



ENDOGENOUS KNOWLEDGE AND INNOVATION

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Abstract:

An empirical model is developed in which economic growth is attributed to the process of endogenous innovation and the rate of knowledge transfer (adoption) across regions. The model is tested using data for the NUTS-2 regions of the EU-27 during the time period 1995-2005. The results suggest that adoption of knowledge and technology has a significant and positive effect in the process of regional growth and convergence in Europe.

Keywords: Transfer of knowledge, Regional Growth, European Regions.

1. INTRODUCTION

The debate on regional convergence has bred, and continues to do so, dozens of empirical studies. While a plethora of paper exists in various international journals (Neven & Gouyette, 1995; Ezcurra *et al.*, 2005; Martin, 2001, to name but a few), the literature has been rather sparse when it comes to the impact of the *transfer* and *adoption* of knowledge/technology has received less attention. Indeed, Bernard & 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. Technological progress is driven not only by indigenous innovation but also by the process of technology absorption, and thus the ability of a region to ‘catch-up’ might substantially depend on its capacity to imitate and adopt innovations developed in more technologically advanced regions.

Abramovitz (1986) offers a lucid explanation of this phenomenon:

‘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).

On similar lines, Kristensen (1974) recognises this possibility by arguing as follows:

‘The most rapid economic growth should be expected to take place in countries that have reached a stage at which they can begin to apply a great deal more of the existing knowledge’ (p. 24).

In this paper a model is developed in an attempt to elucidate the impact of technology transfer in an extensive regional context, that of the NUTS-2 regions of the EU. A scheme of measurement is developed to calibrate these dimensions, and European data for the period 1995-2006 are used to develop a preliminary empirical analysis.

The remainder of the paper is structured in the following manner. Section 2 introduces the theoretical framework. In section 3 the methods employed and the data used in the process of econometric estimations are discussed, followed by the presentation of the econometric results 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. ENDOGENOUS INNOVATION

Knowledge is the driving force behind economic growth. Several models attempt to formalise this argument (Aghion *et al.*, 1999; Jones, 1995) by emphasising the existence of a sector that deliberately produces knowledge and technological innovations. These models, drawing on Schumpeter (1934), suggest the possibility of perpetual growth in capitalist economies due to entrepreneurial innovations. Schumpeter (1934) envisaged firms coming into existence as a result of an innovative idea. If an innovation consists of a radical departure from existing products or technologies it would create a new market and the innovating firm will earn abnormal or monopoly profits. Other firms leave the market, since they cannot compete with the innovative firms; a process known as ‘creative destruction’ (Andersen, 1996). Hence, the market structure loses its competitive nature and moves towards a rather more imperfect structure, such as monopolistic competition or oligopoly and innovative firms earn ‘abnormal’ or monopolistic profits. These profits are the main incentive for firms to devote substantial

resources to Research and Development (R&D) investment. The R&D sector combines human capital together with the existing stock of knowledge to produce new knowledge.

New knowledge enhances productivity and is available to other sectors of the economy at virtually zero marginal cost. Assume that a firm develops a new product, which is positioned higher up the ‘quality ladder’. Such a firm can capture some of the profits of the producers of previous generations of the product. In this way knowledge and innovation is a factor of production contributing to profit and growth and, hence, the overall rate of growth is influenced by innovations; a procedure called ‘innovation-driven’ growth.

Romer (1990) developed the most instructive model in this category. A central tenet is that firms can patent inventions and innovations, which gives them the exclusive right to produce new goods (private knowledge). However, in turn, these products create new ‘general’ knowledge, which is freely available to all firms (public knowledge). The mechanism leading to endogenous growth in Romer’s model can be described as follows. A region’s output is a function of the capital stock, the labour force and technological knowledge available in a region. Romer (1990) assumes that technological knowledge is attached to the labour force, i.e. a ‘knowledge adjusted’ labour force.

Romer’s ideas were incorporated into a generation of models that put primary focus on the level of knowledge in an economy as a principal factor in growth. Such ‘knowledge-based’ models also found application in a regional context. Shefer & Rietveld (1999) state that:

‘[...] regional development, *as a location where technological innovation takes place, is usually accompanied by new economic activities, market expansion and technological adaptation.*’ (p. 260) [Emphasis added]

If the knowledge producing sector is spatially concentrated within a region, then this will constitute a source of further growth through the operation of dynamic externalities. The spatial distribution of innovative sectors is therefore a crucial element in the process of regional growth. This recognition that knowledge creation is crucial for regional development also produces a shift in perspective. As stated by Maskell & Malmberg (1999):

‘The region, the territory, or ‘space, is not seen merely as a ‘container’, in which attractive location factors may (or may not) happen to exist, but rather as a milieu for *collective learning* through intense interaction between a broadly composed set of actors.’ (p. 174) [Emphasis added]

Thus, a region is a ‘created space’ that is both a result of and a precondition for learning – ‘an active resource rather than a passive surface’ (Coffey & Baily, 1996). Thus, the ‘knowledge economy’ model which derives from innovation driven endogenous growth theory, sees regions as competing economies ‘[...] that try to obtain an economic advantage through developing or adopting technologically advanced products or processes’ (Button & Pentecost, 1999, p. 57).

These arguments can be incorporated in a standard regional convergence-framework. Assume that production in a region can be portrayed by a Cobb-Douglas production function:

$$Y_i = K_i^\alpha (E_i L_i)^{1-\alpha} \quad (1)$$

where K and L stand for the physical capital and labour force, respectively.

Of particular importance is the variable E which represents the ‘knowledge-base’ of a region. This is defined as the product of ‘knowledge-creation’ (PI_i) and ‘knowledge-adoption’

(ADP_i) externalities, i.e. $E_i = PI_i ADP_i$. Output in a region, adjusted by knowledge $\tilde{Q}_i = k_i^\alpha$, where $\tilde{Q}_i = Y_i / L_i E_i$ and $k_i = K_i / L_i E_i$, converges towards its steady-state value \tilde{Q}^* : $\dot{\tilde{Q}}_i / \tilde{Q}_i = -\beta(\log \tilde{Q}_i - \log \tilde{Q}^*)$. Therefore, $d \log \tilde{Q}_i / dt + \beta \log \tilde{Q}_i = \beta \log \tilde{Q}^*$. This is a differential equation in $\log \tilde{Q}_{i,t}$ with the solution $\log \tilde{Q}_{i,t} = (1 - e^{-\beta t}) \log \tilde{Q}^* + e^{-\beta t} \log \tilde{Q}_{i,0}$. Given that $\log \tilde{Q}_i = \log(Y/L)_i - (\log PI_i + \log ADP_i)$ and $g_{i,T} = \log(Y/L)_{i,T} - \log(Y/L)_{i,0}$, then $g_{i,T} = c + b_1(Y/L)_{i,0} + b_2 \log PI_{i,0} + b_3 \log ADP_{i,0}$, where $T = t - 0$, $b_1 = -(1 - e^{-\beta t})$, $c = (1 - e^{-\beta t}) \log \tilde{Q}^* + (\log PI_{i,t} + \log ADP_{i,t})$ and $b_2, b_3 = -e^{-\beta t}$.

3. SETTING THE EMPIRICAL FRAMEWORK

The empirical literature on regional convergence makes extensive use of two alternative tests for convergence, namely absolute and conditional convergence, described as follows:

$$g_i = a + b_1 y_{i,0} + \varepsilon_i \quad (1)$$

$$g_i = a + b_1 y_{i,0} + b_{\mathbf{X}_i} \mathbf{X}_i + \varepsilon_i \quad (2)$$

where y_i represents per-capita output of the i^{th} economy, $g_i = (y_{i,T} - y_{i,0})$ is the growth rate over the time interval $(0, T)$, and ε_i is the error-term.

Absolute convergence occurs if $b_1 < 0$ while the speed at which regions move towards the same steady-state level of per capita output 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 technological parameters, captured by the vector (\mathbf{X}_i) in equation (2), then convergence is conditional on these parameters, giving rise to different steady states. It follows, therefore, that a test for conditional convergence is more suitable to accommodate an empirical application of the framework discussed in section 2, and it becomes of critical importance to choose the appropriate variables that will be included in the vector \mathbf{X}_i .

A key feature of the various models of endogenous growth is that technical change, leading to regional productivity growth, originates either from within the region or from other regions (technological spillovers). In the former case, technological growth is related to the ‘propensity to innovate’, as defined by Pigliaru (2003). Following this definition, in this paper the ‘propensity to innovate’ ($PI_{i,t}$) is expressed in terms of the percentage of workers employed in the science and technology sectors of each region¹. For the purpose of this paper, a region’s level of technological development and adoption capacity is thus measured as the percentage of total employment in technologically dynamic sectors. More formally,

$$ADP_{i,t} = \frac{\sum_{j=1}^m \eta_{i,t}^j}{L_{i,t}} \quad (3)$$

¹ Data were obtained using the ‘Human Resources in Science and Technology’ 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 $\eta_{i,t}^j$ refers to personnel employed in high-tech manufacturing and knowledge-intensive high-technology services ($j = 1 \dots m$) and $L_{i,t}$ is the total employment in region i .

Equation (7), represents the level of technological development, but also, indicates a capacity for technology adoption, since these are taken to apply high technology. Therefore, it is possible to express a model of ‘technologically-conditioned’ convergence as follows:

$$g_i = a + b_1 y_{i,0} + b_2 PI_{i,0} + b_3 ADP_{i,0} + \varepsilon_i \quad (4)$$

In equation (4) the variables related to technology are expressed in initial values. There are two primary reasons for such an approach. The first is related to the fact that creation and adoption of innovations, normally, have future or long-run effects on regional growth. In other words, future growth is affected by current efforts to enhance technology. Therefore, including the two technological elements at the initial time captures these long-run effects of technology on regional growth over a specific time period. A second reason for using initial values is that it tests the hypothesis that initial conditions ‘lock’ regions into a high or low position, for example, how high or low levels of technology affect the pattern of regional growth and convergence.

Equation (4), 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 high levels of innovation 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, 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 $ADP_{i,0}$ variable, this variable reflects two distinct features, namely the *initial* level of ‘technological adoption’ and the degree to which existing conditions in a region allow further adoption of technology. A low initial level of $ADP_{i,0}$ 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 advanced regions. It may be argued, therefore, that the condition $b_3 < 0$ promotes convergence. On the other hand, a low initial value for $ADP_{i,0}$ 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.

4. ECONOMETRIC APPLICATION

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 regional groupings used in this paper are those delineated by EUROSTAT and refer to 268 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 & 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 & Stirböck, 2006). The time period for the analysis extends from 1995 to 2005, which might be considered as rather short. However, Islam (1995) points 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’.

Convergence is identified with an inverse relationship between growth and initial level of per capita output. Such a notion of convergence embodies the essence of the neoclassical argument that poor regions grow faster than rich regions, and produces estimates of the rate at which poor regions are catching up with rich regions, should convergence be detected. Therefore, the cross-section test, based on estimation of equation (1) for the 268 NUTS-2 regions of the EU, is applied to the period 1995–2005 using data for GVA per-worker. Furthermore, the hypothesis of ‘technologically-conditioned’ convergence is also estimated. In operational terms, equation (1) and (4) are estimated using the Ordinary Least Squares (OLS) method.

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

Depended Variable: g_i , n = 268 NUTS-2 Regions, OLS Equation (1)	Equation (4)
a	0.5714**
b_1	-0.0747**
b_2	0.0014
b_3	0.0203**
<i>Implied β</i>	0.0065**
AIC	-291.104
SBC	-283.929

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

A positive coefficient is estimated for the variable describing technology creation, which does not necessarily promote convergence as such, since regions with relatively high initial level of innovation exhibit relatively higher rates of growth. A positive value for the $ADP_{i,0}$ variable is also estimated. This suggests that, on average, regions with low values of $ADP_{i,0}$ at the start of the period grow slower than regions with high values, ceteris paribus. If technologically backward regions were successful in adopting technology, which subsequently is transformed into faster growth, then the estimated coefficient b_3 would be negative. Since $b_3 > 0$, this indicates that infrastructure conditions in lagging regions are inhibiting this process of technology adoption. This constitutes a substantial barrier to the diffusion of technology across the regions of the EU-27. These findings 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). It is possible to provide further evidence using a transition probability matrix for the ADP_i variable.

Table 2: Transition probability matrix, Employment in technological advanced sectors

n [1995]		ADP, 2006					n [2006]	
ADP, 1995	51 [0-0.5)	0.1493	0.0299	0.0075	0.0000	0.0037	49	
	34 [0.5-0.75)	0.0261	0.0597	0.0299	0.0112	0.0000	34	

51	[0.75-1)	0.0075	0.0187	0.0970	0.0522	0.0149	51
69	[1-1.3)	0.0000	0.0187	0.0560	0.1194	0.0634	68
63	[1.3-	0.0000	0.0000	0.0000	0.0000	0.0000	66
268	[0-0.5)	[0.5-0.75)	[0.75-1)	[1-1.3)	[1.3-		268

Table 2 shows that over 40 % of the EU-27 NUTS-2 regions have remained to the same range of distribution. About 21 % of the technologically lagging regions² have not changed their low position while over 22 % of the technologically advanced regions remained in the same range of distribution. Fewer upward movements took place, suggesting that the technological differences across the EU-27 regions remained virtually unchanged during the period 1995–2006.

Technology adoption, although it might be the best ‘vehicle’ for lagging regions, nevertheless, this is a process which might be difficult, especially during the early stages of development when conditions are least supportive. Normally, conditional convergence implies a slower rate of convergence. Nevertheless introducing the technological variable increases the estimated rate of convergence (0.71 %). The superiority of the model described by equation (4) is supported by both the criteria for model selection applied here, namely the *Akaike* (AIC) and the *Schwartz-Bayesian* (SBC) information criteria³.

5. CONCLUSIONS

This paper attempt to provide an empirical assessment of the impact of knowledge adoption in regional convergence using data for the 268 NUTS-2 regions of the EU-27 over the period 1995–2006. The results reported in this paper suggest that the NUTS-2 regions of EU-27 exhibit a slow rate of convergence in terms of labour productivity. Such an exercise is, by its very nature, limited; it simplifies a complex reality. It cannot substitute for a detailed analysis of specific regional contexts. Nevertheless, an important conclusion to emerge from the empirical application is that the EU-27 regions converge faster *after* conditioning for technological factors 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 Europe are not able to reap the ‘benefits of backwardness’. This inability can be attributed to inappropriate infrastructure conditions in lagging regions, which prevent or constrain convergence with the technologically advanced regions.

In terms of implications for public policy, especially regional policy, this paper raises a number of pertinent issues. Regional policies should promote high-technology activities, and R&D, including universities, scientific and research institutions, support clusters, modernize the framework of copyright and trademarks, improve access of SMEs to Intellectual Property Protection, speed up setting of interoperable standards, and improve access to capital by reducing transaction costs of doing business. Regional policies should also encourage ‘knowledge partnerships’ and links between business, research, innovation and education. A greater capacity for R&D as well as innovation across all sectors, combined with increased efficiency will foster job creation and improve competitiveness.

² ‘Technologically lagging’ regions are defined as regions with employment shares in technological advanced sectors less than 75 % of the EU-27 average.

³ As a rule of thumb, the best fitting model is the one that yields the minimum values for the AIC or the SBC criterion.

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