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REGIONAL KNOWLEDGE BASE AND PRODUCTIVITY GROWTH: THE EVIDENCE OF ITALIAN MANUFACTURING

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Regional Knowledge Base and Productivity Growth: The Evidence of Italian Manufacturing[1].

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ABSTRACT. This paper empirically analyzes the effects of regional knowledge base on differential growth rates. Beyond the traditional view of knowledge as an homogenous asset, it considers further characteristics that qualify its heterogeneous features. The results of the empirical estimations provide support to the idea that knowledge characteristics are fare more important than knowledge capital. The check for spatial dependence suggests that cross-regional externalities exert additional triggering effects on productivity growth, but without debasing the effects of knowledge. Important policy implications stem from the analysis, in that regional innovation strategies ought to be carefully coordinated so as to reach a higher degree of internal coherence and exert positive effects on productivity.

Keywords: Knowledge, Multifactor Productivity, Regional growth

JEL Classification Codes: O33, R11

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1 Introduction

Since the seminal contributions by Nelson (1959) and Arrow (1962), knowledge has attracted more and more the attention of economists, both with respect to the mechanisms leading to its production, dissemination and exchange, and with respect to its effects on productivity. The view upon knowledge as an economic good has changed very much over time. Formerly, knowledge was mainly seen as a quasi-public good, and significant problems of incentives and consequent under-provision affected its production. Later on, such notion has been challenged and knowledge started to be regarded as a quasi-private, with a high level of natural appropriability and exclusivity (Romer, 1990 and 1994). More recently, the emphasis on the dynamics of knowledge spillovers and on the key role of technological externalities led to the emergence of a new paradigm in which knowledge is viewed mainly as the outcome of a collective activity, whose production goes well beyond the single innovator, and involves a number of interacting agents able to combine internal and external knowledge inputs, both formal and informal (Nelson, 1982; Griliches, 1992; Cooke, 2002; Foray, 2004; Antonelli, 2008).

A wide body of empirical literature estimating the econometric relationship between knowledge and productivity has appeared only after the path-breaking works by Zvi Griliches (1979). Most of them consist of industry- or firm-level analyses, focusing on the evidence from a specific country or on the comparison among a few countries, in which knowledge stock is treated as an input in an extended production function and calculated by applying the permanent inventory method to R&D investments or to patent flows[2]. At the aggregate level, much a lower number of studies provide cross-country comparisons of the relationship between knowledge and productivity growth[3], despite the appearance of endogenous growth theories that explicitly modelled learning dynamics, human capital and the accumulation of technological knowledge through R&D sectors as the main sources of growth (Lucas, 1988; Romer 1986 and 1990).

Yet, the literature dealing with the empirics of regional economic growth, focusing on the investigation of the patterns of cross regional convergence, have missed the opportunity to understand cross regional differences in knowledge and innovation as one of the factors (and perhaps the most important) affecting the uneven distribution of productivity across regions, even within the same

[2] Without pretending to be exhaustive, out of the noteworthy contributions one may look at Nadiri (1980), Griliches (1984), Cuneo and Mairesse (1984), Patel and Soete (1988), Verspagen (1995) and Higón (2007).

[3] See Englander and Mittelstädt (1988), Lichtenberg (1992), Coe and Helpman (1995) and Ulku (2007).

country borders. Indeed, the importance of innovation for the process of economic development has been instead stressed by different streams of literature, grounded on fairly different analytical bases (Acs and Varga, 2002). On the one hand, the concept of learning regions referred to the capacity of areas featured by systemic ties, to enhance the creation of new knowledge and foster innovation (Asheim, 1996). On the other hand the Regional Innovation System (RIS) approach, drawing explicitly upon the notion of national innovation systems, has emphasized the relevance of interactive learning for the different kinds of actors involved in the innovation process (Cooke et al., 1997).

This paper aims at filling this gap, by bringing technological knowledge into an empirical framework analyzing the determinants of cross-regional differential growth rates of TFP. We focus on the dynamics of manufacturing sector within Italian regions over the period 1981-2002.

In particular, we adopt a competence-based view of the region, which draws upon the concept of 'higher-order capabilities', i.e. capabilities going beyond the scope of single firm command, which may be key to regional competitive advantage (Foss, 1996; Lawson, 1999; Lawson and Lorenz, 1999).

By introducing the concept of regional innovation capabilities, we are able to make a further step forward and understand knowledge as an intrinsically heterogeneous good, as it refers to various scientific disciplines and is embodied in diverse technological devices. Therefore different competences need to be integrated to manage and coordinate knowledge production and its successful exploitation. Hence, besides the usual measure of capital stock, which is the sum of homogenous pieces of capital stock, we consider also two additional measures able to qualify the regional knowledge base, i.e. knowledge relatedness and variety (Nesta and Saviotti, 2006; Nesta, 2008).

The case of Italian manufacturing within this picture is very peculiar for a number of reasons. First, since the 1980s the Italian economy has showed a relative delay as to development stage of manufacturing sectors, with respect to most advanced countries, and still such delay is persistent (Fuà, 1980; Antonelli et al., 2007). Second, the internal economic structure has long been characterized by a sharp dualism. On the one hand North-West regions were the cradle of modern industrial firms, and during the 1980s the manufacturing sectors had already completed their growth phase, leaving the floor to service industries. On the other hand, North-Eastern-Central (NEC) regions showed a delayed development of manufacturing activities, carried out mostly by small and medium sized enterprises (SMEs) often operating in peculiar economic and social environments (Fuà, 1983). Finally, such cross-regional differences in the development of manufacturing sectors appeared to be strictly related to differences in the emergence of regional innovation capabilities (Quatraro, 2008).

In this context, the contribution of this paper to the literature is twofold. On the one hand it aims at rejuvenating a field of enquiry which has been lacking appropriate consideration since the 1980s. For this reason, the debate about the economic development of Italian regions has missed the important opportunity of investigating cross-regional differences in the light of the economics of innovation. On the other hand, such an analysis is also relevant for its general implications concerning the relationships between technological knowledge and productivity growth, in particular with respect to regional innovation strategies.

The rest of the paper is organized as follows. In Section 2 we outline the theoretical model linking regional productivity growth and the characteristics of knowledge base. Section 3 presents the methodology. Section 4 provides a picture of the empirical context that will constitute the object of our analysis. In section 5 we describe the data sources and provide descriptive statistics for the main variables. Section 6 presents the results of the empirical estimation and an extension to spatial autoregressive model. Finally, conclusions and policy implications follow in Section 7.

2 The Theoretical Framework

The notion of knowledge as a strategic activity for regional economic performances has been emphasized by the innovation system approach. According to this view, location and spatial proximity are likely to enhance the processes of knowledge generation, favouring interactions among agents with diverse knowledge bases (Cooke, 1998; Antonelli, 2001).

Along these lines, scholars of regional science have focused their attention on the identification of possible proxies for new regional knowledge, and on the empirical investigation of the conditions affecting cross-regional differences in the efficiency of the knowledge creation process, like knowledge spillovers and spatial proximity (Acs et al., 2002; Fritsch, 2002 and 2004; Fritsch and Franke, 2004).

Such literature moves from the seminal contribution by Griliches (1979), and applies the knowledge production function (KPF) to the regional domain. However, the KPF was only an intermediate step aiming at identifying the inputs to knowledge production and then estimating the impact of knowledge on productivity, by elaborating upon the augmented production function. Therefore regional scientists provided convincing evidence about the factors affecting the production of new knowledge, but did not undertake the second task. Moreover, implicit to their empirical approach is the view upon knowledge as a homogenous asset, so that the whole regional knowledge stock equates to the sum of undiversified pieces of knowledge.

The extension of the concept of innovation capabilities to the regional domain allows us to view the region as a bundle of resources and appreciate the variety of the residing competences. This in turn makes it possible to qualify the knowledge produced within the region as essentially heterogeneous in that it is related to a variety of diverse, and not always related, activities (Nesta, 2008).

Within a context shaped by Schumpeterian competition, firms' dynamic capabilities stand for the "ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (Teece et al., 1997: p. 516). Innovation and technological capabilities specifically denote the firm's capacity to combine internal and external sources of both tacit and codified knowledge, directed towards the introduction of product and process innovations (Lall, 1992; Antonelli, 2008).

The emphasis on external linkages calls the attention upon factors going beyond the firm level. Higher-order innovation capabilities relates to knowledge which resides in the region, and "emerge in a historical process from the systemic interaction among firms" (Foss, 1996: p.3). The different institutions involved in the innovation process need time to learn to interact. This requires iterate interactions, the development of common communication codes and the availability of effective channels to access external knowledge. Such a kind of learning is highly localized in the specific context in which it takes place. As a result, regional innovation capabilities are highly idiosyncratic and related to the conditions of the economic and institutional environment, and hence they are difficult to replicate in the same way in other regions (Lawson and Lorenz, 1999; Romijn and Albu, 2002).

The variety of competences emerging within the region, and the centrality of knowledge, calls for dynamic coordination mechanisms. Knowledge is produced by combining formal efforts in research and development and tacit knowledge stemming from learning. However, interacting agents incur transaction costs that decrease over time as an affect of learning dynamics. The positive effects that arise from possible economies of scope are the lower the more unrelated (and then difficult to assess for both parties) are the knowledge inputs to be combined (Rajan et al., 2000).

The diversification across related activities, impinging upon similar knowledge bases, has indeed proved to positively affect productivity. In other words, activities drawing upon related technological knowledge are likely to show better performances than activities based on unrelated, or excessively varied, set of competences (including knowledge capital) (Rumelt, 1974; Montgomery, 1991; Breschi et al., 2003; Teece et al., 1994).

The generation of new knowledge is a core activity strategic for the competitive advantage of regional economies. Cross-regional differences in the development of technological knowledge provide thus a possible, although not exhaustive, explanation for differential growth rates (Fagerberg, 1987). A region can be viewed as a locus for the accumulation of diverse competences and technological knowledge. New knowledge emerges from the recombination of different inputs, which are both internal and external to economic agents. Regional knowledge base is therefore the outcome of a collective process that gathers together innovation efforts of a variety of actors, which have to commit additional resources in order to screen the activities residing in the region and combine the available resources in a non-random way. Knowledge so generated appears to be heterogeneous rather than homogenous, and the diversification strategies matter in shaping the effects that it can have on regional productivity dynamics.

Regions able to implement related diversification can grasp the benefits of knowledge economies of scope, and the related productivity gains. However, knowledge diversification may yield negative effects as long as one tries to combine together different bits of knowledge that are loosely related. Therefore, in order to foster productivity growth, regional actors must pursue diversification in related activities, which are likely to share related knowledge bases.

2.1 *The model*

In view of the arguments elaborated so far we are now able to specify the following relationship:

$$g_{i,t} = f(K_{i,t-1}) \qquad (1)$$

Where subscripts *i* and *t* refer respectively to the region and to time, *g* is the growth rate of productivity and *K* is the regional knowledge base. Traditionally, *K* is defined as the stock of knowledge corrected for technical obsolescence: $K_{i,t} = \dot{k}_{i,t} + (1-\delta)K_{i,t-1}$, where $\dot{k}_{i,t}$ is the flow of new knowledge at time *t* and δ is the rate of obsolescence. This relationship is able to capture the influence only of intangible capital, neglecting the characteristics of regional knowledge.

In order to address the issue of knowledge heterogeneity, stemming from the variety of resources that need to be combined for its production, the *K* term of Equation (1) can be modelled by extending to the regional domain the framework that Nesta (2008) develops at firm level. Let us recall the main passages in what follows.

Assume that a region is a bundle of D productive activities, represented by the vector $P = [p_1, ..., p_d, ..., p_D]$. Each regional activity p_d draws mainly upon a core scientific and technological expertise e_d, so that the regional total expertise is vector $E = [e_1, \ldots, e_d, \ldots, e_D]$. The emphasis on the collective character of knowledge implies that an activity p_d may also take advantage of the expertise developed in other activities l ($l \neq d$), depending on the level of relatedness τ between the technical expertise e_d and e_l. It follows that the knowledge base k used by the dth activity is:

$$k_d \equiv e_d + \sum_{l \neq d}^{D} e_l \tau_{ld} \qquad (2)$$

The meaning of Equation (2) is straightforward. The knowledge base k of each activity d amounts to the sum of its own expertise and the expertise developed by other activities weighted by their associate relatedness. Such equation can be generalized at the regional level to define the aggregate knowledge base:

$$K \equiv \sum_{d}^{D} e_d + \sum_{d}^{D} \sum_{l \neq d}^{D} e_l \tau_{ld} \qquad (3)$$

Let us assume that τ_{ld} is constant across activities d and l, so that $\tau_{ld} = R$ across all productive activities within the region. Since $\sum_{d}^{D} e_D$ is the regional knowledge stock E, Equation (3) boils down to:

$$K \equiv E[1 + (D - 1)R] \qquad (4)$$

According to Equation (4), the regional knowledge is a function of the knowledge capital stock, the number of productive activities residing in the region, and the relatedness R across activities. If the bundle of activities residing within the region are characterized by a high degree of relatedness (R>0), then the aggregate knowledge base increase with the number of activities D, weighted by their average relatedness. Conversely, if regional activities are featured by no relatedness (R=0), then the regional knowledge base is equal to the knowledge capital stock. Therefore, the traditional approach to the computation of the knowledge base turns out to be a special case where R=0.

Equation (4) can be approximated as follows:

$$K \cong EDR \qquad (5)$$

Substituting Equation (5) in (1) we therefore get:

$$g_{i,t} = f(E_{i,t-1} D_{i,t-1} R_{i,t-1}) \qquad (6)$$

Cross-regional differences in the knowledge base are likely to explain differences in productivity growth rates. In particular, the discussion conducted so far leads us to expect knowledge stock (*E*) and knowledge relatedness (*R*) to positively affect productivity growth, while the increase in knowledge variety (*D*) is likely to negatively affect regional performances.

3 The Economic Context

In the 1950s most Italian regions were rural, and populated by a large share of small- and medium-sized enterprises, as opposed to North-Western regions, which specialized in manufacturing activities, carried out by large firms. Analyzing the distribution of growth rates and structural change at the regional level in the period 1950-1970, the Ancona School identified and found the clues of a successful diffusion process of manufacturing activities towards such rural regions in the North-East and eventually in Central Italy, along the Adriatic coast. For this reason they proposed to group such regions into a larger macro-area which has been eventually called NEC (North-East-Centre)[4]. At the same time, the growth of manufacturing industries was slowing down in the North-West, wherein the growth of business service industries was already *in nuce* (Pettenati, 1991; Fuà and Zacchia, 1983).

Different factors were proposed in the 1970s as conducive to the successful territorial diffusion of manufacturing activities towards the NEC. On the one hand it has been argued that the widespread presence of small- and medium-sized firms contributed to create a favourable environment, characterized by low costs of living, intense utilization of labour potential, and the persistence of pretty informal labour relationships. Firms in turn benefited from these peculiarities in terms of lower costs and better business efficiency. Moreover they maintained that the small size scale and the specialization in labour-intensive activities, permitted in many ways swifter adaptation to changes in markets and technologies (Fuà, 1983, 1991a and 1991b; Fuà and Zacchia, 1983; Garofoli, 1981 and 1983).

[4] The grouping of Italian regions is as follows. North-West: Piedmont, Lombardy, Valle d'Aosta and Liguria. North-East: Veneto, Emilia-Romagna, Friuli Venezia-Giulia,Trentino Alto-Adige. Centre: Tuscany, Abruzzi, Marches, Lazio, Umbria and Molise. South: Campania, Apulia, Calabria, Basilicata, Sicilia and Sardegna.

On the other hand the relevance of the features of the social texture has been stressed, whereby the traditions rooted into the sharecropping system largely drawing on the informal institution of the "extended family" were persisting. The gradual diffusion of manufacturing did not seem to be paralleled by a simultaneous change of the social organization. Low wages and temporary jobs were accepted because of the weakness of labour market as an institution, substituted by the "extended family" which worked as a real self-regulatory system. In such a context dynamic pressures and attitude toward self-employment represented a key factor for the successful creation of manufacturing enterprises[5] (Paci, 1973 and 1992). The boosting role of institutional factors (above all embedded in the labour market) and the peculiarities of the economic structure, were maintained to lead to the set of positive-feedbacks well described by the industrial district theorists (Brusco, 1982; Becattini, 1989).

More recent evidence shows that the Italian economy has retained its delay in the industrialization process also during the last decades of the 20th century. The analysis carried out on the evolution of the regional specialization index in manufacturing sectors reveals that the geographical pattern has changed significantly over time. Indeed, the North-Eastern and Central regions are characterized by specialization indexes increasing over the period 1981-2001. It seems that at the turning of the century North-Eastern and Central regions are characterized by specialization indexes very close to (and in the some cases even higher than) the values featuring North-Western regions. Moreover the trend appears to be soundly positive in the former, while the values in the latter are continuously decreasing since the early 1980s (Quatraro, 2008).

4 Methodology

In order to investigate the effects of the characteristics of regional knowledge base on productivity growth, we first calculate an index of multi factor productivity (MFP). To this purpose we follow a standard growth accounting approach (Solow, 1957; Jorgenson, 1995; OECD, 2001). Let us start by assuming that the regional economy can be represented by a general Cobb-Douglas production function with constant returns to scale:

$$Y_{it} = A_{it} C_{it}^{\alpha_{it}} L_{it}^{\beta_{it}} \tag{7}$$

[5] The empirical analysis carried out by Garofoli (1994) addresses the issue of firms creation very exhaustively.

where L_{it} is the total hours worked in the region i at the time t, C_{it} is the level of the capital stock in the region i at the time t, and A_{it} is the level of MFP in the region i at the time t.

Following Euler's theorem, output elasticities have been calculated (and not estimated) using accounting data, by assuming constant returns to scale and perfect competition in both product and factors markets. The output elasticity of labour has therefore been computed as the factor share in total income:

$$\beta_{i,t} = (w_{i,t} L_{i,t}) / Y_{i,t} \tag{8}$$

$$\alpha_{i,t} = 1 - \beta_{i,t} \tag{9}$$

Where w is the average wage rate in region i at time t. Thus we obtain elasticities that vary both over time and across sectors.

Then the discrete approximation of annual growth rate of regional TFP is calculated as usual in the following way:

$$\ln\left(\frac{A_i(t)}{A_i(t-1)}\right) = \ln\left(\frac{Y_i(t)}{Y_i(t-1)}\right) - (1-\overline{\beta})\ln\left(\frac{K_i(t)}{K_i(t-1)}\right) - \overline{\beta}\ln\left(\frac{L_i(t)}{L_i(t-1)}\right) \tag{10}$$

The basic hypothesis of this paper is that growth rates of regions differences are driven by the characteristics of regional knowledge bases. The increase in the variety of activities is likely to create negative effects on productivity, due to coordination problems and the increase of absorption costs. On the contrary the increase in the knowledge stock and in the knowledge relatedness is likely to positively affect productivity growth.

The test of such hypothesis needs for modelling the growth rate of MFP as a function of the characteristics of the knowledge base. Moreover, as is usual in this kind of empirical settings, we include in the structural equation also the lagged value of MFP, $\ln A_{i,t-1}$, in order to capture the possibility of mean reversion. Therefore the econometric specification of Equation (1) becomes:

$$\ln\left(\frac{A_i(t)}{A_i(t-1)}\right) = a + b\ln A_{i,t-1} + c\ln K_{i,t-1} + \rho_i + \sum \psi t + \varepsilon_{i,t} \tag{11}$$

Substituting Equation (5) in (11), we obtain the following relationship:

$$\ln\left(\frac{A_i(t)}{A_i(t-1)}\right) = a + b\ln A_{i,t-1} + c_1\ln E_{i,t-1} + c_2\ln D_{i,t-1} + c_3\ln R_{i,t-1} + \rho_i + \sum \psi t + \varepsilon_{i,t} \tag{12}$$

Where the error term is decomposed in ρ_i and $\Sigma\psi t$, which are respectively region and time effects, and the error component ε_{it}. Equation (12) can be estimated using traditional panel data techniques implementing the fixed effect estimator.

4.1 *Panel Data and Spatial Dependence*

The analysis of the effects of knowledge on productivity growth at the regional level calls for a special focus on the geographical attributes of such relations, i.e. on locational aspects. Regional scientists have indeed showed that geographical proximity may affect correlation between economic variables.

While the traditional econometric approach has mostly neglected this problem, a new body of literature has recently developed, dealing with the identification of estimators able to account for both spatial dependence between the relationships between observations and spatial heterogeneity in the empirical model to be estimated. Former treatment of spatial econometric issues can be found in Anselin (1988), subsequently extended by Le Sage (1999).

The idea behind the concept of spatial dependence is straightforward. The properties of economic and social activities of an observed individual are likely to influence economic and social activities of neighbour individuals. Formally this relationship can be expressed as follows:

$$y_{i,t} = h(y_{j,t}),\ i = 1,\ldots,n,\ j \neq i \tag{13}$$

The dependence can therefore be among several observations. If this is the case, structural forms like equation (12) are likely to produce a bias the estimation results. There are different ways to cope with this issue. First, one may apply spatial filters to the sample data, so as to remove the spatial structure and then apply traditional estimation techniques. Second, the relationship can be reframed using a spatial error model, in which the error term is further decomposed so as to include a spatial autocorrelation coefficient. Third, one may apple the spatial lag model, which consists of including the spatially lagged dependent variable in the structural equation.

We decided to adopt the spatial lag model in order to have a direct assessment of the spatial dependence of productivity growth between close regions. However, most of the existing literature on spatial econometrics propose estimator appropriate for cross-sectional data. Given the panel data structure of our sample, we therefore follow Elhorst (2003) extending the Equation (12) so as to introduce the spatially lagged dependent variable:

$$\ln\left(\frac{A_i(t)}{A_i(t-1)}\right) = \xi W \ln\left(\frac{A_i(t)}{A_i(t-1)}\right) + b \ln A_{i,t-1} + c_1 \ln E_{i,t-1} + \\ + c_2 \ln D_{i,t-1} + c_3 \ln R_{i,t-1} + \rho_i + \sum \psi t + \varepsilon_{i,t} \tag{14}$$

Where ξ is referred to as spatially autoregressive coefficient and W is a weighting matrix. This latter can be defined either as a contiguity or as a normalized distance matrix. In the analysis that follows we chose the second alternative, by building a 19x19 symmetric matrix reporting the distance in kilometres among the city centre of the regional chief towns.

4.2 *The Implementation of Regional Knowledge Indicators*

As far as the measures of regional knowledge are concerned, we used patent statistics to derive three variables. First of all regional knowledge stock is computed by applying the permanent inventory method to patent applications. We calculated it as the cumulated stock of past patent applications using a rate of obsolescence of 15% per annum: $E_{i,t} = \dot{h}_{i,t} + (1-\delta)E_{i,t-1}$, where $\dot{h}_{i,t}$ is the flow of regional patent applications and δ is the rate of obsolescence.

Secondly, we decided to calculate variety in regional knowledge by using the information entropy index. Entropy measures the degree of disorder or randomness of the system, so that systems characterized by a high entropy will also be characterized by a high degree of uncertainty (Saviotti, 1988).

Such index was introduced to economic analysis by Theil (1967). Its earlier applications aimed at measuring diversity of an industry (or of a sample of firms within an industry) against a uniform distribution of economic activities in all sectors, or among firms (Attaran, 1985; Frenken et al., 2007). Recently Frenken et al. (1999) and Frenken et al. (2004) analyzed the degree of variety and uncertainty within a technological population.

Differently from common measures of variety and concentration, the information entropy has the interesting property of decomposability (Frenken, 2004). In particular the total index can be decomposed in a "within" and a "between" part anytime the events to be investigated can be aggregated in a smaller numbers of subsets. Within-entropy measures the average degree of disorder or variety within the subsets, while between-entropy focuses on the subsets measuring the variety across them.

Another important feature of the entropy measure for our purposes is its multidimensional extension. Consider a pair of events (X_i, Y_j), and the probability of co-occurrence of both of them p_{ij}. A two dimensional (total) entropy measure can be expressed as follows:

$$H(X,Y)=\sum_{i=1}^{m}\sum_{j=1}^{n}p_{ij}\log_2\left(\frac{1}{p_{ij}}\right) \tag{15}$$

It can be easily shown that the decomposition theorem holds also for the multidimensional case. Hence if one allows $i \in S_g$ and $j \in S_z$ (g = 1,…,G; z = 1,…, Z), we can rewrite $H(X,Y)$ as follows:

$$H(X,Y)=H_Q+\sum_{g=1}^{G}\sum_{z=1}^{Z}P_{gz}H_{gz} \tag{16}$$

Where the first term of the right-hand-side is the between-entropy and the second term is the (weighted) within-entropy. In particular:

$$P_{gz}=\sum_{i\in S_g}\sum_{j\in S_Z}p_{ij}$$

$$H_Q=\sum_{g=1}^{G}\sum_{z=1}^{Z}P_{gz}\log_2\frac{1}{P_{gz}} \tag{17}$$

$$H_{gz}=\sum_{i\in S_g}\sum_{j\in S_z}\frac{p_{ij}}{P_{gz}}\log_2\left(\frac{1}{p_{ij}/P_{gz}}\right) \tag{18}$$

If one considers p_{ij} to be the probability that two technological classes i and j co-occur within the same patent, then the measure of multidimensional entropy focuses on the variety of co-occurrences of technological classes within regional patents applications. It must be stressed that to introduce some rigidities in the regional technological portfolio, and to compensate for intrinsic volatility of patenting behaviour, each patent application is meant to last five years.

Third, we calculated the coherence of the regional knowledge base, defined as the average relatedness of any technology randomly chosen within a region with respect to any other technology (Nesta and Saviotti, 2005 and 2006; Nesta, 2008). Thus it is a measure on how much the technologies present within the region are related each other.

Let us start by calculating the relatedness matrix. The technological universe consists of k patent applications. Let P_{ik} = 1 if the patent k is assigned the technology i [i = 1, …, n], and 0 otherwise. The total number of patents assigned to technology i is $O_i=\sum_k P_{ik}$. Similarly, the total number of patents assigned to technology j is $O_j = \sum_k P_{jk}$. Since two technologies may occur within the same patent, $O_i \cap O_j \neq \varnothing$, and thus the observed the number of observed co-occurrences of technologies i and j is $J_{ij} = \sum_k P_{ik} P_{jk}$ .. Applying this relationship to all possible pairs, we yield a square matrix Ω (n × n) whose generic cell is the observed number of co-occurrences:

$$\Omega = \begin{bmatrix} J_{11} & & J_{i1} & & J_{n1} \\ \vdots & \ddots & & & \vdots \\ J_{1j} & & J_{ij} & & J_{nj} \\ \vdots & & & \ddots & \vdots \\ J_{1n} & \cdots & J_{in} & \cdots & J_{nn} \end{bmatrix} \tag{19}$$

We assume that the number x_{ij} of patents assigned to both technologies i and j is a hypergeometric random variable of mean and variance:

$$\mu_{ij} = E(X_{ij} = x) = \frac{O_i O_j}{K} \tag{20}$$

$$\sigma_{ij}^2 = \mu_{ij} \left(\frac{K - O_i}{K} \right) \left(\frac{K - O_j}{K - 1} \right) \tag{21}$$

If the observed number of co-occurrences J_{ij} is larger than the expected number of random co-occurrences μ_{ij}, then the two technologies are closely related: the fact the two technologies occur together in the number of patents *xij* is not casual. The measure of relatedness hence is given by the difference between the observed number and the expected number of co-occurrences, weighted by their standard deviation:

$$\tau_{ij} = \frac{J_{ij} - \mu_{ij}}{\sigma_{ij}} \tag{22}$$

It is worth noting that such relatedness measure ha so lower and upper bounds: $\tau_{ij} \in \left]-\infty;+\infty\right[$. Moreover, the index shows a distribution similar to a t-student, so that if $\tau_{ij} \in \left]-1.96;+1.96\right[$, one can safely accept the null hypothesis of non-relatedness of the two technologies i and j. The technological relatedness matrix Ω′ may hence be thought about as a weighting scheme to evaluate the technological portfolio of regions. To yield the coherence index (or knowledge relatedness), a number of steps is still required. In what follows I will describe how to obtain the index at the regional level. First of all, one should calculate the weighted average relatedness WAR_i of technology i with respect to all other technologies present within the sector. Following Teece et al. (1994), WAR_i is defined as the degree to which technology i is related to all other technologies $j \neq i$ within the region k, weighted by patent count P_{jkt}:

$$WAR_{ikt} = \frac{\sum_{j \neq i} \tau_{ij} P_{jkt}}{\sum_{j \neq i} P_{jkt}} \tag{23}$$

Finally the coherence of knowledge base within the sector is defined as weighted average of the WAR_{ikt} measure:

$$R_{kt} = \sum_{i \neq j} WAR_{ikt} \times \frac{P_{ikt}}{\sum_i P_{ikt}} \tag{24}$$

5 The Data

The data we used to test the relationship between productivity growth and regional knowledge have been drawn from two main sources. We employed data from the regional accounts provided by Italian Institute of Statistics (ISTAT) to calculate the MFP index. We used real GDP (1995 constant prices) as a measure of regional output, regional labour income to compute the output elasticity of labour, regional employment level as a proxy for labour input, real gross fixed investments to derive capital stock (see Appendix).

To calculate the measures of regional knowledge base we employed an original dataset of patent applications submitted to the European Patent Office, as proxy of technological activities within the manufacturing sector[6]. Each patent is assigned to a region, on the basis on the inventors' addresses. Detailed information about the patents' contents has been drawn from the Thomson Derwent World Patent Index®. Each patent is classified in different technological field according to the Derwent classification. All technologies are covered by 20 subject areas designated as follows: classes A to M are in chemicals, P to Q refer to engineering, S to X refer to Electrical and Electronic. Each of the subject areas is in turn subdivided intro 3-digit classes.

We used the 3-digit classification to calculate both knowledge relatedness and information entropy. The decomposition of the entropy measure has been

[6] The debate about the nature of innovation activities within service sectors has recently received increasing attention. Tether (2005) and Consoli (2007) offer good critical syntheses of it. Evangelista and Sirilli (1998) and Evangelista (2000) present the Italian evidence, emphasizing the very marginal role played by patents in innovation dynamics within service sectors.

conducted by the subject areas as subsets, so as to obtain information entropy both 'within' and 'between' subject areas.

The initial patent dataset consists of 55377 observations and 336 3-digit classes spread across 19 regions over the period ranging from 1979 to 2003. After the calculations we ended up with a vector of three knowledge variables, observed for each region over the time period 1981 – 2002. Such vector has then been matched with the vector of regional productivity growth rates for over the same period for the corresponding regions.

Table 1 and 2 provide the descriptive statistics for the set of variables used in the analysis and show general information about the various sampled regions. The sample is made of 19 Italian regions[7] and is characterized by a high degree of variance for what concerns both the knowledge variables and the growth rates of multi factor productivity.

>>>INSERT TABLES 1 AND 2 ABOUT HERE<<<

In particular, from Table 2 it seems to emerge a puzzling pattern of geographical distribution for the knowledge variables. For example, while we expected negative values for knowledge relatedness in North-Western regions, similar evidence for some North-Eastern regions is slightly puzzling. Negative values of knowledge relatedness are indeed to be associated with periods of random screening in research activities, typical of exploration stages. Innovation systems featured by the predominance of a mature paradigm are likely to undertake research efforts along a variety of paths, unless new profitable fields are sorted out, leaving room for the exploitation stage (and the consequent rise in knowledge relatedness). The evidence of regions like Emilia Romagna and Tuscany suggests therefore that their industrial and technological development is more similar to that of North-Western regions than to that of North-East, maybe due to their faster growth patterns during the 1980s.

6 Empirical Results

Table 3 report the fixed-effects panel data estimations of Equation (12). In column (1) we report the estimation conducted using the total information entropy as a proxy variable for variety. The coefficients for the knowledge variables are all highly significant and have the expected sign. Both knowledge capital stock and knowledge relatedness show positive coefficients. However, it is worth emphasizing that the coefficient for the latter variable is twice that for the former variable. This provides strong support to the idea that knowledge has to be regarded as a heterogeneous rather than a homogenous asset, and that

[7] We left out the Molise region due to very low levels of innovation activity over time.

the internal coherence of the knowledge base has a far higher effect on productivity growth than the indiscriminate accumulation of knowledge capital. Conversely, the degree of variety turns out to show a negative and significant coefficient. A higher number of observed combination of technological classes is likely to signal a random screening process, associated to periods of productivity losses.

>>> INSERT TABLE 3 ABOUT HERE <<<

Columns (2) and (3) of Table (3) try to assess the separate effects of between-group and within-group entropy respectively. The results for knowledge capital and knowledge relatedness are pretty persistent. Both display positive and significant coefficients, and the ratio between the effects of knowledge relatedness on productivity growth is still twice that of knowledge capital. The coefficient for the between-group information entropy is very low and is not statistically significant. On the contrary the within-group information entropy is characterized by a negative and significant coefficient, suggesting that the negative effect of total information entropy is driven by its within-group component.

The results of the empirical analyses provide supporting evidence for the basic hypotheses of this paper. First, differences in the level of technological development are likely to affect regional differences in productivity growth. Second, The characteristics of the knowledge base, in terms of the coherence of its knowledge base and the variety of technological combinations, are even more important in shaping regional productivity dynamics.

6.1 Productivity Growth and Spatial Dependence

The results showed in the previous section provide interesting evidence about the effects of regional knowledge base on productivity dynamics. However, recent advances in the analysis of spatial economic dynamics has pointed to the importance of proximity among economic agents. While the focus on the regional level does not allow to investigate this issue from a microeconomic viewpoint, nonetheless the presence of cross-regional external economies may cause a bias in the estimation using techniques that do not account for spatial dependence.

There are good reasons to expect spatial dependence to affect regional productivity growth. The simple idea is that productivity growth in one region is likely to boost productivity growth in neighbour or close regions. This is the case when pecuniary knowledge externalities are at stake (Scitovski, 1954; Antonelli, 2007). The commitment of resources to research and development activities within a region is likely to trigger productivity growth, provided such efforts are directed towards the integration of closely related activities and the reduction of variety in technological combinations. Such productivity gains are likely to lower production costs of the economic agents that take benefits of them. Coeteris paribus, such reduction in production costs is (at least) partially transferred to final prices of produced goods. Would these goods be intermediate inputs to other production process, such reduction of the price in upstream markets translates into a reduction in the production costs for agents in downstream markets. This is in turn reflected in productivity growth.

Now, a large body of literature has stressed the importance of geography for vertical relationships. Therefore, productivity gains of agents operating in upstream markets are likely to influence productivity dynamics of those operating downstream in the value chain. Should this phenomenon be very significant, it should be also reflected in aggregate industrial productivity dynamics[8].

Table 4 reports the results from the econometric estimation of Equation (15)[9]. The first two columns report the model that consider total information entropy as a variety measure. In particular the results in column (1) are yielded by including only time-dummies, while those in column (2) include both time and region dummies. The results are fairly interesting. First of all it must be noted that all the knowledge variables are statistically significant, and that the sign of coefficients are consistent with the previous estimations. Therefore, our results are robust to the checks for spatial dependence. Knowledge relatedness and knowledge capital have positive effects on the growth of regional multifactor productivity. The impact of knowledge relatedness is far stronger than that of knowledge capital. On the contrary, the higher the variety of technological combinations, the lower will be productivity growth.

>>> INSERT TABLE 4 ABOUT HERE <<<

A striking result concerns the coefficient for the (time) lagged value of multifactor productivity, which turns out now to be negative and statistically significant. Such evidence would suggest that, once controlling for spatial dependence in productivity growth, regional productivity shows a convergence pattern, although the magnitude of the coefficient is not very high. Finally, the coefficient on the spatially lagged dependent variable turns out to be positive and statistically significant, although the fixed effect estimation performs better than the no-fixed effects one. This positive coefficient supports the idea of the

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[8] One may argue that the exclusion of service sectors of course does not allow to fully appreciate the transmission of productivity gains downwards in the value chain. Yet, the emphasis on productivity gains stemming from knowledge production signalled by patents data once again makes it necessary to focus sharply on manufacturing.

[9] We employed the log-likelihood fixed-effects panel data estimator implemented by Paul Elhorst and available at the web address www.spatial-econometrics.com.

transmission of productivity gains from one region to the closest ones, through the effects of cross-regional pecuniary knowledge externalities.

The remainder columns estimate the separate effects of between-group entropy (cols (3) and (4)) and of within-group entropy (cols (5) and (6)). Also in this case the results are very consistent with the estimations in the previous section. Once again coefficients for knowledge capital and knowledge relatedness are positive and statistically significant, while the negative effect seems to be driven by within-group rather than between-group entropy, which in turn did not prove to be statistically significant. The results concerning the lagged productivity variable are robust to the different specifications, suggesting that indeed cross-regional convergence patterns emerge once spatial dependence of productivity growth is accounted for. The same applies to the spatially lagged dependent variable, according to which productivity growth of regions tends to be influences by that of their neighbours.

7 Conclusions

A wide body of literature has emphasized the importance of knowledge as a strategic asset for the competitive advantage of regions. Both the regional innovation system approach and the school emphasizing the concept of learning regions have provided important contributions to the understanding of the spatial dynamics of knowledge generation.

Yet, empirical analyses of the determinants of regional differential growth rates have quite neglected the investigation of the effects of knowledge and innovation on productivity. Much attention has been given to the analysis of convergence patterns across regions and to the identification of the variables allowing for a reliable estimation of conditional convergence. Recent contributions have partially filled this gap, by focusing on the investigation of the determinants of the efficiency of knowledge generating activities by adopting a knowledge production approach.

In this paper we have made some steps forward, by providing an empirical estimation of the impact of regional knowledge base on multifactor productivity growth. In doing so, we have adopted a competence-based view of the region, which has allowed us to go beyond the simplistic view of knowledge as a homogenous asset and to follow the more recent developments that have proposed notion of knowledge as heterogeneous (Nesta, 2008).

We have conducted our analysis on a sample of 19 Italian regions over the period 1981-2002, focusing on manufacturing sectors. We have calculated annual multifactor productivity growth for each region, and then we have computed as knowledge variables the traditional knowledge capital, knowledge relatedness and knowledge variety (proxied by information entropy).

The results of empirical analysis confirm that the regional knowledge base do affect productivity growth rates. In particular, not only the level of knowledge production matters, but the characteristics of the knowledge base exert even a higher impact. In particular, as expected, the degree of internal coherence of the knowledge base has a positive effect, while the variety of technological combinations negatively affects productivity growth. Such results are fairly robust, and persist also when accounting for spatial dependence in productivity growth. Moreover, when the role of cross-regional pecuniary knowledge externalities is accounted for, the results of the estimations provide evidence of a slow convergence process across regions.

Such results have important policy implications, in terms of regional strategies for innovation and knowledge production. In particular, an effective regional innovation strategy should be complemented by intentional and careful coordination mechanisms, able to provide an integrated direction to research and innovation efforts undertaken by the variety of agents that made up the innovation system. The regional production system would then take advantage of a bundle of technological activities showing a high degree of relatedness and therefore more likely to be properly absorbed and successfully exploited.

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Table 1 - Descriptive Statistics

Variable		Mean	Std. Dev.	Min	Max	Observations		
E	overall	1232.625	2380.950	1.000	15795.300	N	=	418
	between		1979.379	29.605	8106.422	n	=	19
	within		1391.848	-6400.797	8921.506	T	=	22
R	overall	0.373	0.953	-0.545	6.407	N	=	418
	between		0.671	-0.316	2.125	n	=	19
	within		0.697	-2.243	5.041	T	=	22
IE	overall	7.371	2.262	0	11.297	N	=	418
	between		1.862	4.139	10.771	n	=	19
	within		1.382	-0.086	9.884	T	=	22
IEW	overall	2.525	1.293	0	5.178	N	=	418
	between		1.129	0.839	4.649	n	=	19
	within		0.703	-1.838	3.821	T	=	22
IEB	overall	4.866	1.138	0	6.416	N	=	418
	between		0.799	3.459	6.118	n	=	19
	within		0.841	0.188	6.816	T	=	22
dlogA/dt	overall	0.014	0.048	-0.203	0.292	N	=	418
	between		0.009	0.000	0.037	n	=	19
	within		0.047	-0.200	0.269	T	=	22

E: knowledge capital; *R*: knowledge relatedness; *IE*: information entropy; *IEW*: within-group information entropy; *IEB*: between-group information entropy; dlogA/dt: growth rate of multifactor productivity.

Table 2 - Regional Decomposition of Variables (1981-2002)

	E	*R*	*IE*	*IEW*	*IEB*	*dlogA/dt*
Piemonte	3860.667	-0.316	10.097	4.340	5.756	0.007
Valle d'Aosta	29.605	2.125	4.703	1.232	3.459	0.003
Liguria	708.112	0.532	8.306	2.707	5.617	0.000
Lombardia	8106.422	-0.232	10.772	4.651	6.117	0.016
Trentino Alto Adige	246.614	0.189	6.930	2.277	4.635	0.019
Veneto	2088.573	-0.206	9.036	3.654	5.386	0.023
Friuli Venezia Giulia	834.670	-0.103	7.846	2.737	5.118	0.018
Emilia Romagna	2993.007	-0.223	9.651	4.357	5.285	0.017
Toscana	1219.773	-0.155	8.903	3.161	5.742	0.011
Umbria	175.860	0.253	6.676	1.948	4.766	0.003
Marche	355.378	0.036	6.856	2.31	4.555	0.019
Lazio	1380.175	0.038	8.934	3.071	5.876	0.022
Abruzzo	414.795	0.921	6.161	2.306	3.828	0.025
Campania	260.018	0.357	6.965	2.026	4.997	0.011
Puglia	175.072	0.243	6.436	1.803	4.649	0.014
Basilicata	34.280	1.496	4.292	0.8581	3.326	0.042
Calabria	46.251	1.060	5.357	1.216	4.102	0.016
Sicilia	308.488	0.063	6.387	1.699	4.661	0.000
Sardegna	73.174	1.114	5.423	1.176	4.237	0.007

E: knowledge capital; *R*: knowledge relatedness; *IE*: information entropy; *IEW*: within-group information entropy; *IEB*: between-group information entropy; dlogA/dt: growth rate of multifactor productivity.

Table 3 - Panel Data Estimates of Equation (12)

	(1)	(2)	(3)
$\log A_{t-1}$	0.0066	-0.004	0.003
	(0.021)	(0.022)	(0.021)
$\log(E)_{t-1}$	0.056***	0.021**	0.036***
	(0.012)	(0.009)	(0.016)
$\log(R)_{t-1}$	0.121***	0.096**	0.077**
	(0.038)	(0.039)	(0.038)
$\log(IE)_{t-1}$	-0.043***		
	(0.009)		
$\log(IEB)_{t-1}$		0.0002	
		(0.005)	
$\log(IEW)_{t-1}$			-0.015***
			(0.005)
Regional dummies	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes
Rsq	0.31	0.28	0.29
F	6.63***	5.59***	5.93***
N	418	418	418

Dependent Variable: $\log(A_t / A_{t-1})$. * : $p<0.1$; ** : $p<0.05$; *** : $p<0.01$. Standard errors between parentheses.

Table 4 - Results for the Estimation of Equation (23) (Spatial Autoregressive Model)

	(1)	(2)	(3)	(4)	(5)	(6)
$logA_{t-1}$	-0.026***	-0.029***	-0.026***	-0.032***	-0.026***	-0.030***
	(-3.886)	(-3.817)	(-3.888)	(-3.974)	(3.906)	(-3.907)
$W[log(A_t /A_{t-1})]$	0.188*	0.192**	0.184*	0.189*	0.186*	0.187*
	(1,74)	(1.816)	(1.712)	(1.781)	(1.723)	(1.766)
$log(E)_{t-1}$	0.010***	0.018***	0.006***	0.007***	0.008***	0.014***
	(2.846)	(3.509)	(2.939)	(3.141)	(2.556)	(3.384)
$log(R)_{t-1}$	0.076**	0.093***	0.057*	0.061*	0.067**	0.091***
	(2.171)	(2.317)	(1.739)	(1.585)	(1.922)	(2.227)
$log(IE)_{t-1}$	-0.009	-0.020**				
	(-1.438)	(-2.311)				
$log(IEB)_{t-1}$			-0.0002	-0.0007		
			(-0.049)	(-0.148)		
$log(IEW)_{t-1}$					-0.003	-0.009**
					(-0.800)	(-1.898)
Regional dummies	No	Yes	No	Yes	No	Yes
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	649.093	658.874	648.187	656.563	648.452	658.004
N	418	418	418	418	418	418

Dependent Variable: $log(A_t /A_{t-1})$. *t* of Student between parentheses. * : p<0.1; ** : p<0.05; *** : p<0.01.