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Knowledge Coherence, Variety and Productivity Growth: Manufacturing Evidence from Italian Regions:

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Knowledge Coherence, Variety and Productivity Growth: Manufacturing Evidence from Italian Regions[1].

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ABSTRACT. This paper analyzes the effects of the evolution of knowledge base in the manufacturing sectors on regional productivity growth. Knowledge is viewed as a heterogeneous asset, and an evolutionary perspective is adopted. The results of the empirical estimations corroborate the hypothesis that beyond the traditional measure of knowledge stock, knowledge coherence and variety matter in shaping productivity dynamics. The check for spatial dependence suggests that cross-regional externalities exert additional triggering effects on productivity growth, without debasing the effects of knowledge. Important policy implications stem from the analysis, in that regional innovation strategies should be carefully coordinated so as to reach a higher degree of internal coherence and exert positive effects on productivity.

Keywords: Knowledge, Variety, Regional growth, Productivity

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.

However, empirical contributions estimating the relationship between knowledge and productivity has appeared only after the path-breaking works by Zvi Griliches (1979). Most of them consisted of industry- or firm-level analyses[2], while much a lower number of studies provided cross-country comparisons of the relationship between knowledge and productivity growth[3].

For what concerns the regional dimension of technological knowledge, econometric works have appeared quite recently, and are mainly focused on the investigation of the determinants of cross-regional differences in the efficiency of knowledge production, like knowledge spillovers and spatial proximity (Acs et al., 2002; Fritsch, 2002 and 2004; Fritsch and Franke, 2004; Crescenzi et al., 2007).

Yet, to the best of author's knowledge, no econometric investigations can be found in literature analyzing the effects of technological knowledge on regional productivity growth. 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 multifactor productivity (MFP). We focus on the dynamics of manufacturing sector within Italian regions over the period 1981-2002.

[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).

The effects of knowledge on productivity growth are investigated by adopting an evolutionary viewpoint, which is likely to provide a better understanding of the dynamics of regional economic development (Scott, 2004; Boschma and Frenken, 2006).

Within this theoretical framework we introduce the concept of regional innovation capabilities, which draws upon the competence-based theory of the region (Lawson, 1999; Lawson and Lorenz, 1999). They consist in the ability to generate new variety within regional economic contexts, and emerge over time from local systemic interactions in relationship to the stage of industrial development (Kuznets, 1930). The evolution of regional knowledge is indeed a path dependent process, in which variety is likely to follow the evolution of the business cycle. Moreover innovation activities are localized in that dynamic irreversibilities make them highly idiosyncratic, i.e. shaped by the set of competences that have been accumulated within the region over time (Boschma and Lambooy, 1999; Antonelli, 2008a; Quatraro 2008a).

The emphasis on systemic interactions, and therefore on the collective character of knowledge production, allows us to understand the regional knowledge base as a co-relational structure. Thus, besides the traditional measure of knowledge capital stock, additional properties of the knowledge base can be derived, drawing upon the co-occurrence of technological classes within patent documents (Saviotti, 2004 and 2007). In view of this, our empirical investigation also includes two additional variables able to qualify the regional knowledge base, i.e. knowledge coherence and variety (Nesta and Saviotti, 2005; Nesta, 2008).

The case of Italian manufacturing within this picture deserves to be investigated 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). Such cross-regional differences in the development of manufacturing sectors appeared in turn to be strictly related to differences in the emergence of regional innovation capabilities. In particular, manufacturing sectors have proved to be the pillars of sustained productivity in NEC areas along the 1980s and the 1990s, due to their relatively intensive innovative potentials (Quatraro, 2008a and b).

In this context, the contribution of this paper to the literature is twofold. On the one hand such analysis is relevant for its general implications concerning the relationships between the dynamics of technological knowledge and regional productivity growth, in particular with respect to regional innovation strategies. On the other hand, it also 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 knowledge and innovation.

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

2 The Theoretical Framework

The theoretical underpinnings of evolutionary economics are rooted in the seminal contributions by Schumpeter. Innovation is regarded as the main engine of economic development. In the first place, it was the innovative entrepreneur who brings about new products, process, intermediate goods and markets in the economic system (Schumpeter 1911/1934). Large firms eventually became the main innovating agents, in a context shaped by the search for extra-profits and by the sacrifice of static to dynamic efficiency (Schumpeter, 1942).

The triggering effects of innovation on productivity growth are due to the efficiency gains in the production process. Moreover, the introduction of innovations brings about new variety within the economic system, providing the basis for restless economic growth (Metcalfe, 2002). Indeed, the creation of new sectors by means of innovations is likely to counterbalance the tendency to underemployment in mature sectors and favours the shift of employment from older and less productive to newer and more productive sectors (Saviotti, 1996).

In this direction evolutionary economics is quite close to Perroux' growth pole theory (Perroux, 1955). Following Schumpeter he indeed emphasized the role of technological change regional development, providing the (neglected) bases for an evolutionary economic geography. Regional economic systems are characterized by rounds of growth, i.e. periods in which firms within the propulsive industry grow at faster rates, propagating the positive effects across firms directly and indirectly related to the propulsive industry. The main driving factor of such expansion is technical efficiency gained through innovation efforts. Therefore cross-regional differences in innovation dynamics are likely to be associated to differences in productivity growth.

The competitive forces driving the expansion of such an industry however do not work indefinitely, as growth rates are expected to slacken. New industries are then likely to emerge, as an effect of the introduction of radical innovations within the system (Kuznets, 1930; Burns, 1934). Within the new industry firms will innovate to gain competitive advantages and gales of incremental innovations show up in a positive climate in which one firm introduces an innovation, stimulating the creative response of other economic agents[4].

The economic development of regions is therefore strictly related to the main industries they are specialized in. Path-dependence and dynamic irreversibilities make it difficult for regions locked into earlier specializations with mature lifecycles to promptly adapt to the emergence of new sectors and new product specialization. Such regions are therefore expected to decline, unless a set of intentional actions are undertaken aimed at fostering the shift towards newer and more productive economic activities (Boschma and Frenken, 2006).

In sum, the dynamics of industrial development within regional context is intertwined with innovation dynamics, and hence with the dynamics of variety creation. The extension of the concept of innovation capabilities to the regional domain allows us both to appreciate such historical dimension and to view the region as a bundle of resources. This in turn makes it possible to qualify the knowledge base within the region as essentially heterogeneous, as it stems from the recombination of diverse, and not always related, locally available bits of knowledge (Antonelli, 2008; Nesta, 2008).

[4] Thomas (1975) articulated the implications of Perroux' framework on regional economic growth using a product life-cycle perspective, wherein the saturation of product markets are the main responsible for the slowdown of growth rates and the quest for innovations aims at opening new markets.

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, 2008a).

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).

Thus, the very essence of knowledge base lies in its collective nature, which confers the basic properties of being a co-relational structure. This allows for qualifying both the cumulative character of knowledge and the key role played by complementarity in the activity of recombination. The knowledge base can be represented as a network in which the nodes are constituted by units of knowledge at a given level of aggregation. The higher the complementarity among such diverse smaller units of knowledge, the stronger the degree of internal coherence of the aggregate knowledge base. This in turn makes it possible the working of knowledge externalities and the effective cross-fertilization across the diverse technological activities within the local system of innovation (Saviotti, 2004 and 2007).

2.1 The model

The discussion conducted above leads us to propose a simple model to appreciate the effects of the properties of technological knowledge on regional economic growth:

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

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:

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

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:

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

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:

$$K \equiv E[1 + (D-1)R] \tag{4}$$

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 *coherence* (*R*) across activities. If the bundle of activities residing within the region are characterized by a high degree of coherence (*R*>0), then the aggregate knowledge base increase with the *variety of technological competences* (*D*), weighted by their average relatedness. Conversely, if regional activities are featured by no coherence (*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:

$$K \cong EDR \tag{5}$$

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

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

In view of the arguments elaborated so far we are now able to spell out or working hypotheses. 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). We therefore expect *E* to be positively related to productivity growth.

A region can be viewed as a locus for the accumulation of diverse competences and technological knowledge. Not only differences in knowledge stock matter. The creation of new technological knowledge is likely to engender the introduction of innovations. These in turn are the main way through which variety is brought about in the economic system. Variety is therefore a key feature, whose effects deserve to be carefully investigated. The increase in the variety of technological knowledge is likely to be related to an increase in technological opportunities and therefore to economic development. We may therefore expect D to be positively related to productivity growth.

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.

The positive effects on productivity stemming from cross-fertilization and knowledge externalities, are more likely to occur in regions able to combine together different and yet complementary technological activities. Conversely, the attraction of activities based upon weak complementarity of technological competences makes it difficult to implement effective systemic interactions that are at the core of the collective process of knowledge production. In this case regional productivity dynamics are hardly driven by innovation performances. Therefore, in order to foster productivity growth, regional actors must pursue diversification in related activities, which are likely to share related knowledge bases. Knowledge coherence (R) is thus expected to positively affect productivity growth.

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, 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)[5]. 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).

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

[5] 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.

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[6] (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, 2008a and b).

4 Methodology

In order to investigate the effects of the properties of regional knowledge base on productivity growth, we first calculate an index of multi factor productivity (MFP)[7]. To this purpose we follow a standard growth accounting approach (Solow, 1957; Jorgenson, 1995;

[6] The empirical analysis carried out by Garofoli (1994) addresses the issue of firms creation very exhaustively.
[7] Some basic questions of course remain as to what interpretations to give to these kinds of index. While Solow (1957) associated TFP growth with technological advances, Abramovitz (1956) defined the residual as some sort of measure of ignorance. Nonetheless it remains a useful signalling device, in that it provides useful hints on where the attention of the analysts should focus (Maddison, 1987).

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:

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

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 regions.

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

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

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 (6) becomes:

$$\ln\left(\frac{A_i(t)}{A_i(t-1)}\right) = a + b\ln A_{i,t-1} + c_1 \ln E_{i,t-1} + c_2 \ln D_{i,t-1} + c_3 \ln R_{i,t-1} + \rho_i + \sum \psi t + \varepsilon_{i,t} \quad (11)$$

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 (11) can be estimated using traditional panel data techniques implementing the fixed effect estimator. It relates the rates of productivity growth to the characteristics of knowledge base. However, one needs to control for the impact on the one hand of agglomeration economies, on the other hand of changing regional industrial specialization, so as to rule out the possibility that such effects are somehow captured by the knowledge-related variables. In view of this, we can write Equation (11) as follows:

$$\begin{aligned} \ln\left(\frac{A_i(t)}{A_i(t-1)}\right) &= a + b\ln A_{i,t-1} + c_1 \ln E_{i,t-1} + c_2 \ln D_{i,t-1} + c_3 \ln R_{i,t-1} + \\ &+ c_4 AGGL_{t-1} + c_5 LOQ_{t-1} + \rho_i + \sum \psi t + \varepsilon_{i,t} \end{aligned} \quad (12)$$

Productivity growth rates depend now not only on knowledge capital stock, variety and coherence (respectively E, D and R). Following Crescenzi et al. (2007), the effects agglomeration economies are captured by the variable $AGGL$, which is calculated as the (log) ratio between regional population and size (square kilometres). The changing specialization is instead proxied by LOQ, i.e. the location quotient for manufacturing added value.

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:

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

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 (SEM), in which the error term is further decomposed so as to include a spatial autocorrelation coefficient. Third, one may apple the spatial autoregressive model (SAR), which consists of including the spatially lagged dependent variable in the structural equation.

We decided to compare the SAR and SEM models 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 Equation (12) so as to obtain the SAR (Eq. 14) and the SEM (Eq. 15) specifications:

$$\ln\left(\frac{A_i(t)}{A_i(t-1)}\right) = \xi W \ln\left(\frac{A_i(t)}{A_i(t-1)}\right) + b\ln A_{i,t-1} + c_1 \ln E_{i,t-1} + \\ + c_2 \ln D_{i,t-1} + c_3 \ln R_{i,t-1} + c_4 AGGL_{t-1} + c_5 LOQ_{t-1} + \rho_i + \sum \psi t + \varepsilon_{i,t} \qquad (14)$$

$$\ln\left(\frac{A_i(t)}{A_i(t-1)}\right) = b\ln A_{i,t-1} + c_1 \ln E_{i,t-1} + c_2 \ln D_{i,t-1} + c_3 \ln R_{i,t-1} + \\ + c_4 AGGL_{t-1} + c_5 LOQ_{t-1} + \rho_i + \sum \psi t + \varepsilon_{i,t} + \phi_t \qquad (15)$$

$$\phi_t = \delta W \phi_t + \mu_t, \; E(\mu_t) = 0, \; E(\mu_t \mu_t^{'}) = \sigma^2 I_N$$

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. 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.

1) 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.

2) Secondly, we decided to measure *D* (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).

Differently from common measures of variety and concentration, the information entropy has some interesting properties (Frenken, 2004). An important feature of the entropy measure 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 (*IE*) measure can be expressed as follows:

$$IE \equiv H(X,Y) = \sum_{i=1}^{m}\sum_{j=1}^{n} p_{ij} \log_2\left(\frac{1}{p_{ij}}\right) \qquad (16)$$

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.

Moreover, 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. Frenken et al. (2007) refer to between- and within- group entropy respectively as unrelated and related variety.

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:

$$H(X,Y) = H_Q + \sum_{g=1}^{G}\sum_{z=1}^{Z} P_{gz} H_{gz} \qquad (17)$$

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

$$IEB \equiv H_Q = \sum_{g=1}^{G}\sum_{z=1}^{Z} P_{gz} \log_2 \frac{1}{P_{gz}} \qquad (18)$$

$$IEW \equiv \sum_{g=1}^{G}\sum_{z=1}^{Z} P_{gz} H_{gz} \qquad (19)$$

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

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

We can therefore refer to between- and within-entropy respectively as *unrelated technological variety* (*IEB*) and *related technological variety* (*IEW*), while total information entropy is referred to as *general technological variety*.

3) Third, as a proxy of knowledge relatedness we calculated the *coherence* (*R*) 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.

To yield the knowledge coherence index, a number of steps are 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. Such a measure builds upon the measure of technological relatedness τ, which is introduced in Appendix A. 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}:

$$WAR_{ikt} = \frac{\sum_{j \neq i} \tau_{ij} P_{jkt}}{\sum_{j \neq i} P_{jkt}} \tag{20}$$

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

$$R_{kt} = \sum_{i \neq j} WAR_{ikt} \times \frac{P_{ikt}}{\sum_i P_{ikt}} \tag{21}$$

This measure captures the degree to which technologies making up the regional knowledge base are complementary one another. The relatedness measure τ_{ij} indicates indeed that the utilization of technology i implies that of technology j in order to perform specific functions that are not reducible to their independent use. This makes the coherence index appropriate for the purposes of this study.

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 B).

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 manufacturing sectors[8]. 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 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

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[8] 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.

of 19 Italian regions[9] 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

In order to assess the effects of variety and relatedness on regional productivity growth, we carried out a fixed-effect panel data estimation of Equation (12), which is reported in table 3. Different estimations are shown, in which we consider alternatively general, related and unrelated technological variety. The first column shows the results for the estimation including the measure of general technological variety. The results are quite in line with what expected according to our working hypotheses. Firstly, cross regional differences in the accumulation of knowledge capital stock matter in explaining productivity differentials, as is shown by the positive and significant coefficient on the variable *E*. Secondly, knowledge capital stock is not sufficient to characterize the production of knowledge at the regional level.

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

It is important to account also for qualitative changes in the knowledge base. In this direction, the internal degree of coherence of regional knowledge base exhibits a positive and significant coefficient. The more related are the diverse technological activities carried out within the region, the higher the rates of productivity growth. Dynamic economies of scope are at stake as long as they are searched through the combination of close technologies. It is also worth noting that the coefficient of knowledge relatedness (*R*) is four times that of knowledge capital, suggesting that the effect of relatedness is far higher. Finally, variety is a measure of how much the system is able to develop new technological opportunities, and eventually foster economic growth. As expected, the coefficient of information entropy is positive and significant, though lower than the other two knowledge-related variables. For what concerns our control variable, it must be stressed that the proxy for agglomeration economies is not significant, while the location quotient for manufacturing activities is, as one could expect, negative and significant.

Column (2) reports the results for the estimation including unrelated technological variety. Also in this case the coefficient for knowledge capital is positive and significant, like the one for knowledge relatedness. Again, the effect of the latter appears to be stronger than that of the former. For what concerns variety, our estimations show that unrelated technological variety is not likely to exert statistically significant effects on regional productivity growth. Also in this case the only significant control variable is the location quotient, which shows a negative sign.

INSERT TABLE 3 ABOUT HERE

The estimation in column (3) takes account of related technological variety. Differently from the other estimations, the coefficient for the lagged levels of productivity is now (weakly) significant, and with positive sign. This would support the idea, quite realistic indeed, that growth rates of Italian regions are diverging. For what concerns the effects of knowledge capital, the results are well in line with what we have seen so far. The coefficient is indeed positive and significant: The same applies to knowledge relatedness, whose coefficient is again much higher than knowledge capital. Not surprisingly, the coefficient for related technological variety is positive and statistically significant. This means that the positive effects observed in the case of general variety is driven by related variety. Econometric results in column (4), where unrelated and related technological variety are put together, are coherent with column (3). Knowledge relatedness affects positively productivity growth, and to a greater extent than knowledge capital. Again, only related variety appears to significantly affect productivity growth.

This evidence deserves to be better discussed in light of the peculiarities of manufacturing sectors in the Italian context. As described in Section 3, they gained momentum in Italy in the 1960s, i.e. quite later than in the other advanced countries. Within national borders, NEC regions were in turn characterized by a delayed diffusion of manufacturing activities in the 1970s, as compared to North-Western regions. Aggregate productivity dynamics in these sectors along the 1980s appeared to be driven by NEC regions, which in the 1990s were going through the retardation stage of the lifecycle. Within this framework, innovation dynamics started spreading along the 1980s and gained momentum in the 1990s. The massive diffusion of innovation capabilities across North-Western and eventually NEC regions is likely to be related to the identification of profitable research paths and the sorting out of the unprofitable ones. Gales of incremental innovations appear as the result of organized research strategies along well defined trajectories. The relevance of related technological variety in our sample is therefore to be ascribed to the interplay between industry and innovation lifecycle (Quatraro, 2008).

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 have pointed to the importance of proximity among economic agents. While the focus on the regional level does not allow for investigating 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 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, 2008b). 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[10].

Table 4 reports the results from the econometric estimation of the SAR model (Equation (14)). For the sake of homogeneity, different models have been estimated, including alternatively general, related and unrelated technological variety. As is immediately clear, the inclusion of the spatially lagged dependent variable changes our results only to a limited extent. Let us start from column (1). First of all, the coefficient for the spatially lagged variable is positive and significant. This evidence supports the idea that productivity gains are likely to be also transferred to neighbour regions, through the mechanism of pecuniary knowledge externalities. The coefficients of both knowledge capital and knowledge relatedness are significant and, as expected, positive. Moreover, the latter is quite higher than the former. Interestingly enough, the coefficient for general variety is not statistically significant. This might be explained by arguing that the positive coefficient of variety observed in the standard fixed-effects estimations, captures the effects of stimuli coming from outside the region. For what concerns the control variables, it may be noted that the location quotient shows also in this case a negative and significant coefficient. Differently from the previous estimates, the coefficient for agglomeration is now negative and statistically significant. Such result also finds explanation in the peculiarity of regional development paths followed by Italian regions. Population density is indeed likely to be higher in early-industrialized areas in the North-West, while late-industrialized regions in the so-called 'third Italy' were characterized by lower population density due to diffusion of population across larger areas rather than its concentration within metropolitan cities.

INSERT TABLE 4 ABOUT HERE

[10] One may argue that the exclusion of the service sectors of course does not allow us 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 suggests to focus sharply on manufacturing.

Columns (2) and (3) include respectively unrelated and related technological variety. The results are fairly persistent, in that still knowledge capital and relatedness are positive and significant, while none of the two variety measures turns out to be significant. Once again, the spatially lagged dependent variable exhibits a positive and significant coefficient, while both the control variables negatively affect regional productivity growth. Finally, the estimation in column (4) includes related and unrelated variety together, providing results consistent with the previous estimations.

In order to check for the robustness of our results, we present in table 5 the results for the estimation of the SEM model (Equation (15)). The results are basically the same across the four models estimated, and are very coherent with the SAR estimations. The effects of variety are statistically significant in none of the models, while knowledge capital and knowledge relatedness confirm to positively and significantly affect regional productivity growth. Both agglomeration and the relative location quotient show negative and significant coefficients, supporting the relevance of the idiosyncratic features of regional development paths in Italy. Finally, the coefficient for spatial autocorrelation is positive and significant across all the models, corroborating the argument of cross-regional transmission of productivity gains.

INSERT TABLE 5 ABOUT HERE

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 a collective and heterogeneous good (Saviotti, 2007; 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 tested the explanatory role of knowledge variables such as the traditional knowledge capital, knowledge coherence and knowledge variety, both related and unrelated.

The results of empirical analysis confirm that the regional knowledge base do affect productivity growth rates. In particular, not only the level of knowledge stock 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 across all the estimations, while the positive effects of technological variety are statistically significant only when spatial autocorrelation is not accounted for. The issue of spatial dependence is quite relevant, as both the SAR and the SEM models confirm that productivity gains are likely to be transferred to neighbour regions through the mechanism of pecuniary knowledge externalities, boosting their productivity growth rates.

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.

Appendix A

In order to calculate the knowledge coherence index, it is necessary to define the parameter τ, i.e. *technological relatedness*, which appears in equation (20). 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:

$$\Omega = \begin{bmatrix} J_{11} & & J_{i1} & & J_{n1} \\ \vdots & \ddots & & & \vdots \\ J_{1j} & & J_{ij} & & J_{nj} \\ \vdots & & & \ddots & \vdots \\ J_{1n} & \cdots & J_{in} & \cdots & J_{nn} \end{bmatrix} \tag{A1}$$

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:

$$\mu_{ij} = E(X_{ij} = x) = \frac{O_i O_j}{K} \tag{A2}$$

$$\sigma_{ij}^2 = \mu_{ij} \left(\frac{K - O_i}{K} \right) \left(\frac{K - O_j}{K - 1} \right) \tag{A3}$$

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:

$$\tau_{ij} = \frac{J_{ij} - \mu_{ij}}{\sigma_{ij}} \qquad \text{(A4)}$$

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.

Appendix B

In order to calculate the stock of fixed capital at the regional level, we follow the procedure set out by Maffezzoli (2006), which can be summed up as follows. The official procedure to compute the capital stock is the Permanent Inventory Method (PIM). We assume fixed expected service lives, simultaneous exit mortality patterns and linear depreciation. As a consequence, the real gross capital stock can be computed as:

$$\tilde{C}_t = \sum_0^{d-1} I_{t-i} \qquad \text{(B1)}$$

Where *d* is the expected service life, and I_t the real investment flow at time *t*. The depreciation of capital stock is simply equal to $D_t = \tilde{C}_t / d$. The discrete approximation of such a relationship is:

$$D_t = (\tilde{C}_t + \tilde{C}_{t+1})/(2d) \qquad \text{(B2)}$$

Finally the net capital stock obtains directly from $C_t = \sum_{i=0}^{d-1} I_{t-1}[1-(2i+1)/2d]$ or via the accumulation equation $C_t = C_{t-1} + I_t - D_t$.

The accounting data at regional level provide series about gross fixed investments. To make calculations of regional capital stocks we drew the capital stock estimations and the depreciation data at the national level. Then we estimated the average expected service life of aggregated assets by rearranging Equation (B2) as follows:

$$d = (\tilde{C}_t + \tilde{C}_{t+1})/(2D_t) \tag{B3}$$

The results suggest that the aggregate assets are expected to live on average about 34 years. Unfortunately the data about regional accounts are available only starting from 1980, so that we have not enough observation to compute the capital stock. We hence constructed a time series for the actual, time-varying and nation wide depreciation rate, defined as $\delta_t = D_t / K_{t-1}$, and then took the 2001 as a benchmark starting point. We finally extended the series before and after 2001 using the following relationships respectively:

$$C_{i,t-1} = (C_{i,t} - I_{i,t})/(1-\delta_t) \tag{B4}$$

$$C_{i,t} = (1-\delta_t)C_{i,t-1} + I_t \tag{B5}$$

This methodology has some drawbacks, like approximating a linear depreciation scheme with a geometric one, ruling out regional differences in depreciation rates and some necessary degree of measurement error. However, given the availability of the data, it provides a good approximation for the purposes of our work.

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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)	(4)
intercept	-0.212**	0.203**	-0.295***	-0.302***
	(0.093)	(0.93)	(0.101)	(0.102)
$\log A_{t-1}$	0.0315	0.0223	0.041*	0.0399*
	(0.022)	(0.021)	(0.023)	(0.022)
$\log(E)_{t-1}$	0.0212**	0.028***	0.0185**	0.0173*
	(0.009)	(0.009)	(0.008)	(0.010)
$\log(R)_{t-1}$	0.0878***	0.0792**	0.0911***	0.0929***
	(0.035)	(0.035)	(0.035)	(0.035)
$\log(IE)_{t-1}$	0.0153**			
	(0.007)			
$\log(IEB)_{t-1}$		0.0007		0.0011
		(0.001)		(0.002)
$\log(IEW)_{t-1}$			0.005**	0.005**
			(0.002)	(0.002)
$\log(AGGL)_{t-1}$	-0.0007	-0.0018	-0.0012	-0.0012
	(0.002)	(0.003)	(0.003)	(0.003)
$\log(LOQ)_{t-1}$	-0.1581***	-0.1506***	-0.1725***	-0.1743***
	(0.032)	(0.032)	(0.033)	(0.033)
Regional dummies	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Rsq	0.33	0.32	0.33	0.33
F	6.55***	6.33***	6.61***	6.37***
N	395	395	395	395

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 (14) (Spatial Autoregressive Model)

	(1)	(2)	(3)	(4)
$logA_{t-1}$	-0.012	-0.012	-0.005	-0.005
	(-0.914)	(-0.92)	(-0.40)	(-0.38)
$W[log(A_t /A_{t-1})]$	0.188**	0.188**	0.190**	0.190*
	(1.98)	(1.98)	(1.99)	(1.80)
$log(E)_{t-1}$	0.0145**	0.014***	0.006	0.006
	(1.99)	(3.22)	(1.19)	(0.87)
$log(R)_{t-1}$	0.081***	0.081**	0.091***	0.091***
	(2.36)	(2.28)	(2.52)	(2.51)
$log(IE)_{t-1}$	-0.001			
	(-0.14)			
$log(IEB)_{t-1}$		-0.0002		0.003
		(-0.11)		(1.36)
$log(IEW)_{t-1}$			0.003	0.0002
			(1.36)	(0.147)
$log(AGGL)_{t-1}$	-0.005***	-0.004***	0.004***	-0.004***
	(-4.15)	(-4.15)	(-4.22)	(-4.21)
$log(LOQ)_{t-1}$	-0.131***	-0.131***	-0.143***	-0.144***
	(-4.08)	(-4.09)	(-4.32)	(-4.31)
Regional dummies	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Log-likelihood	653.18	653.17	663.4	654.07
N	395	395	395	395

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

Table 5 - Results for the Estimation of Equation (15) (Spatial Error Model)

	(1)	(2)	(3)	(4)
$\log A_{t-1}$	-0.013	-0.019*	-0.005	-0.005
	(-0.94)	(-1.79)	(-0.36)	(-0.36)
$\log(E)_{t-1}$	0.016**	0.009***	0.010*	0.008
	(2.22)	(3.29)	(1.68)	(1.17)
$\log(R)_{t-1}$	0.083***	0.033	0.092***	0.093***
	(2.41)	(1.102)	(2.58)	(2.60)
$\log(IE)_{t-1}$	0.001			
	(0.160)			
$\log(IEB)_{t-1}$		-0.0002		0.0006
		(-0.54)		(0.39)
$\log(IEW)_{t-1}$			0.003	0.003
			(1.39)	(1.45)
$\log(AGGL)_{t-1}$	-0.006***	-0.002***	-0.006***	-0.006***
	(-4.59)	(-2.55)	(-4.75)	(-4.69)
$\log(LOQ)_{t-1}$	-0.126***	0.005	-0.138***	-0.139***
	(-4.02)	(0.52)	(-4.25)	(-4.27)
Spatial autocorrelation	0.50***	0.48***	0.51***	0.50***
	(6.82)	(6.22)	(7.12)	(6.91)
Regional dummies	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Log-likelihood	661.99	636.58	662.96	
N	395	395	395	395

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