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Entrepreneurship and Global Competitiveness in Regional Economies: Determinants and Policy Implications

Chapter 9

Knowledge Structure and Regional Economic Growth: The French case*

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Purpose:

The paper investigate the effects of knowledge on economic growth at the regional level

Methodology approach:

We elaborate a view on knowledge as the result of a combinatorial search activity and implement indicators synthesizing the network architecture of knowledge structure

Findings:

Empirical estimations corroborate the hypothesis that knowledge coherence and variety, besides the traditional measure of knowledge stock, matter in shaping regional economicperformances.

Social implications:

Important policy implications stem from the analysis, in that regional innovation strategies, in order to trigger economicperformances, should be carefully coordinated so as to foster exploration strategies, but taking into full account the technological competences accumulated in the course of time.

Originality/value of the paper:

The originality of the paper lies mainly in the methodological approach, which provides operational translation to the view of knowledge as an outcome of a combinatorial search. In this perspective, the paper also shed light on previously unexplored aspects of the relationships between knowledge and growth.

Keywords: Recombinant Knowledge, Coherence, Variety, 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 attention of economists, both with respect to the mechanisms leading to its production, dissemination and exchange, and its effects on productivity.

Despite this, empirical contributions estimating the effects of knowledge on economic growth has appeared only after the path-breaking works by ZviGriliches (1979). Within this strand of literature, the traditional production function has been extended to include knowledge as an additional input. Knowledge is conceived as a bundled stock, as if it were the outcome of a quite homogenous and fluid process of accumulation made possible by R&D investments, the same way as capital stock[1].

Empirical analyses at the regional level have instead appeared quite recently. These mainly focus on the determinants of cross-regional differences in the efficiency of knowledge creation, like knowledge spillovers and spatial proximity, within the context of a knowledge production function approach (Acs et al., 2002; Fritsch, 2002 and 2004; Fritsch and Franke, 2004; Crescenzi et al., 2007).

Yet, to the best of author's knowledge, very fewempiricalinvestigations can be found in literature analyzing the effects of technological knowledge on regional growth.

This paper aims at bringing technological knowledge into an empirical framework analyzing the determinants of cross-regional differential growth rates. To this purpose, we consider technological knowledge as the outcome of a combinatorial search activity carried out across a technological space in which combinable elements reside (Weitzman, 1998; Fleming, 2001; Fleming and Sorenson, 2001). In this direction we are able to specify a set of properties that can describe the internal structure of the regional knowledge base that go beyond the traditional measure of knowledge capital stock. Indicators like knowledge coherence and knowledge variety can be calculated by exploiting the information contained in patent documents, and in particular, by looking at the co-occurrence of technological classes which patents are assigned to (Saviotti, 2007). While studies can be found investigating these properties at the firm level (Nesta and Saviotti, 2006; Nesta, 2008), and at the sectoral level (Krafft, Quatraro and Saviotti, 2010; Antonelli, Krafft and Quatraro, 2010), there is no empirical evidence at the regional level yet.

Following a previous paper analyzing the case of Italian regions (Quatraro, 2010), our analysis focuses on the effects of knowledge dynamics on the evolution of the manufacturing sector within French regions over the period 1995-2007[2].

In this context, the contribution of this paper to the literature is twofold. First, it applies to notion of recombinant knowledge at the regional level, by identifying a set of properties able to define the structure of the architecture of regional knowledge bases. Second, such analysis is relevant for its general implications concerning the relationships between the dynamics of

[1] Without pretending to be exhaustive, out of the noteworthy contributions at the firm level one may look at Nadiri (1980), Griliches (1984), Cuneo and Mairesse (1984), Patel and Soete (1988), Verspagen (1995) and Higón (2007). Studies at the country level include Englander and Mittelstädt (1988), Lichtenberg (1992), Coe and Helpman (1995) and Ulku (2007).

[2] Unfortunately the results are not directly comparable due to at least two reasons. First, the empirical analysis on the Italian regions has been carried out on the time span 1981-2003, while in this paper we focus on the period 1995-2007. Second, in this paper technological classes are defined according to the International Patent Classification (IPC) standard, while in the previous analysis we used the Derwent classification codes.

technological knowledge and regional growth, in particular with respect to regional innovation strategies.

The rest of the chapter 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 presents the methodology and Section 4 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, while conclusions and policy implications follow in Section 7.

2 The Theoretical Framework

Innovation and technological change represent the main engine of economic development. This is even more evident in the present context of advanced economies, in which the creation and utilisation of knowledge have become the key factors affecting the competitiveness of firms, regions and countries (Freeman and Soete, 1997). The creation of new knowledge indeedbrings about new variety within the economic system, providing the basis for restless economic growth (Metcalfe, 2002).

The recombinant knowledge approach provides a far reaching framework to represent the internal structure of regional knowledge bases as well as to enquire into the effects of its evolution. If knowledge stems from the combination of different technologies, knowledge structure can be represented as a web of connected elements. The nodes of this network stand for the elements of the knowledge space that may be combined with one another, while the links represent their actual combinations. The frequency with which two technologies are combined together provides useful information on the basis of which one can characterize the internal structure of the knowledge base according to the average degree of complementarity of the technologies which knowledge bases are made of, as well as to the variety of the observed pairs of technologies. In view of this, the properties of knowledge structure may be made operative through the use of different methodologies, like social network analysis or the implementation of indicators based on co-occurrence matrixes in which rows and columns elements are bits of knowledge, while each cell reports the frequency with which each pair of technologies is observed.

The dynamics of technological knowledge can therefore be understood as the patterns of change in its own internal structure, i.e. in the patterns of recombination across the elements in the knowledge space. This allows for qualifying both the cumulative character of knowledge creation and the key role played by the properties describing knowledge structure, as well as for linking them to the relative stage of development of a technological trajectory (Dosi, 1982; Saviotti, 2004 and 2007; Krafft, Quatraro and Saviotti, 2010). Moreover, the grafting of this approach into the analysis of the determinants of cross-regional growth differentials allows for a better understanding of the interplay of knowledge dynamics and the patterns of regional industrial development. The ability to engage in a search process within cognitive spaces that are distant from the original starting point is likely to generate breakthroughs stemming from the combination of brand new components (Nightingale, 1998; Fleming, 2001; Fleming and Sorenson, 2001; Sorenson et al., 2006). In this direction, regional innovation capabilities may be defined as the ability of regional actors to engage in the combinatorial process that gives rise to the structure of the regional knowledge base (Lawson and Lorenz, 1999; Romijn and Albu, 2002; Antonelli, 2008).

The economic development of regions is indeed strictly related to the innovative potentials of the industries they are specialized in. Firms within a propulsive industry grow at faster rates, propagating the positive effects across firms directly and indirectly related to the propulsive industry. The potentials for creating new knowledge are at the basis of regional growth, and they happen to be unevenly distributed across sectors according to the relative stage of lifecycle (Perroux, 1955; Kuznets, 1930; Burns, 1934; Schumpeter, 1939)[3].

The intertwining of industrial and technological lifecycles is therefore of great importance, as well as the distinction between exploration and exploitation (March, 1991). The introduction of new technologies is indeed more likely to show a boosting effect on economic performances as long as the search activity enters an exploitation stage wherein potential dominant designs are selected and implemented. The creation of new knowledge in this phase, and hence the resulting knowledge base, is more likely to involve by the recombination of knowledge bits characterized by a great deal of complementarity and by the identification of diverse and yet highly related knowledge bits. A further dichotomy between random screening and organized search seems to be relevant in this direction. The transition to organized search is typical of phases in which profitable technological trajectories have been identified, and the recombination activity occurs out of a sharply defined region of the knowledge space. The likelihood of successful innovations is greater in this stage, and marks the difference between mature and growing sectors (Krafft, Quatraro and Saviotti, 2010 and 2011).

2.1 The model

The discussion conducted above leads us to propose a simple model to appreciate the effects of the properties of knowledge structure 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 appreciate the implications of the recombinant knowledge approach on the operationalization of the properties of knowledge structure, 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 $P = \langle p_1, \ldots, p_d, \ldots, p_D \rangle$. Each regional activity p_d draws mainly upon a core scientific and technological expertise e_d, so that the regional total expertise is the vector $E = \langle e_1, \ldots, e_d, \ldots, e_D \rangle$. The regional knowledge base emerges out of a local search process aimed at combining different and yet related

[3] 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.

technologies. This 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 *d*th 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:

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

According to Equation (4), the regional knowledge is a function of i) the knowledge capital stock, ii) the number of technologies residing in the region, and iii) the *coherence*(*R*)among 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 our 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, Maleki, 2000). In line with a well established tradition of analysis we therefore expect *E* to be positively related to productivity growth.

The creation of technological knowledge is likely to exert a triggering effect on regional economic growth. Traditional analyses of the relationships between knowledge and growth has viewed the former as a bundled stock, i.e. a sort of black box the dynamics of which are rather obscure. Recent advances in the understanding of the cognitive mechanisms underlying the process of knowledge production allows for proposing that knowledge is the outcome of a combinatorial activity. Agents undertake their search across a bounded area of the knowledge landscape, so as to identify combinable pieces of knowledge. In other words, recombinant knowledge is the outcome of a local search process.

Knowledge structure may therefore be represented as a network, the nodes of which represent the combinable technologies, while links represent the actual combinations. Regional knowledge base turns out to be featured by a fairly heterogeneous structure, rather than a bundled stock. Due to the local character of search, the positive effects of knowledge on productivity which stem from the recombination of different technologies, are more likely to occur in contexts where agents are able to combine together different and yet complementary technologies. Conversely, the presence of activities based upon weak complementarity of technological competences makes it difficult to implement effective knowledge production. In this case, knowledge dynamics may hardly trigger regional growth. Therefore, in order to foster productivity growth, the internal structure of regional knowledge ought to be characterized by a high degree of complementarity across technologies. The specialization in technological activities undergoing organized search strategies is thus likely to trigger regional economic performances and as a consequence knowledge coherence (*R*) is expected to positively affect productivity growth.

Knowledge structure is not supposed to be stable over time. Changes may be brought about by trying new combinations among technologies or by introducing brand new technologies within regional competences. Variety may turn out to be a key resource to the creation of new knowledge, and therefore to economic development. It is indeed related to the technological differentiation within the knowledge base, in particular with respect to the diverse possible combinations of pieces of knowledge in the regional context. The localness degree of search implies that variety is likely to engender sensible results in terms of knowledge creation when such diverse technologies are somehow related to one another. Within an established technological trajectory, the combination of technologies that are unrelated is less likely to enhance the process of knowledge creation, and hence it is not expected to contribute economic growth. The expectation about *D* therefore depends very much on the qualification of the variety of combined elements. Within contexts featured by organized search strategies within selected technological trajectories, related variety is likely to dominate over unrelated variety. The combination of a variety of related technologies is likely to exert a positive effect on knowledge production, and hence growth, while the combination of unrelated technologies is likely to exert a negative effect on knowledge production, and hence on regional growth.

3 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)[4]. 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:

$$Y_{it} = A_{it} C_{it}^{\alpha_{it}} L_{it}^{\beta_{it}} \qquad (7)$$

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

[4] 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 usefulsignallingdevice, in that it provides useful hints on where the attention of the analysts should focus (Maddison, 1987).

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 differences in regional growth rates are driven by the characteristics of regional knowledge bases. The increase in the knowledge stock and in the knowledge coherence is likely to positively affect productivity growth, while the effects of variety are likely to depend on the degree to which the diverse technological competences are related to one another.

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:

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

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 also to control for the impact on the one 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:

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

Productivity growth rates depend now not only on knowledge capital stock, variety and coherence (respectively *E*, *D* and *R*). As in previous analyses (Quatraro, 2009 and 2010) we proxied changing specialization is instead by *LOQ*, i.e. the location quotient for manufacturing valueadded.

4 The Implementation of Regional Knowledge Indicators

The implementation of regional knowledge indicators rests on the recombinant knowledge approach and on the model elaborated in Section 2. In order to provide an operational translation of such variables one needs to identify both a proxy for the bits of knowledge and a proxy for the elements that make their structure. For example one could take scientific publications as a proxy for knowledge, and look either at keywords or at scientific classification (like the JEL code for economists) as a proxy for the constituting elements of the knowledge structure. Alternatively, one may consider patents as a proxy for knowledge, and then look at technological classes to which patents are assigned as the constituting elements of its structure, i.e. the nodes of the network representation of recombinant knowledge. In this paper we will follow this latter avenue[5]. Each technological class *j* is linked to another class *m* when the same patent is assigned to both of them. The higher is the number of patents jointly assigned to classes *j* and *m*, the stronger is this link. Since technological classes attributed to patents are reported in the patent document, we will refer to the link between *j* and *m* as the co-occurrence of both of them within the same patent document[6]. We may now turn to explain how knowledge characteristics may be translated into computable variables.

1) Let us start by the traditional regional knowledge stock. This 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[7].

2) As for the properties of knowledge we are interested in, 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 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 the diversity degree of industrial activity (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; Boschma and Iammarino, 2009).

   Differently from common measures of variety and concentration, the information entropy has some interesting properties (Frenken, 2004). An important feature of the

[5] The limits of patent statistics as indicators of technological activities are well known. The main drawbacks can be summarized in their sector-specificity, the existence of non patentable innovations and the fact that they are not the only protecting tool. Moreover the propensity to patent tends to vary over time as a function of the cost of patenting, and it is more likely to feature large firms (Pavitt, 1985; Griliches, 1990). Nevertheless, previous studies highlighted the usefulness of patents as measures of production of new knowledge, above all in the context of analyses of innovation performances at the regional level. Such studies show that patents represent very reliable proxies for knowledge and innovation, as compared to analyses drawing upon surveys directly investigating the dynamics of process and product innovation (Acs et al., 2002). Besides the debate about patents as an output rather than an input of innovation activities, empirical analyses showed that patents and R&D are dominated by a contemporaneous relationship, providing further support to the use of patents as a good proxy of technological activities (Hall et al., 1986). Moreover, it is worth stressing that our analysis focuses on the dynamics of manufacturing sectors.

[6] It must be stressed that to compensate for intrinsic volatility of patenting behaviour, each patent application is made last five years.

[7] Different depreciation rates have been implemented, which provided basically similar results.

entropy measure, which we will exploit in our analysis, is its multidimensional extension.Consider a pair of events (X_j, Y_m), and the probability of co-occurrence of both of them p_{jm}. A two dimensional (total) entropy measure can be expressed as follows (region and time subscripts are omitted for the sake of clarity):

$$H(X,Y)=\sum_{j=1}^{q}\sum_{m=1}^{w}p_{jm}\log_2\left(\frac{1}{p_{jm}}\right) \tag{16}$$

If one considers p_{jm} to be the probability that two technological classes *j* and *m* co-occur within the same patent, then the measure of multidimensional entropy focuses on the variety of co-occurrences of technological classes within regional patent 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.It can be easily shown that the decomposition theorem holds also for the multidimensional case. Hence, if one allows $j \in S_g$ and $m \in S_z$(g = 1,…,G; z = 1,…, Z), we can rewrite *H(X,Y)* as follows:

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

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

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

$$P_{gz}=\sum_{j\in S_g}\sum_{m\in S_Z}p_{jm} \tag{17b}$$

$$H_{gz}=\sum_{j\in S_g}\sum_{m\in S_z}\frac{p_{ij}}{P_{gz}}\log_2\left(\frac{1}{p_{jm}/P_{gz}}\right) \tag{17c}$$

Following Frenken et al. (2007), we can refer to between-group and within-group entropy respectively as *unrelated technological variety* (*UTV*) and *related technological variety*(*RTV*), while total information entropy is referred to as *general technological variety (TV)*. The distinction between related and unrelated variety is based on the assumption that any pair of entities included in the former generally are more closely related, or more similar to any pair of entities included in the latter. This assumption is reasonable when a given type of entity (patent, industrial sector, trade categories etc.) is organized according to a hierarchical classification. In this case each class at a given level of aggregation contains “smaller” classes, which, in turn contain yet “smaller” classes. Here, small refers to a low level of aggregation.

We can reasonably expect then that the average pair of entities at a given level of aggregation will be more similar than the average pair of entities at a higher level of aggregation. Thus, what we call related variety is measured at a lower level of aggregation (3 digit class within a 1 digit macro-class) than unrelated variety (across 1 digit macro-classes). This distinction is important because we can expect unrelated (or inter-group) variety to negatively affect productivity growth, while related (or intra-group) variety is expected to be positively related to productivity growth. Moreover, the evolution of total variety is heavily influenced by the relative dynamics of related and unrelated variety, such that if unrelated variety is dominant the effects of total variety on productivity growth can be expected to be negative, while the opposite holds if related technological variety dominates the total index (Krafft, Quatraro, Saviotti, 2010).

3) Third, we calculated the *coherence*(*R*)of the regional knowledge base, defined as the average complementarity of any technology randomly chosen within a region with respect to any other technology (Nesta and Saviotti, 2005 and 2006; Nesta, 2008).

To yield the knowledge coherence index, a number of steps are required. In what follows we 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_j is defined as the degree to which technology *j* is related to all other technologies $m \neq j$ within the region *i*, weighted by patent count P_{mit}:

$$WAR_{jit} = \frac{\sum_{m \neq j} \tau_{jm} P_{mit}}{\sum_{m \neq i} P_{mit}} \tag{18}$$

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

$$R_{it} = \sum_{j \neq m} WAR_{jit} \times \frac{P_{jit}}{\sum_{j} P_{jit}} \tag{19}$$

This measure captures the degree to which technologies making up the regional knowledge base are complementary one another. The relatedness measure τ_{jm} indicates indeed that the utilization of technology *j* implies that of technology *m* 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

In this paper we investigate the relationship between productivity growth and regional knowledge in French regions[8]. The data we used have been drawn from two main sources. We employed data from the regional accounts provided by the Eurostat website to calculate the MFP

[8]We acknowledge that the use of administrative regions to investigate the effects of knowledge creation represents only an approximation of the local dynamics underpinning such process. Indeed administrative borders are arbitrary, and therefore might not be representative of the spontaneous emergence of local interactions. It would be much better to investigate these dynamics by focusing on local systems of innovation. However, it is impossible to find out data at such a level of aggregation. Moreover, the identification of local systems involve the choice of indicators and threshold values according to which one can decide whether to unbundle or not local institutions. This choice is in turn arbitrary, and therefore it would not solve the problem, but it would only reproduce the issue at a different level. Thus we think that despite the unavoidable approximation, our analysis may provide useful information on the dynamics under scrutiny.

index. We used real GDP as a measure of regional output, regional labour compensation to compute the output elasticity of labour, working hours as a proxy for labour input, and real gross fixed capital stock. All variables, where necessary, have been deflated by using the data on deflators provided by the OECD Stan database.

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. Each patent is assigned to a region, on the basis of the inventors' addresses[9]. We exploited the detailed information about the patents' contents reported in the Espacenet database (updated to 2010), with particular respect to the technological classes patents are assigned to, following the International Patent Classification (IPC) scheme. All technologies are covered by 8 broad macro-areas, which are in turn subdivided in smaller groups, whereby the most detailed level of aggregation is at 9 digits. We used the 4-digit classification to calculate both knowledge coherence and information entropy. The decomposition of the entropy measure has been conducted by considering the subject areas as subsets, so as to obtain information entropy both 'within' and 'between' subject areas.

The initial patent dataset consists of 855538 observations and 628 4-digit classes spread across 27 regions over the period ranging from 1969 to 2008[10]. We decided to drop from our analysis observations concerning overseas French regions (Guadeloupe, Martinique, Guyane and Réunion), which account for the 0.35% of the total observations. After the calculations we ended up with a matrix of five knowledge variables, observed for each region over the time period 1981 – 2007. Such matrix has then been matched with the vector of regional productivity growth rates, which can be however calculated only since 1995 onwards due to data constraints.

Tables 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. Table 1 in particular shows the overall distribution of variables across the 22 French regions. This first evidence shows a great deal of variance for what concerns both the knowledge variables and the growth rates of MFP. It is fair to note that in the case of knowledge coherence and MFP growth rates, within-group dispersion is higher than the between-group one, suggesting that variations over time are more important than variations across regions. For all the other variables the situation is the opposite.

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

Table 2 provides instead, the regional breakdown of the most important descriptive statistics.With the help of figure 1, we can notice how the average values of MFP growth rates are quite unevenly distributed across French regions. Indeed, only for 7 out of 22 regions average MFP growth rates are positive. Such regions are located mostly in Southern and Western France. In particular, the Provence-Alpes-Cote d'Azur (PACA), the Corsica, the Aquitaine and the Midi-Pyrénées regions are in uppermost group, showing growth rates between 0.9% and 2.3%. The following group

[9] The assignment of patent to regions on the basis of inventors' addresses is the most widespread practice in the literature (see for example Maurseth and Verspagen, 2002; Henderson et al., 2005; Breschi and Lissoni, 2009, Paci and Usai, 2009, to quote a few). A viable alternative may rest on the use of applicants' addresses, above all when the assessment of knowledge impact on growth is at stake (see Antonelli, Krafft and Quatraro, 2010). However, when the analysis is conducted at local level of aggregation, and the geography of collective processes of knowledge creation is emphasized, the choice of inventors' addresses remains the best one.

[10]French regions present pretty heterogeneous features both from the economic and the social viewpoint. The purpose of this paper is to understand the extent to which differences in regional knowledge bases might be responsible of such economic variety. Of course, this implies that some other factors may interact in explaining the observed variety. The econometric model we will propose is meant to reduce the bias due to omitted variables and spurious relationships.

collect regions with average growth rates between 0.1% and 0.9%, and includes the Languedoc-Roussilon, the Aquitaine, the Bretagne and the Pays-de-la-Loire regions. All the other regions in the country are characterized by negative average growth rates of MFP in the manufacturing sectors.

>>> INSERT FIGURE 1 ABOUT HERE <<<

As far as the properties of the knowledge structure are concerned, we can notice a far higher polarization in the case of knowledge coherence than in the case of knowledge variety. This appears clearly if we look at Figures 2 and 3. High levels of knowledge coherence can be found in the north and in western regions like the Alsace, the Lorraine and the Franche Comte. Moving southwards, high levels of coherence can be found also in the Auvergne region and, to a lesser extent, in the Midi-Pyrenees region.

>>> INSERT FIGURE 2 ABOUT HERE <<<

Knowledge variety seems to be more evenly distributed across French regions. In particular, very high levels can be noticed in the Ile-de-France and in the Rhone-Alpes regions, where indeed the rate of creation of new knowledge is by far higher than in the other areas of the country. High levels of variety can also be found in central and northern regions. The less performing regions in this respect are the Corse and the Limousin region. It must be notices that, while the Provence-Alpes-Côte d'Azur and the Aquitaine regions are characterized by low levels of coherence, they are nonetheless characterized by good levels of knowledge variety, which suggests the existence of high rates of knowledge creation, maybe dispersed across different and loosely related fields.

>>> INSERT FIGURE 3 ABOUT HERE <<<

This preliminary descriptive evidence shows the existence of a great deal of variance across French regions both in terms of productivity dynamics and in terms of the properties of the regional knowledge base, which deserves further investigation. In the next section we will therefore present the results of the estimations of the econometric model presented in Section 3. Before proceeding, it is worthwhile to look at the correlation matrix concerning the variables to be used in the estimation.

>>> INSERT TABLE 3 ABOUT HERE <<<

We can notice that with very few exceptions, variables are not significantly correlated with one another, and that when correlation is significant, the magnitude of the coefficient does not create important problems. The only exceptions concern the correlation between the lagged value of productivity and total variety, and the one between RTV and UTV. With these specifications in mind we can move to the econometric analysis.

6 Empirical Results

In order to assess the effects of knowledge coherence and variety on regional productivity growth, we carried out a fixed-effect panel data estimation of Equation (12), which is reported in table 4. As expected, the coefficient on the lagged level of MFP is negative and significant across all the estimated models. This means that series are at least affected by mean reversion, and that a convergence process is possibly at stake.

For what concerns the knowledge variables, we can notice that, consistently with previous research, knowledge coherence shows a positive and significant coefficient. It is therefore 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. 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 TV is positive and significant. For what concerns our control variables, it must be stressed that the proxy for agglomeration economies is characterized by a positive and significant coefficient, while the location quotient for manufacturing activities ispositive and significant. This suggests that untraded interdependencies as well as the relative specialization in manufacturing matters in shaping regional productivity dynamics in France over the observed period.

>>> INSERT TABLE 4 ABOUT HERE <<<

Column (2) reports the results for the estimation including UTV. Also in this case the coefficient for knowledge coherence is positive and significant. For what concerns variety, our estimations show that UTV is not likely to exert statistically significant effects on regional productivity growth, as in previous analyses on the Italian regions. Also in this case the proxies for manufacturing specialization and agglomeration economies show positive and significant coefficients.

The estimation in column (3) takes account of RTV, while in column (4), UTV and RTV are put together. For what concerns the effects of knowledge coherence, the results are well in line with what we have seen so far. The coefficient is indeed positive and significant. Not surprisingly, the coefficient for RTV is positive and, in column (4), statistically significant. This would suggest that the positive effects observed in the case of TV is driven by RTV.

The results showed so far provide interesting evidence about the effects of regional knowledge base on productivity dynamics. It can be useful to also look at the coefficients on standardized variables, which are reported in table 5. Standardized coefficients are indeed helpful in that they allow to directly comparing the effects of the explanatory variables not only in terms of sign but also of magnitude.

>>> INSERT TABLE 5 ABOUT HERE <<<

Of course the patterns of statistical significance as well as the signs of coefficients are the same as in table 4. We can notice that the lagged levels of productivity exert a very strong effect on productivity growth rates. This allows appreciating the fact that, despite such a huge contribution to growth coming from past experience, knowledge structure still plays an important role. Out of these variables, knowledge coherence shows a coefficient which almost twice that of total variety, and three times that of related variety. This confirms the importance of knowledge coherence as a variable able to explain cross regional patterns of productivity growth.

The results obtained in this chapterare well in line with the path of empirical analysis of theeffects of knowledge creation on cross-regional growth differentials. Moreover, the set of indicators we used in our analysis can be well used to explore the determinants of efficiency of knowledge production processes within a knowledge production function approach. However, while the contribution the such a debate provides an important example of how this framework may be of interest to scholars in regional economics, some limits need to be discussed concerning the extension of Nesta's model, which was elaborated at the firm level, to the regional domain.

The regional extension of Nesta's model indeed presents pros and cons deserving consideration. While the application of the framework at the firm level has the merit to stress and valorise the heterogeneous nature of firms' competences, an important limit can be identified in the focus on the firm as a single innovating agent, with no emphasis on cross-firm knowledge spillovers.

The shift to the regional domain is favoured by the consistency of the model with an interpretative framework blending the collective knowledge and the recombinant knowledge approaches. New knowledge stems out of a complex set of interactions among different institutions, of which firms represent only one out of different actors. Such interactions allows for the recombination of bits of knowledge that are fragmented and dispersed among the different agents (Hayek, 1939). The regional glance is thus more appropriate to grasp the local dimension of such dynamics (Antonelli, Patrucco, Quatraro, 2011), so as to investigate the intertwining of the features of the topology of geographical and of knowledge spaces. The architecture of knowledge network, as proxied by the knowledge indicators we described in Section 4, proved to matter in shaping regional growth rates. In particular, the internal coherence of the regional knowledge base is positively related to productivity growth. This is because it is maintained that such index is likely to signal the transition towards a phase of organized search within regional industrial activities. The likelihood of generation of new useful knowledge is higher during this phase, and therefore one expects to also observe positive effects on production processes and hence productivity growth.

A problem might be raised by the framework we developed in this paper, similar to the one we observed to affect Nesta's model. While the regional approach allows for accounting for the dynamics of inter-organizational knowledge flows within local contexts, it risks underestimating the important role of external knowledge as emphasized by Bathelt et al. (2004), who suggest that global pipelines add value to the local buzz by fuelling variety. Further analyses should therefore develop sensible proxies able to account for such dynamics, although data constraints may represent a serious threat in this respect.

7 Conclusions

Innovation and technological knowledge have long been considered as key elements triggering productivity growth. Empirical analyses of this relationship have emerged in the line of Zvi Griliches' extended production function, according to which knowledge has been considered as an additional input in the traditional production function. In this framework, knowledge has been considered as a bundled stock, which has been operationalized by applying a sort of permanent inventory method to cumulate an innovation flow measure subject to a depreciation rate.

A step forward is represented by the studies introducing the knowledge production function. This strand of literature has mainly been developed to investigate innovation dynamics at the regional level. Drawing upon the regional innovation systems approach, it has basically provided a former empirical assessment of the degree to which knowledge is the result of the interaction of a number of different and yet complementary institutions involved in innovation activities, like firms, universities, R&D labs and the like (Cooke et al., 1997; Antonelli, 2008).

While these studies enquired into the determinants of the effectiveness of knowledge production at the regional level, they said very little about the effects of knowledge on regional growth. Moreover, knowledge kept being represented as a bundled stock, although conceived as stemming from interactive dynamics (Krafft and Quatraro, 2011).

In this paper,

we have attempted to provide evidence of the effects of knowledge on regional growth by going beyond the traditional representation of knowledge found in literature. The recombinant knowledge approach and its cognitive underpinnings proved to be very fertile in this respect. Knowledge is understood as the result of the combination of bits of knowledge identified in the knowledge space by means of a local search process. This allows for representing the structure of knowledge as a web, the nodes of which are bits of knowledge, while the links stand for their actual combination. Such representation is susceptible of different operational translations. In this paper we have followed the methodology elaborated by Nesta (2008), relying on information provided within patent documents.

We have grafted this methodology into an empirical framework analyzing the effects of the characteristics of knowledge structure on regional productivity growth, in the footsteps of Quatraro (2010). Our analysis concerned a sample of 22French regions over the period 1995-2007, 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.

Summing up, the results of empirical analysis confirm that the regional knowledge base do affect productivity growth rates. In particular, the characteristics of the knowledge base exert also a strong impact. The effects of variety are appreciable in this respect. In particular, we decomposed total variety into related and unrelated variety. We have found that the positive effects of total variety are driven by related variety, while unrelated variety yields not significant effects. For what concerns knowledge coherence, its effects are persistent and robust across all the alternative models and estimators implemented. The higher is the internal degree of coherence of knowledge structure, the faster regional productivity is supposed to grow.

Such results have important policy implications, in terms of regional strategies for innovation and knowledge production. The internal coherence of the knowledge base proved indeed to positively affect productivity growth rates. An effective regional innovation strategy should therefore be characterized by a careful assessment of local specificities. The identification of industries which the areas are specialized in is of paramount importance in order to devise the most appropriate incentive schemes.On the one hand, regions dominated by declining industries should be helped to find out new trajectories for development, trying and valorising the existing competences by directing search efforts towards complementary fields. On the other hand, in those regions featured by industries at the frontier, innovation policies might be much more directed towards the generation of incrementally new knowledge drawing upon exploitation strategies.

In conclusion, regional innovation policies should be characterized 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. In other words, policies aiming at fostering innovation should boost the development of industries in which the innovation process is mature enough to set in motion organized search strategies. Demand-driven innovation policies should therefore be redesigned so as to move away from the conventional wisdom on the importance of aggregate sustain to demand, in favour of *selective demand policies*, according to which national and local governments should identify a number of key sectors able to exert the most powerful influence on aggregate growth in the long run. The regional production system would then take advantage of a bundle of technological activities showing a high degree of coherence and therefore be more likely to be properly absorbed and successfully exploited.

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Table 1 – Descriptive Statistics, overall sample

Variable		Mean	Std. Dev.	Min	Max	Observations
dlogA/dt						
	overall	0.020	0.022	-0.044	0.084	N = 220
	between		0.007	0.010	0.037	n =22
	within		0.021	-0.036	0.070	T= 10
logA(t-1)						
	overall	10.693	0.838	8.299	13.003	N = 220
	between		0.851	8.484	12.914	n =22
	within		0.071	10.508	10.902	T = 10
Kn. capital						
	overall	3430.924	6706.013	8.108	34868.640	N =242
	between		6791.661	15.625	31824.700	n =22
	within		819.437	2740.190	6474.870	T = 11
Kn. coherence						
	overall	1.130	0.846	-3.900	4.186	N =242
	between		0.351	0.579	2.183	n =22
	within		0.774	-3.736	4.350	T =11
TV						
	overall	7.687	1.355	1.500	10.055	N =242
	between		1.473	2.363	9.899	n =22
	within		0.355	6.564	8.505	T = 11
RTV						
	overall	5.438	1.234	0.333	7.760	N =242
	between		1.308	1.099	7.503	n =22
	within		0.353	4.286	6.293	T = 11
UTV						
	overall	2.249	0.312	0.000	2.775	N =242
	between		0.283	1.263	2.632	n =22
	within		0.182	0.986	3.237	T = 11
Loc. quotient						
	overall	0.019	0.329	-1.015	0.474	N =242
	between		0.335	-0.945	0.464	n =22
	within		0.027	-0.051	0.239	T = 11
Agglomeration						
	overall	4.551	0.728	3.395	6.875	N =242
	between		0.743	3.454	6.836	n =22
	within		0.026	4.482	4.644	T = 11

Table 2 - Descriptive Statistics, breakdown by region

	dlogA/dt				Coherence				Knowledge Capital			
	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
FR10	-0.009	0.048	-0.092	0.089	1.14	0.56	0.00	1.61	31824.70	3297.23	25653.58	34868.64
FR21	-0.002	0.035	-0.043	0.074	1.21	0.37	0.53	1.79	798.42	112.39	622.27	923.74
FR22	-0.019	0.027	-0.068	0.029	1.28	0.46	0.34	1.75	1543.78	141.94	1219.54	1660.20
FR23	-0.006	0.052	-0.055	0.098	1.17	0.69	-0.11	1.99	1750.17	345.93	1091.63	2189.32
FR24	-0.005	0.034	-0.066	0.058	0.91	0.38	0.23	1.46	2150.59	298.37	1550.88	2447.05
FR25	-0.008	0.044	-0.089	0.046	1.32	0.61	0.01	1.96	768.19	100.20	593.66	900.62
FR26	-0.004	0.026	-0.050	0.035	1.07	0.36	0.35	1.45	1324.48	90.06	1170.16	1447.30
FR30	-0.008	0.037	-0.070	0.046	1.35	0.64	0.04	2.02	1690.40	180.97	1417.93	1918.48
FR41	-0.013	0.044	-0.081	0.061	1.31	0.46	0.48	1.86	1555.17	156.31	1234.74	1718.89
FR42	-0.011	0.036	-0.077	0.055	1.22	0.89	-0.53	2.11	3738.83	811.42	2527.04	4881.08
FR43	-0.017	0.058	-0.070	0.121	1.52	0.29	1.04	1.91	1075.84	160.94	790.76	1297.69
FR51	0.008	0.036	-0.040	0.080	1.01	0.28	0.40	1.29	1541.12	321.16	1059.20	1955.67
FR52	0.006	0.035	-0.032	0.066	1.47	0.84	-0.15	2.36	2144.95	695.71	1162.94	3036.39
FR53	0.000	0.034	-0.053	0.047	1.07	0.41	0.45	1.54	783.10	100.53	614.27	909.72
FR61	0.008	0.057	-0.091	0.106	0.66	0.53	-0.48	1.26	1510.54	70.09	1389.71	1600.91
FR62	0.017	0.065	-0.094	0.113	1.07	0.59	-0.05	1.97	2283.81	446.78	1587.16	2969.45
FR63	-0.007	0.036	-0.050	0.056	0.89	0.40	0.02	1.56	263.35	57.96	172.93	350.09
FR71	0.001	0.036	-0.049	0.062	0.87	0.52	-0.11	1.48	12077.10	1662.83	9092.44	13968.38
FR72	-0.008	0.046	-0.066	0.089	2.18	0.85	0.44	3.08	1142.63	257.84	684.98	1395.24
FR81	0.009	0.041	-0.064	0.076	0.58	0.91	-1.35	1.65	1288.71	204.86	943.56	1527.10
FR82	0.015	0.037	-0.046	0.072	0.58	0.75	-0.72	1.38	3946.12	583.19	2910.61	4633.53
FR83	0.023	0.056	-0.045	0.152	0.97	2.60	-3.90	4.19	15.62	8.23	8.11	35.61

Table 2 continued.

	Total Variety				Related Variety				Unrelated Variety			
	mean	sd	min	max	mean	sd	min	max	mean	sd	min	max
FR10	9.61	0.26	9.29	10.01	7.18	0.27	6.81	7.57	2.43	0.03	2.38	2.47
FR21	6.77	0.51	5.90	7.53	4.64	0.57	3.76	5.46	2.13	0.09	1.96	2.27
FR22	8.22	0.52	7.34	8.89	5.92	0.48	5.14	6.44	2.30	0.10	2.16	2.47
FR23	7.84	0.43	7.05	8.29	5.82	0.39	5.04	6.21	2.02	0.07	1.89	2.11
FR24	8.29	0.26	7.78	8.70	5.86	0.26	5.43	6.32	2.43	0.08	2.34	2.56
FR25	7.14	0.39	6.34	7.51	4.73	0.35	4.21	5.22	2.40	0.12	2.13	2.58
FR26	7.85	0.45	7.00	8.37	5.51	0.40	4.80	6.11	2.34	0.13	2.15	2.50
FR30	8.22	0.23	7.71	8.52	6.14	0.27	5.52	6.42	2.08	0.10	1.93	2.21
FR41	7.82	0.44	7.23	8.46	5.48	0.37	4.94	6.01	2.34	0.08	2.23	2.46
FR42	7.94	0.65	6.82	8.65	5.91	0.57	4.97	6.55	2.03	0.10	1.85	2.21
FR43	7.38	0.24	7.00	7.71	5.00	0.21	4.57	5.39	2.37	0.15	2.01	2.49
FR51	8.11	0.18	7.90	8.41	5.79	0.23	5.44	6.12	2.32	0.08	2.20	2.49
FR52	7.57	0.23	6.98	7.84	5.19	0.27	4.59	5.54	2.38	0.07	2.29	2.48
FR53	7.33	0.33	6.87	7.86	5.04	0.30	4.53	5.52	2.29	0.09	2.14	2.42
FR61	8.26	0.29	7.60	8.62	5.95	0.31	5.31	6.51	2.31	0.11	2.07	2.49
FR62	8.19	0.24	7.88	8.66	5.79	0.24	5.52	6.25	2.40	0.07	2.28	2.49
FR63	5.64	0.47	4.94	6.26	3.00	0.52	2.19	3.86	2.63	0.14	2.40	2.78
FR71	9.90	0.08	9.79	10.06	7.50	0.16	7.28	7.76	2.40	0.09	2.28	2.51
FR72	7.20	0.31	6.33	7.47	5.29	0.42	4.13	5.57	1.92	0.13	1.78	2.19
FR81	7.20	0.19	6.90	7.47	5.24	0.17	4.97	5.52	1.96	0.11	1.79	2.13
FR82	8.63	0.30	8.07	8.97	6.19	0.28	5.71	6.49	2.43	0.04	2.37	2.48
FR83	2.36	0.59	1.50	3.18	1.10	0.61	0.33	1.93	1.26	0.93	0.00	2.25

Table 3 – Correlation Matrix

	dlogA/dt	logA(t-1)	Knowledge Capital	Knowledge Coherence	TV	UTV	RTV	Loc. quotient	Aggl.
dlogA/dt	1								
logA(t-1)	-0.1073	1							
	0.0958								
Kn. Capital	-0.0431	0.5847*	1						
	0.5046	0							
Kn. Coherence	-0.0099	0.0398	-0.0511*	1					
	0.8779	0.5376	0.3888						
TV	0.004	0.9352*	0.4792*	0.0677*	1				
	0.9505	0	0	0.2578					
UTV	-0.0294	0.4205*	0.1690*	-0.2854*	0.4741*	1			
	0.6512	0	0.0045	0	0				
RTV	0.0121	0.9208*	0.4818*	0.1471*	0.9744*	0.2638*	1		
	0.8521	0	0	0.0136	0	0			
loc. quotient	-0.2026	0.4800*	-0.1481*	0.2152*	0.3857*	0.2712*	0.3532*	1	
	0.0015	0	0.016	0.0004	0	0	0		
Aggl.	-0.0765*	0.7438*	0.7349*	0.0285	0.4978*	0.0889*	0.4789*	0.1085*	1
	0.2355	0	0	0.6307	0	0.1393	0	0.0784	

Table 4 – Results of fixed effects estimation of eq. 12

	(1) Dlog(A)/dt	(2) Dlog(A)/dt	(3) Dlog(A)/dt	(4) Dlog(A)/dt
Log[A(t-1)]	-0.879***	-0.881***	-0.882***	-0.869***
	(0.0634)	(0.0641)	(0.0646)	(0.0645)
Ln[Kn. Capital (t-1)]	0.0105	0.00947	0.00497	0.00191
	(0.0192)	(0.0175)	(0.0186)	(0.0188)
Ln[Kn. Coherence (t-1)]	0.108**	0.104**	0.121**	0.101*
	(0.0464)	(0.0507)	(0.0522)	(0.0529)
Ln[TV (t-1)]	0.0594**			
	(0.0278)			
Ln[RTV (t-1)]		0.0103		0.0337*
		(0.0118)		(0.0179)
Ln[UTV (t-1)]			-0.00124	0.0256
			(0.0172)	(0.0222)
Ln[Iq (t-1)]	0.769***	0.768***	0.760***	0.756***
	(0.0666)	(0.0672)	(0.0690)	(0.0686)
Ln[Aggl(t-1)]	1.338***	1.414***	1.408***	1.335***
	(0.152)	(0.148)	(0.150)	(0.154)
Constant	1.425**	1.076**	1.050*	1.293**
	(0.568)	(0.545)	(0.557)	(0.569)
Observations	242	242	242	242
R-squared	0.804	0.802	0.803	0.805
Number of regions	22	22	22	22

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5 – Results of fixed effects estimation of eq. 12, standardized coefficients

	(5) Dlog(A)/dt	(6) Dlog(A)/dt	(7) Dlog(A)/dt	(8) Dlog(A)/dt
Log[A(t-1)]	-19.46***	-19.52***	-19.53***	-19.25***
	(1.404)	(1.419)	(1.431)	(1.430)
Ln[Kn. Capital (t-1)]	-0.349	0.315	0.165	-0.0635
	(0.636)	(0.581)	(0.616)	(0.624)
Ln[Kn. Coherence (t-1)]	0.131**	0.126**	0.146**	0.122*
	(0.0562)	(0.0614)	(0.0632)	(0.0641)
Ln[TV (t-1)]	0.336**			
	(0.157)			
Ln[RTV (t-1)]		0.0876		0.286*
		(0.0996)		(0.152)
Ln[UTV (t-1)]			-0.00390	0.0807
			(0.0544)	(0.0703)
Ln[Iq (t-1)]	5.981***	5.975***	5.910***	5.880***
	(0.518)	(0.523)	(0.537)	(0.533)
Ln[Aggl(t-1)]	22.96***	24.26***	24.16***	22.91***
	(2.602)	(2.538)	(2.574)	(2.643)
Constant	-1.528***	-1.814***	-1.666***	-1.506***
	(0.269)	(0.236)	(0.264)	(0.276)
Observations	242	242	242	242
R-squared	0.804	0.802	0.803	0.805
Number of regions	22	22	22	22

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 1 - Distribution of average TFP growth rates across French regions

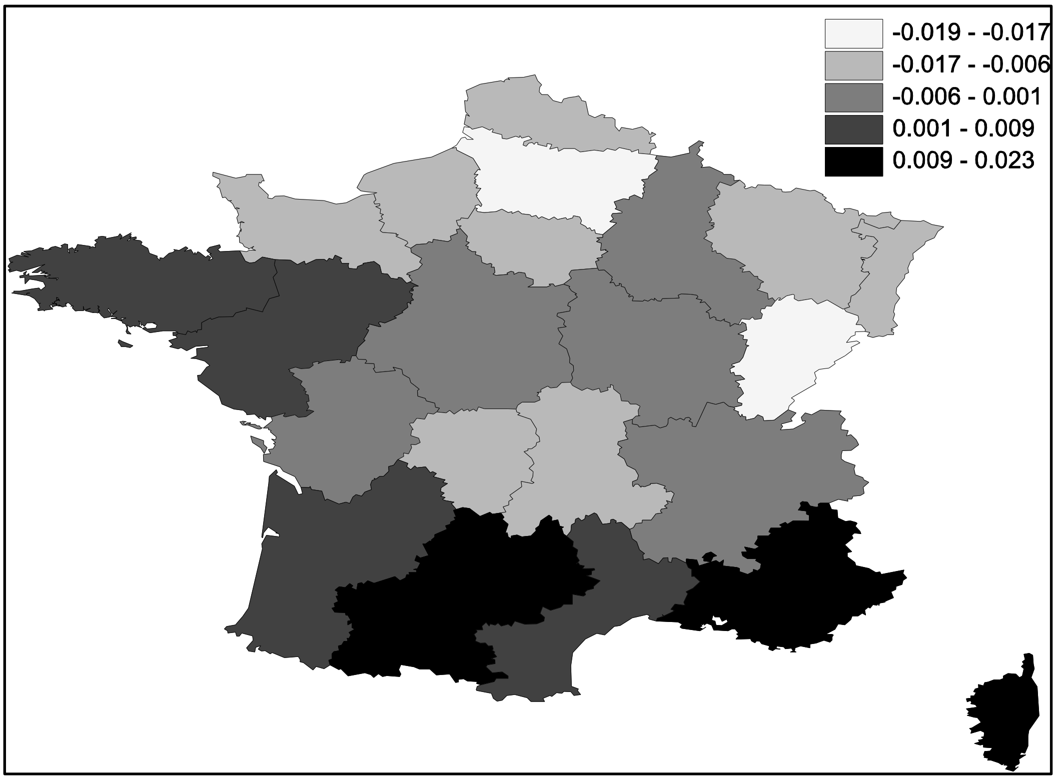


Figure 2 - Distribution of average coherence across French regions

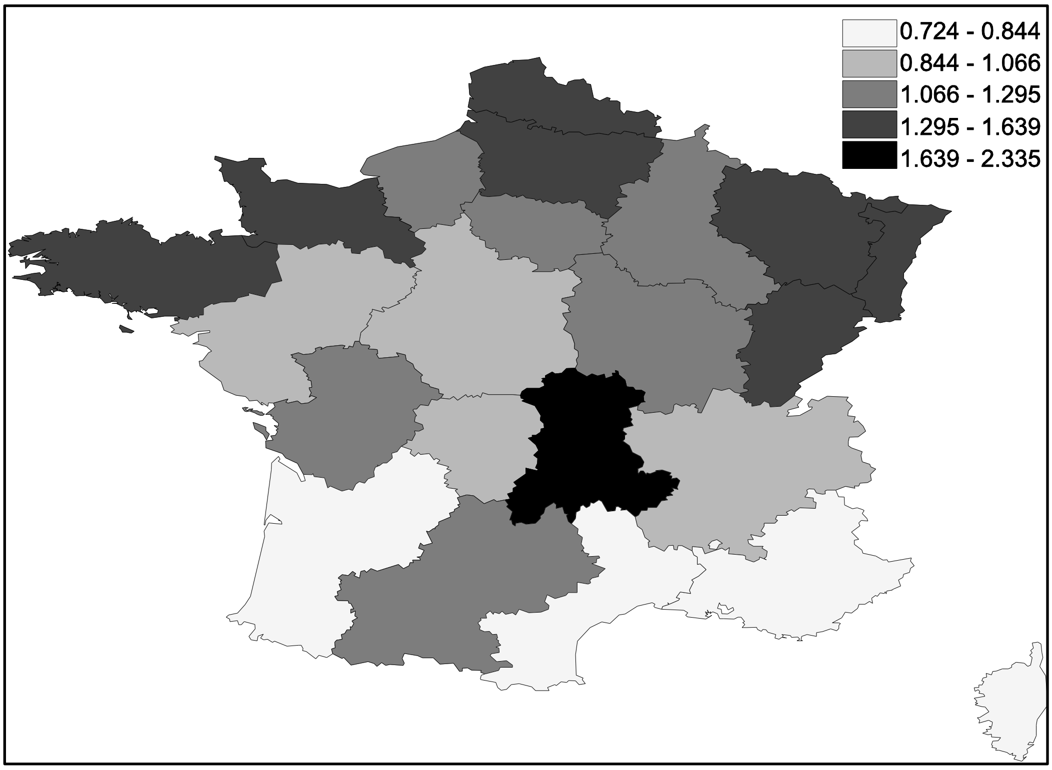
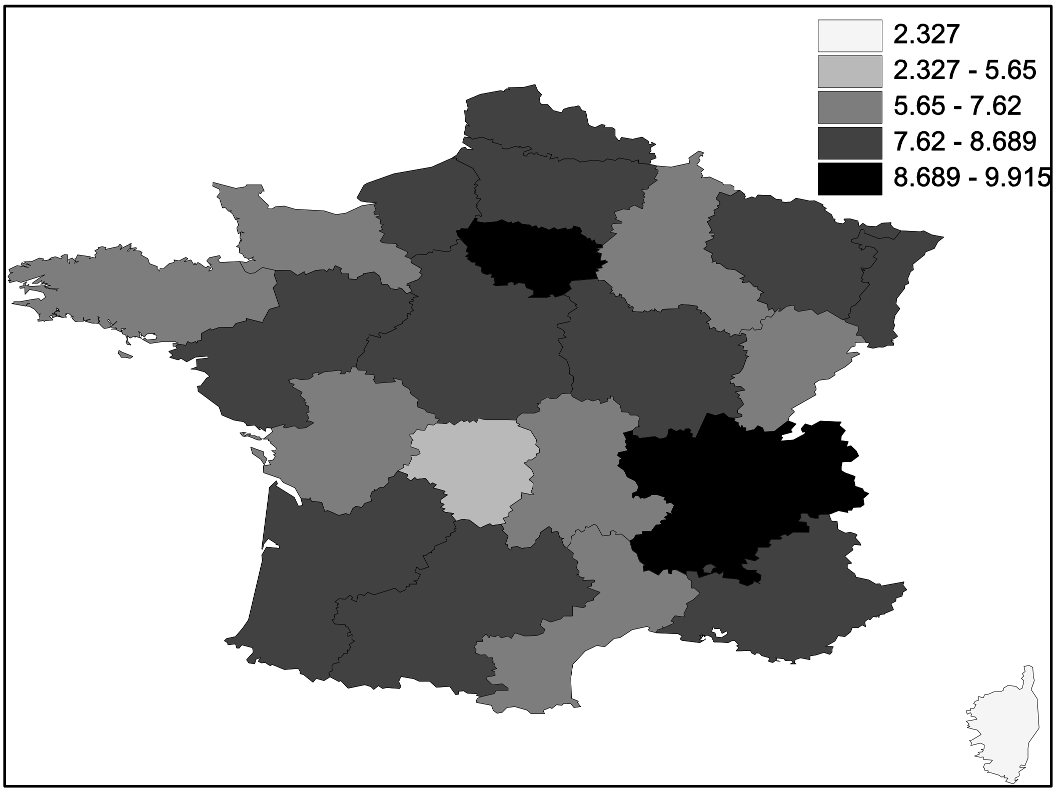


Figure 3 - Distribution of average variety across French regions



Appendix 1 - Correspondence between nuts codes and Regions

FR10	Île de France
FR21	Champagne-Ardenne
FR22	Picardie
FR23	Haute-Normandie
FR24	Centre (FR)
FR25	Basse-Normandie
FR26	Bourgogne
FR30	Nord - Pas-de-Calais
FR41	Lorraine
FR42	Alsace
FR43	Franche-Comté
FR51	Pays de la Loire
FR52	Bretagne
FR53	Poitou-Charentes
FR61	Aquitaine
FR62	Midi-Pyrénées
FR63	Limousin
FR71	Rhône-Alpes
FR72	Auvergne
FR81	Languedoc-Roussillon
FR82	Provence-Alpes-Côte d'Azur

FR83	Corse