friedman, 1992, Quah, 1993). For a more detailed review see Capolupo (1998).

[3] For example Hobijin and Frances (2000) use time-series techniques, whilst Je Su (2003) utilises 'tree-regressions'. However, data availability constrains the application of these methods.

[4] In this case, a random shock on the growth rate of any one region will also spread to other regions, and the spatial lag model can be re-written as $g_i = (I-\rho W)^{-1}(a + b_1 y_{i,0} + b_2 y_{i,0}^2) + (I-\rho W)^{-1}\varepsilon_i$

[5] NUTS Level 3 regions. The term 'region' is used substitute for prefecture throughout the remainder of the paper. A list of regions is provided in the Appendix. Figures 2 to 4 provide maps to show the location of the regions.

[6] Marjit and Beladi (1998) make a distinction between product and process patents.

[7] SIC codes 31, 36, 37 and 72. The pharmaceutical and veterinary produce sector is included in sector 31.

[8] Similar proxies have been used in empirical studies, for example, de la Fuente, 1997.

[9] Although there is no completely satisfactory way to measure diversity, the Hirschman-Herfindahl index is a standard measure and one of the most frequently used (see, for example, Rigby and Essletzbichler, 2002; Lucio, Herce and Goicolea, 2002).

[10] This result is consistent with the findings of Christopoulos and Tsionas (2004) for the period 1971-1995.

[11] As outlined in Rey and Montouri (1999), the presence of spatial interaction in the error term in equation (3) implies a non-spherical covariance matrix: $E[\varepsilon_t \varepsilon_t'] = (\mathbf{I} - \zeta\mathbf{W})^{-1}\sigma^2\mathbf{I}(\mathbf{I} - \zeta\mathbf{W})^{-1'}$. This leads to unbiased OLS estimators but biased estimations of the parameter's variance.

[12] SBC is superior to the Akaike information criterion (AIC) which is biased towards an over-parameterized model. The Log-Likelihood and Lagrange-Multiplier are extensively used in spatial econometrics, such that the best fitted model is the one that yields the greatest value for these criteria (Anselin, 1988).