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THE GOVERNANCE OF LOCALIZED KNOWLEDGE EXTERNALITIES

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THE GOVERNANCE OF LOCALIZED KNOWLEDGE EXTERNALITIES[1]

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ABSTRACT. This paper articulates the hypothesis that there is an optimal size of knowledge pools. Too little a density of innovation activities reduces the accessibility of external knowledge. Too large a density enhances congestion and reduces appropriability. Firms can benefit from actual increasing returns stemming from the indivisibility, replicability and non-exhaustibility of knowledge only when the size of innovation networks is comprised between the two extremes. The empirical evidence confirms that the output elasticity of knowledge, included in a typical Griliches production function, is itself a quadratic function of the size of innovation networks. Knowledge externalities do trigger increasing returns that are external to each firm, only within a well defined interval. Knowledge externalities are a property of the system into which firms are embedded. As such they are endogenous to the system and likely to exhibit specific properties related to the changing characteristics of the system itself. The quality of knowledge governance mechanisms in place plays a key role in assessing the actual size of the net positive effects of knowledge externalities.

KEYWORDS: KNOWLEDGE EXTERNALITIES; LOCALIZED INCREASING RETURNS; KNOWLEDGE GOVERNANCE.

JEL Classification Codes: O33.

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1 INTRODUCTION

Recent models on innovation and economic growth have increasingly appreciated the role of technological learning and knowledge spillovers, with a particular attention to the generation and dissemination of knowledge. In particular, endogenous growth theory models tried and integrated the classical Marshallian tradition of analysis about technological externalities into the stream of literature initiated by the path breaking contributions of Robert Solow and Zvi Griliches.

On the one hand, new growth theory received the Marshallian idea that, within circumscribed geographical and technological spaces, knowledge is an input that spills free across actors embedded in the system. Firms co-located in the geographical and technological space are able to benefit from knowledge spillovers without occurring in any learning or transaction costs. In this perspective, the dissemination, communication, acquisition and implementation of external technical competencies entail no direct investments and no proactive behaviour for the firm to take advantage from such knowledge spillovers.

On the other hand, endogenous growth theory formally distinguishes between specific and generic knowledge. Specific knowledge is idiosyncratic to the organisational, technological and geographical space where it has been generated, while generic knowledge resembles the typical Arrovian public good, with strong, if not complete, overlapping with the notion of information. The creation of new knowledge and the introduction of a given innovation is the result of the complementarity between generic and specific portion of knowledge, and more specifically of the implementation of generic knowledge upon the idiosyncratic competencies of the firm. In new growth theory, innovation takes advantage of two factors, therefore: 1) the public availability of generic knowledge, which spills freely and ubiquitously as in the Marshallian tradition and engenders no acquisition costs for the firm; and 2) the specificity of the context in which generic knowledge is introduced and further elaborated and implemented, which makes it possible to appropriate new knowledge and innovation. Although generic knowledge has a public good character, incentives to further invest in knowledge creation and innovation are given by the appropriable character of the specific application of such generic knowledge.

Although new growth models appreciate the nature of knowledge as a quasi-public good, they present important shortcomings. In particular, the relation between innovation and growth is understood as a linear, steady (in the sense of both constant in rate and continuous in direction) and balanced evolution, where knowledge spillovers and technological learning arise spontaneously from labour, capital and R&D accumulation in a completely permeable system. Moreover is mostly characterized as information, despite its claimed proprietary nature. In this context, knowledge spillovers exert positive, unconditional and ubiquitous effects on output and productivity growth. The latter are in fact assumed to converge across regions, nations and technologies (Romer, 1986 and 1990; Aghion and Howitt, 1998; Jones, 2002).

On the contrary, an array of constraints and conditions that are idiosyncratic to the structure and history of economic systems, may affect learning and further accumulation of technological knowledge. Such constraints cannot be neglected when explaining the conditions under which technological knowledge and innovation are produced and accumulated. In other words, they must be taken into account in order to explain the empirical fact that innovation and, consequently, growth rates differ widely and are highly cumulated and concentrated in very specific historical periods, as well as in specific technologies, industries and regions (Abramovitz, 1986, 1989 and 1993; Abramovitz and David, 1973).

In this perspective the analysis of the localised conditions under which technological change and technological learning take place, as it has been articulated in the economics of localized technological change approach, challenges and augments endogenous growth models.

The economics of localized technological change appreciates technological knowledge as a collective good rather than a (quasi) public good. Here the exploitation of the positive effects of knowledge spillovers is not free. Important both technological and pecuniary factors qualify and bound the exploitation of knowledge externalities. The generation of technological knowledge and innovation, and the impact on economic growth, impinges upon the dissemination and accessibility of previous innovations. It also affects the complementary bodies of knowledge that can be understood, integrated and implemented, as long as a number of conditions and appropriate investments in learning, knowledge communication and knowledge transaction are at stake. Technological learning and the introduction of innovations benefit from knowledge externalities only when favourable conditions have been intentionally implemented and the appropriate economic structure constructed in the system. Technological learning and technological change emerge as the outcomes of idiosyncratic characteristics of both regions and technologies and localisation is understood both in geographical and technological sense. A few examples of the features that qualify 'good' contexts for the exploitation of knowledge externalities might be the following: the variety of types of firms and sectors, the presence of knowledge-intensive business services, technology transfer offices, venture capitalists, the development of appropriate intellectual property rights policies, university-industry relations, user-producer networks, international R&D alliances, as well as the diffusion and adoption of information and communication technologies (Antonelli, 2005, 2007, 2008).

At the geographical level a larger and larger body of the literature convincingly shows that the creation of technological knowledge and the introduction of innovation stem from collective and systemic efforts. These in turn emerge from a thick net of horizontal and vertical complementarities between firms specialised in different technologies, and between these and University, technology transfer centres and knowledge-intensive business services, located in the same region and linked by formal and informal ties (Breschi e Malerba, 2005). At the same time however it is true that some threshold effects can be identified, according to which co-location and agglomeration exert a positive effect on the absorption and exploitation of knowledge spillovers but only until a certain extent. Beyond a given threshold, 'too much' agglomeration and 'too' dense networks can spoil technological learning and the effect of technical externalities.

In this context our paper tries and identifies the effects of agglomeration on the relation between knowledge spillovers, innovation and growth. The rest of the paper is organized as follows. In Section 2 we outline the theoretical framework, proposing a simple model of agglomeration and growth. Section 3 presents the data and the results of the econometric analysis. Finally the concluding remarks follow in Section 4.

2 KNOWLEDGE SPILLOVERS, INNOVATION AND AGGLOMERATION

2.1 The Theoretical Background

The analysis of the characteristics and processes through which technological learning can take place, and technological knowledge be produced and disseminated, paid in recent years increasing attention to the particular conditions shaping specific geographical spaces. Idiosyncratic factors are seen as key drivers in sustaining the rate of production of new technological knowledge, its transformation into new products, processes, technologies, markets and organisational solutions, and which ultimately account for the productivity and output growth of local firms (Clark et al., 2000; Caniëls, 2000; Feldman and Massard, 2002; Cantwell and Iammarino, 2003; Boschma, 2005).

Well-established empirical evidence gathered in regional and innovation economics has revealed that agglomeration economies can display their positive effects only in well-defined technical and geographical spaces. This is true for both the generation of externalities and their absorption through learning activities, and hence for the emergence of higher rates of innovation (e.g., Audretsch and Feldman, 1996; Jaffe and Trajtenberg, 1999; Paci and Usai, 2000).

Among others, Frenken et alii (2007) recently reviewed the literature on the sources of knowledge spillovers and the way in which they affect economic growth. Three main sources of agglomeration economies can be identified: 1) localisation economies that take the form of traditional Marshallian externalities, 2) urbanisation economies that stem from urban size and density, and 3) the well-known Jacobs externalities that derive from local concentration of a plurality of sectors. The Marshallian externalities tradition argues that geographical concentration and specialisation in a single industry, coupled with local division of labour, favour externalities to be generated, transmitted and accumulated by local firms. The localised generation of technological knowledge and the local introduction of innovation are the result of intra-industry and geographically well-defined processes of technological learning that internalise flows of technical know-how. Moreover, urbanisation economies suggest the idea that the density of institutional and scientific actors within cities is the crucial factor shaping the progressive generation, dissemination, imitation and recombination of diverse know-how and competencies within narrow but thick geographical space. Finally, the so-called Jacobs externalities tradition alternatively stresses the fact that economic differentiation plays a prominent role in creating opportunities for inter-industrial knowledge spillovers that make geographically proximate but technologically different firms able to learn each other.

However, a much-neglected issue in this field is the existence of threshold effects in the relationship between knowledge spillovers, innovation and agglomeration. More specifically two questions ought to be explored. First, does agglomeration always exert a positive impact on the firm's capacity to absorb knowledge spillovers, irrespective of the degree of geographical concentration of, say, firms, universities, laboratories, sectors? In other words, are there any congestion effects at place beyond a given degree of agglomeration? Second, is geographical agglomeration per se a sufficient condition for the deployment of knowledge spillovers and the positive effects of externalities to be absorbed by co-located firms? Or whether on the contrary is agglomeration a vehicle for complementary conditions to operate?

In this field of analysis, Noteboom et alii (2007) explicitly analysed the relationship between cognitive proximity and technological learning as characterised by some threshold effects. Boschma (2005) generalised such an analysis of whether the effect exerted by proximity on the innovative output of the firm could be positive rather than negative. Geographical proximity per se is neither a necessary nor a sufficient condition for knowledge spillovers and learning to take place as it should be complemented by other forms of proximity. Proximity includes not only geographical proximity, but also cognitive, organisational, social and institutional proximity. Not only too little, but also too much proximity can be detrimental to the accumulation and creation of technological knowledge and the innovative capabilities of the firms.

In this perspective, the understanding of technological knowledge as a collective good can provide a useful tool to grasp the relation between agglomeration, technological learning and spillovers in the process of innovation. Technological knowledge can be understood as a collective good when and where it requires the absorption of external knowledge and its integration into the research, development and learning activities internal to the firm. External knowledge results from investments in R&D that cannot be fully appropriated by firms and therefore spill out. However, the exploitation of such knowledge spillovers is not free as in the Marshallian and new growth theory tradition, but requires specific investments in knowledge communication and learning.

The emphasis recently given to communication opportunities and recombinatorial learning as the micro-foundations of innovation, underlines that the integration and recombination of existing complementary kinds of knowledge, most of which are external to the firm, is central in the creation of new further technological knowledge and technological change. Agglomeration economies are not only crucial in supporting technological learning per se, but especially in that they favour the accumulation of knowledge over time, and cumulative effects (i.e., standing on the shoulders of giants) in the generation and diffusion of knowledge apply when and if geographical spaces have appropriate concentrations of varied supporting institutions and opportunities for communication (Antonelli, 2001).

In this literature, it is generally agreed that agglomeration and co-location provide an appropriate context for interactions between actors that command different and complementary skills and competencies. These allow for the transmission of different and yet complementary kinds of knowledge, and favour their recombination and implementation into a new portion of technological knowledge. Firms are not merely involved in their internal R&D activities, but also developed innovation processes in cooperation along the entire supply chain. Cross-sectors user-producer interactions between small firms and multinationals can also play a major role in enhancing the circulation and integration between generic knowledge and more technical know-how. Moreover, the scientific and research community acts crucially to disseminate a plurality of portions of general knowledge in complementary industrial fields. Through science-industry relations firms are able to internalise flows of generic knowledge through formal organisations. Knowledge intensive business services (KIBS), such as consultants, financial services, patent experts and venture capitalists play also a key role and intermediate between small and large firms, and between these and scientific institutions. New firms formation, local entrepreneurship, generative relations and the process of spin-off provide, furthermore, opportunities for the dissemination of technical competencies mainly embedded in human capital, together with labour mobility within local markets.

In this context, the analysis of the conditions under which networking, interaction and collaboration can benefit from agglomeration and proximity, exerting a positive impact on knowledge externalities and ultimately on the innovative and output performances of the firm, deserves specific consideration.

2.2 *Towards a Simple Model*

The dissemination of knowledge is now a key determinant in the generation of new knowledge and innovation. Knowledge dissemination is different from the mere diffusion of existing information and implies not only that actors have access to external portions of knowledge, but that they also understand, elaborate, internally implement and change these. Knowledge dissemination implies the modification of knowledge itself. Technological knowledge and the eventual introduction of innovation are now understood as the results of a cumulative process of distribution, recombination and transformation of different, pre-existing bits of knowledge embodied in a variety of actors. However, an array of problematic consequences arises from such collective character of technological knowledge. First, access conditions to existing external knowledge are key factors improving the effectiveness and rate of knowledge production, enabling the acquisition and accumulation of technological knowledge already stored but dispersed in a number of different but yet complementary artefacts, technologies and users. Yet, since technological knowledge is industry- and region-specific and ultimately individual, it is also very idiosyncratic and difficult to be used elsewhere, i.e. in other regions, other industries and also other firms and individuals. Consequently, access conditions are harmed by the efforts agents must undertake to search, understand, acquire and implement internally the relevant bits of idiosyncratic knowledge owned by different and complementary actors (Antonelli, 1999 and 2005).

Evidence on regional networks showed that geographical proximity per se is less relevant than specific characteristics of both the firms and the system, and in particular the ability of the firms to exploit the local endowment in terms of, for instance, R&D institutions, innovative clients, complementary partners, and to implement selective networking strategies. Congestion problems and negative effects on technological learning and innovation can however easily arise when excess proximity and agglomeration are reached, due to, for instance, lock-in, inertia, higher communication costs, redundant interaction structures between actors and overlapping competencies (e.g., Patrucco, 2005; Giuliani, 2007).

Individual actors put in place connections in order to access and generate new knowledge, and thus to react to cognitive and structural boundaries and the changes occurred in the environment. Learning by creative and yet myopic firms, i.e. firms characterised by limited and specific knowledge, underpins the generation of new knowledge. New knowledge takes advantage from the complementarity rather than the substitutability between internal and external bodies of knowledge. The larger the adoption of networking as a means to access and use external knowledge, and the larger the complementary internal know-how required to the firm to be able to understand, command and recombine external capabilities. However, the exploitation of knowledge complementarities is not unconstrained and the ratio of internal to external knowledge is most important. Both internal and external resources are needed and cannot be used both below and above a given amount. Increasing returns in the generation of new knowledge build upon the constrained exploitation of complementarities between internal and external knowledge and the implementation of a collective pool of knowledge and competencies through interactions. Agglomeration within technological systems favours the generation of the optimal amount of technological knowledge when and where the properties of economic system can guarantee the appropriate mix of internal and external resources. An important case for the understanding of the properties and mechanisms of effective knowledge governance emerges here (Patrucco, 2008).

The governance of knowledge is an essential component in collective knowledge creation processes and takes many forms: 1) knowledge transactions directly in the markets for technological knowledge, with incomplete prices and pecuniary externalities; 2) cooperative strategies based on outsourcing, technological clubs and platforms, patent thicketing, joint ventures and sponsored spin-offs; 3) knowledge interactions based on trust and reciprocity, where social and institutional proximity complement geographical and technological proximity. However knowledge governance is affected by the limits to knowledge coordination and communication associated with the number of connections and actors within a network. The effectiveness of governance decreases more than proportionately with the increase in the size of the network, i.e. with the increase in its density, as it ultimately causes congestion problems.

In knowledge governance the interplay between the positive externalities provided by knowledge spillovers and the negative externalities stemming from congestion problems is crucial. Firms located in a given technological and geographical network can benefit from agglomeration only when positive effects prevail on negative effects, and thus can display processes of technological learning properly. In other words, technological learning and the absorption of technological externalities by co-located firms is the result of contrasting, centrifugal and centripetal forces. On the one hand, centripetal factors reinforce the process of agglomeration and create thicker and denser local networks. When centripetal forces exaggerate, negative effects are the result of excess proximity and agglomeration and give place to well-known lock-in solutions, inertia and congestion problems. On the other hand, centrifugal forces blur the space of agglomeration and increase divergence and distance between actors within the system. When centrifugal forces overcome, too high technological and geographical distance between actors can also harm the positive effect of knowledge externalities. Clearly, the 'optimal' degree of agglomeration and proximity and the 'correct' density of the network, as well as the deployment of collective knowledge dynamics, are the result of the appropriate mix of centrifugal and centripetal forces (Antonelli, 2007 and 2008).

>>> INSERT TABLE 1 ABOUT HERE <<<

The density of innovation activities within a region shapes the balance between positive and negative knowledge externalities. We can now fully articulate the hypothesis that there is an optimal size of networks. Too little a density of innovation activities reduces the accessibility of external knowledge. Too large a density enhances congestion and reduces appropriability. Firms can benefit from actual increasing returns stemming from the indivisibility, replicability and non-exhaustibility of knowledge only when the size of innovation networks is comprised between the two extremes. In other words we put forward the hypothesis that the output elasticity of knowledge, included in a typical Griliches production function, is itself a quadratic function of the size of the local innovation networks into which each firm is embedded. Knowledge externalities do trigger increasing returns that are external to each firm. Such increasing returns, however, are indeed internal to the localized context of action of firms. Knowledge externalities are a property of the system into which firms are embedded. As such they are endogenous to the system and likely to exhibit specific properties related to the changing characteristics of the system itself.

The following system of equations formalizes our hypothesis. Following Griliches (1979) Equation (1) shows that the total output of the region *i* at time *t* is a function of its capital stock K, its total labour force L and its capacity to introduce innovation and technological change T. In equation (2) the coefficient γ measures the extent to which within each region, firms are able to take advantage from the positive effects of agglomeration, to exploit knowledge externalities and implement appropriate technological learning; or whether on the contrary their innovative and learning potential is spoiled by excessive proximity and congestion problems. The coefficient γ is set as a dependent variable of the quadratic specification of N, the size of the innovation networks rooted in the region:

$$Y_{i,t} = K_{i,t}^{\alpha} L_{i,t}^{\beta} T_{i,t}^{\gamma} e^{t} \quad (1)$$

$$\gamma = (N + N^2) \quad (2)$$

The absorption of external knowledge is clearly affected by the need to implement specific and purposive knowledge interaction and communication process. In other words, if knowledge spills over and can be disseminated in the system, the exploitation of the benefits of such dissemination is not free. Specific efforts and investments in communication infrastructures and processes need to be implemented for external knowledge to be absorbed. Increasing returns stemming from knowledge externalities are found only in specific circumstances: when the net effects of centripetal forces are positive.[2]

The effectiveness of knowledge externalities is bounded to the specific mix of positive and negative knowledge externalities, centripetal and centrifugal forces, and ultimately to the degree of agglomeration that characterises a given region (Figure 1). Clearly the threshold N* identified the correct degree of agglomeration and proximity, achieved in a system by the appropriate matching of centrifugal and centripetal forces. Technological learning reaches the 'optimal' amount of learning γ^* and its effect on the amount of output Y is maximum. Below the optimal amount of learning γ^* increasing returns in the production function are still possible only for a minimum amount of learning $\gamma 1 < \gamma < \gamma^*$. For an amount of learning between γ^* and $\gamma 1$, the degree of agglomeration in the region can be both below and beyond the optimal degree N*. For a given degree of agglomeration comprises between N -1 and N + 1, a minimum amount of learning $\gamma 1 < \gamma < \gamma^*$ can be guaranteed, and the effect of positive knowledge externalities still prevails. Finally, the space below N -1 and beyond N + 1 represents those conditions where a negative effect on technological learning prevails, with negative knowledge externalities being the result of 'too little' and 'too much' proximity respectively. Here, decreasing returns in production are the effect of a mismatch between centrifugal and centripetal forces that bounds technological learning below $\gamma 1$.

>>> INSER FIGURE 1 ABOUT HERE <<<

Finally, the size of γ, beyond the threshold $\gamma = (1 - \overline{\alpha} - \overline{\beta})$, and hence the actual extent of increasing returns stemming from knowledge externalities depends upon the quality and efficiency of the local governance processes. In figure 1 we see that the dotted line represents the case of high efficiency knowledge governance processes, where $\gamma^{**} > \gamma^*$.

Let us now turn to the empirical test of the hypothesis developed so far.

3 ECONOMETRIC ANALYSIS

In order to estimate the effects of the scale of regional innovation networks on economic performances, we start from the extended production function specified in Equation (1). It is worth noting that we do not make any assumption about the homogeneity of the

[2] The analogies with the argument elaborated by Sheshinsky (1967) are clear. Sheshinsky argued in fact that effects of learning by doing *may* add on in a standard Cobb-Douglas production function with constant returns to scale according to specific circumstances. With respect to Sheshinsky we are able to specify the conditions that shape the actual emergence of localized increasing returns.

production function. In particular, we argue that increasing or decreasing returns to scale may apply, according to the factors shaping the output elasticity of technological change.

Following the arguments elaborated so far, we maintain that a reliable measure of the size of innovation networks is the density of innovators in a geographical area. Therefore, the density of innovation activities within a local context is likely to affect its effectiveness and hence its impact on economic performances. The more is the density of innovation efforts, the higher the likelihood that interactions among agents arise that foster positive feedback dynamics. The increase in the density of innovating agents is hence likely to increase their relative proximity. However proximity engenders positive feedbacks unless the density of innovating agents reaches a critical threshold. The trespassing of such a threshold may generate negative knowledge externalities, due to lock-in and inertia, and the low propensity to seek for external ideas and sources of novelty (Boschma, 2005; Antonelli, 2007 and 2008).

This amounts to propose a functional relationship between the output elasticity of technological activities and the local density of such activities themselves. In order to empirically test our hypotheses, the level of technological activity (*T*) is proxied by patenting activity. The density of innovation networks (*D*) is therefore defined as the ratio between *T* and the labour force employed in the region (*L*). In view of the arguments elaborated so far, we can now specify the following relationship:

$$\gamma = g(D) \qquad \text{s.t. } g' > 0 \text{ if } D < D^*, \qquad g' < 0 \text{ if } D > D^*, \qquad g'' < 0 \ \forall D$$

A convenient way to represent such a kind of relationship consists of specifying a quadratic relationship between γ and *D* as follows:

$$\gamma = aD^2 + bD + c \qquad (3)$$

Where $D^* = -(b/2a)$ and $a < 0$.

3.1 The data

In order to investigate the relationships between economic performances and the density of innovation activities, we drew the data about GDP, employment, capital stock and patent applications from the Eurostat regional statistics.

Innovation activity is measured by using patent applications submitted to the European Patent Office (EPO), classified according to inventor's address. Although some drawbacks characterize patents as economic indicators[3], previous studies highlighted the usefulness of patents as measures of production of new knowledge, above all in the

[3] 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; Levin *et al*., 1987; Griliches, 1990).

context of analyses of innovation performances at the aggregate regional level (Acs et al., 2002).

Moreover, there is an extended debate about the sectoral patterns of patenting, according to which patents are more likely to characterize manufacturing rather than service sectors (Evangelista, 2000; Consoli, 2007). It must be noted that the use of patent applications does not simply imply the focusing on manufacturing industries in general. Indeed traditional and low-tech industries like textiles, are very unlikely to patent their products as their product is pretty easy to imitate. They will more likely rely upon other protecting tools like the brand. Low-tech industries are characterized by low levels of natural appropriability of their technology, while high-tech firms are instead characterized by high natural appropriability. The latter are thus more stimulated to patent than the former. The use of patent applications constrains the attention to the subset of high-tech manufacturing industries.

Due to the high variance of patenting activity over time, we decided to calculate the 5-years moving average at each year. In Table 2 we report the descriptive statistics concerning of main variables, showing also the values for within- and between-groups transformation. Cross-regional variance in patenting is very high, the overall standard deviation being almost twice the mean value. Moreover, the observed values range from about 2 to 3 thousands.

>> INSERT TABLE 2 ABOUT HERE <<

The other variables show a different pattern, being the standard deviation across regions almost the same as the mean value. This happens also for the patent applications per worker, where the number of employees smoothes very much the data.

However this preliminary analysis, while indicating some general patterns, say very little about which regions patenting activity tends to concentrate in, and where patents density is higher. In order to gain more detailed knowledge about these issues it may be useful to report thematic maps showing how the variables distributes across the regions in the dataset. In particular we focus on three variables, i.e. the absolute number of patent applications; its ratio with employment and with GDP.

In Figures 2 – 4 the maps assign the regions to the percentiles of the distribution of each variable[4]. As far as the absolute number of patent applications is concerned, one can see that in 1996 the regions with the highest level of patenting activity is located in the Ile de France, Stuttgart and Oberbayern. In France there is only one region falling between the 90th and the 99th percentile, i.e. the Rhone Alpes. In the same group there are the Lombardy and Emilia Romagna regions in Italy; East Anglia and Oxfordshire in the UK; Stockholm, Denmark and Southern Finland. The map also shows the clustering of patenting activity mostly in German regions, within the Bavaria, the Baden-Württemberg and North Rhine-Westphalia states. The regions with the lowest level of patenting activity are located in Eastern Europe, Southern Italy and in Spain, with the

[4] A percentile is the value of a variable below which a certain percent of observations fall. So the 20th percentile is the value (or score) below which 20 percent of the observations may be found. The 25th percentile is also known as the first quartile; the 50th percentile as the median.

only exception of the Madrid and Cataluña regions. The evidence shows that in 2003 the situation changed very little. It is fair to note that patenting the Veneto region joined the second rank group, and that there also was an improvement in the Marche and the Comunidad Valenciana regions.

>> FIGURE 2 ABOUT HERE <<

As already observed, the amount of employees provides a good smoothing tool controlling for regional dimensions. In Figure 3 the distribution of patent applications across European regions follows a slightly different pattern from the previous one. Fist of all, the 1996 evidence about France is drastically reorganized, as the Rhone Alpes region is not within the first rank group any longer. On the contrary, all the French regions are below the 90th percentile. Germany confirms to contain most of the highest-level patenting regions. However, there is only one region above the 99th percentile, i.e. Rheinhessen, while the other regions in Bavaria and Baden-Württemberg are between the 90th and the 99th percentile. Two new regions appear in the uppermost group, i.e. the Noord-Brabant in the Netherlands and the East Anglia in the UK, while Oxfordshire retains the same position. Northern-Italy regions and the Abruzzi are now below the 90th percentile, while the rest of Italy falls in the penultimate group. It is also fair to note that Northern-Finland and the Swedish regions of Mellansverige and Sydsverige moved upward in the second group. In 2003 some significant changes can be found. In particular, in Germany the Rheinhessen lost its position, while Stuttgart and Freiburg are in the first group, along with the Noord-Brabant. All other regions within the Bavaria, the Baden-Württemberg and North Rhine-Westphalia states are in the second group of regions, along with Herefordshire and East Anglia. It is quite interesting to note that the Oxfordshire moved downward to the third group. Moreover, most of Finnish regions are between the 90th and 99th percentile.

>> FIGURE 3 ABOUT HERE <<

In Figure 4, the ratio between patent applications and GDP expenditure is a measure of the cost of a patent, and hence of the relative effectiveness of innovation activity. In 1996 the more effective regions are again Stuttgart and Rheinhessen in Germany and Noord-Brabant in the Netherlands. Regions in the Bavaria and the Baden-Württemberg follow, along with East Anglia and Oxfordshire in the UK, Northern and Southern Finland and three Swedish regions. Northern Italy and France regions are between the 50th and the 90th percentile, while Spain, Greece and Eastern Europe are at very low levels of effectiveness. In 2003 the leading position was still retained by Stuttgart and Noord-Brabant, but Rheinhessen left the floor to Freiburg. The German area falling in the second group got smaller, focusing mainly on Bavaria. In the UK the Oxfordshire lost importance in favour of Herefordshire, while in the rest of Europe there were not dramatic changes.

>> INSERT FIGURE 4 ABOUT HERE <<

This preliminary evidence shows that there is a sensible variance across European regions, in all the observed variables. This is even more strikingly for patenting activity. However the smoothing of patent data with employment and GDP changed the scenario in different ways. Economic effectiveness and patents density seems hence to follow different, and yet related, patterns that deserve more careful investigation.

3.2 *The methodology*

The empirical analysis is carried out by rearranging equation (1) and equation (3), and applying panel data techniques. As a first step, let us take the log of Equation 1:

$$\log Y_{i,t} = \alpha \log K_{i,t} + \beta \log L_{i,t} + \gamma \log T_{i,t} \qquad (4)$$

Then we divide both sides of the equation by $\log T$ as follows:

$$\frac{\log Y_{i,t}}{\log T_{i,t}} = \alpha \frac{\log K_{i,t}}{\log T_{i,t}} + \beta \frac{\log L_{i,t}}{\log T_{i,t}} + \gamma \qquad (5)$$

This specification allows us to treat γ as a regressor rather than a parameter to be estimated. Substituting Equation (3) in (5) we yield:

$$\frac{\log Y_{i,t}}{\log T_{i,t}} = \alpha \frac{\log K_{i,t}}{\log T_{i,t}} + \beta \frac{\log L_{i,t}}{\log T_{i,t}} + aD^2 + bD + c \qquad (6)$$

Equation (6) allows for the estimation of long-run output elasticities of capital and labour and the coefficients of patent density, where we expect $a < 0$ and $b > 0$. By total differentiating Equation (3) one can also perform the short-run estimation. Call g_Y, g_K, g_L and g_T respectively the growth rates of GDP, capital, labour and patent applications we can write:

$$g_y = \alpha \cdot g_k + \beta \cdot g_L + \gamma \cdot g_T \qquad (7)$$

Let's divide by g_T and substitute Equation (3):

$$\frac{g_y}{g_T} = \alpha \frac{g_K}{g_T} + \beta \frac{g_L}{g_T} + aD^2 + bD + c \qquad (8)$$

Both Equation (6) and Equation (8) are suitable to econometric estimations. Unfortunately, long-run data are available only in the case of patent applications, while all the other variables are available since 1995, when the European Standard Accounts (ESA) has been introduced. The initial dataset consisted of an unbalanced panel of 317 regions observed on a time span ranging from one to nine years. In the econometric test we kept only the regions with the maximum number of observations, ending up with 143 regions and 1287 observations.

3.3 The econometric results

Table 3 shows the results of the panel estimation of Equation 6, controlling for regional fixed effects and including time dummies. Due to the small number of available observations, we considered only the first lag of covariates in the regression. All regressors are statistically significant, and the model explains a very high share of variance in the dependent variable.

It is interesting to note that the sum of output elasticities of capital and labour is about 0.6, which means that without innovation activity decreasing returns to scale would be at stake. The coefficients on patent density have the expected sign, supporting the idea that there is an inverse U-shaped relationship between economic performances and the concentration of innovating agents.

>> INSERT TABLE 3 ABOUT HERE <<

Although the numbers should be taken cautiously, we can calculate the threshold level of patent density. Recalling that in the parabola function the maximum level is reached at $D^* = -b/2a$, it follows that $D^* = (-0.57)/(-0.6) = 0.95$. The long-run threshold level hence would seem to be at about 1 patent every 1000 workers.

In order to check for the results obtained so far, we carried out the estimation also on the growth rates of the variables, as in Equation (8). It must be noted that taking the growth rates and considering the first lag of regressors vector, reduces very much the number of observation for each group. For this reason we carried out an OLS regression on the pooled sample, controlling for time fixed effects.

The results of the estimation are reported in Table 4. The variables are statistically significant and the sum of capital and labour elasticities in the short-run is slightly lower than in the long-run. The evidence about the density of patent applications is consistent with the results of the previous estimation, as the coefficient on D is positive while the one on D^2 is negative.

>> INSERT TABLE 4 ABOUT HERE <<

We can compute also in this case the critical value of D, which is now half the value obtained in the long-run. In brief we can conclude that empirical investigation carried out on the sample of 143 regions from 15 European countries provides a strong support to our leading hypothesis. Positive feedbacks in innovation activities apply only to a limited extent, i.e. as long as the density of innovative activity is below a critical threshold. When the population of innovators becomes too dense, negative externalities are likely to arise as a consequence of lock-ins, inertia and the difficulty to feed the variety of knowledge sources.

4 CONCLUDING REMARKS

The analysis developed so far can be placed under the broader umbrella of the investigation of the relationship between knowledge, innovation and economic growth.

The analysis of localized dynamics of technological knowledge and technological change represents a fruitful terrain for the integration between Schumpeterian perspectives on the discontinuous character of growth, the Kaldorian approach to economic growth and change based on increasing and self-reinforcing returns, as well as the path-breaking work of Simon Kuznets on differential economic growth. In this regard, the analyses of localized technological change can bear important analytical and policy implications in understanding the relationships between innovation and economic growth.

The key role played by innovation and, more generally, technological knowledge in sustaining economic growth is one of the most important stylised facts in recent economic analysis (Romer, 1994; Aghion and Howitt, 1998). Nevertheless, new endogenous growth theory fell short in understanding the two-way relation between the contextual properties of the system, technological change and growth (Schumpeter, 1928 and 1934; Young, 1928).

Specifically, the appropriation and accumulation of technological knowledge cannot take place automatically, as in endogenous growth models. In the endogenous growth theory knowledge is treated as a (quasi) public good and ultimately reduced to information. The implications of complementarities, interdependencies and feedbacks between the micro and the aggregate levels are neglected, and learning and the appropriation of knowledge spillovers arise spontaneously from labour, capital and R&D accumulation in a completely permeable system. In other words, neo-classical growth theory explored the conditions allowing for exogenous accumulation of technological knowledge in a steady (i.e., both constant and continuous) growth, moving towards a stable and unique equilibrium. It rather seems that neo-classical theory explored the conditions for the general equilibrium analysis tools to be applied. The new-growth-theory assumes equilibrium and perfectly permeable conditions for the appropriation of spillovers and the accumulation of knowledge. Endogenous growth theory is deterministic, characterised by agents that behave as spillovers were free and thus that do not actually learn.

To the contrary, the reorganisation and recombination of activities and resources open new opportunities for further recombination and organisation that feed a continual process of change that never converges towards equilibrium. Economic growth and change are the result of cumulative processes that impinge upon non-linear and self-reinforcing feebacks over time between technologies, science, and further innovations, i.e. technological and structural change. They develop over time and are biased by the historically and economically constrained sequence of single changes at any time. Such feedbacks together with the very localised character of institutional, industrial, technological and more generally economic conditions lead to the concentration of higher growth rates in very definite economic spaces. Higher growth rates concentrate in those economic spaces that exhibit more favourable conditions for such reorganisation and recombination. Punctuated and non linear, cumulative growth is the result of the interaction between negative feedbacks and positive feedbacks that concentrate in specific economic spaces provided with some favouring and idiosyncratic (initial) conditions, and which tend to reinforce divergence through increasing returns.

In this regard, economic change and growth cannot be reduced to a mere resources allocation problem. The essence of growth as an economic problem involves the creation of complementary resources (for instance, human and physical capital, technologies) over time in a dynamic process of accumulation, rather than the mere allocation of substitutable resources. Growth rates differ widely across time, technologies, industries, and regions, and tend to concentrate in those periods, technologies, industries and regions characterised by better structural conditions favouring feedbacks and increasing returns. Growth dynamics are therefore better described as a cumulative process that cannot be fully anticipated *ex ante*, rather than by trends towards predefined long-run equilibrium positions. The case for economic divergence rather than convergence applies (Kuznets, 1930, 1950 and 1977; Kaldor, 1972, 1975, 1978 and 1989: 90-99).

In this context, the economics of localized technological change provides new tools for a research agenda on the relationship between knowledge, innovation and growth. One that is able to provide an endogenous explanation of the uneven distribution of knowledge, innovation and growth rates according to the changing characteristics of economic systems in terms of technological communication and knowledge distribution (Antonelli, 2007 and 2008).

In this regard, a new research agenda for growth theory might be found in the exploration of the effects of the changing conditions of non-appropriability, access to external knowledge, knowledge governance onto the capacity of different systems to generate, accumulate and disseminate technological knowledge, and on their capacity to implement the dynamics of growth. This paper contributes this line of analysis. First, and most important we have shown that knowledge externalities are endogenous and localized. Indeed we have confirmed that too little agglomeration limits the access to the benefits of knowledge spillovers. The analytical foundations for the case of excess agglomeration however have been made. The empirical evidence has confirmed that too much agglomeration may harm the actual positive effects of localized increasing returns. Next and consequently we have laid down the methodology to identify the optimal size of knowledge networks. Finally, we have shown that the quality of knowledge governance plays a key role in assessing the range of values for which actual increasing returns stemming from knowledge externalities do take place.

The policy implications of our analysis are far reaching. In traditional approaches to technological knowledge as a pure private or a pure public good, public provision of knowledge, IPRs regimes and fiscal allowances have been seen as the appropriate ways for the policy maker to sustain innovation. When knowledge, instead, is collective, policy-making should direct the focus of public intervention on the creation of the conditions and incentives for the implementations of technological communication and intentional cooperation between firms, technological and scientific institutions and intermediary players. A wide scope for innovation policy emerges in terms of direct interventions geared towards the creation of successful local networks by means of dedicated and augmented incentives for co-operation and the dissemination of knowledge.

When the results of our analysis are integrated in this approach, it seems clear that an innovation policy at the national or European level that is not able to identify the specific conditions of the local regional systems risks to fail. It seems also clear the need to articulate a regional innovation policy that is able to appreciate the characteristics of the local innovation systems. Each region should be aware of the specific opportunities and constraints that characterize the local innovation system.

Policy makers should be aware that the agglomeration of research-intensive activities may be unsuccessful. Huge opportunity costs may be identified. Opportunity costs are found when policy makers insist in attracting firms in locations where the specific localized increasing returns are lower than in other locations.

Furthermore, our analysis stresses the complementarity between different resources and different actors. Appropriate and effective knowledge governance should match both the correct size of the network and the quality of its elements, identifying the appropriate members of the local cluster. Each of these members is necessary and non-disposable. Policies aiming at the creation of successful local knowledge clusters should therefore guarantee the variety of the participants to the network, with implication for both industrial and science policy intervention. Finally and consequently, under appropriate conditions for positive knowledge externalities to take place, innovation is a collective event and, because of the feedback from the diffusion of previous artefacts and innovations to new technological developments, policies should focus on bundles of knowledge and innovations rather than on singles technologies and artefacts. A policy aimed at improving the local conditions for knowledge governance should match all policies aimed at creating local knowledge clusters.

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Table 1 - Centripetal and centrifugal forces in agglomeration economies

Centripetal forces	*Centrifugal forces*
• Positive knowledge externalities • Shared knowledge communication codes • Social embeddedness	• Negative knowledge externalities • Congestion • Loss of appropriability

Table 2 – Descriptive Statistics

Variable		Mean	ST. Dev.	Min	Max
Patents	overall	251.157	427.9039	1.19672	3324.983
	between		418.7144	2.16854	2769.128
	within		94.10433	-479.5896	959.5023
GDP (millions)	overall	435.5414	472.2742	37.34416	4321.959
	between		470.8684	41.41505	3935.466
	within		42.51954	68.89446	822.0353
Employment (thousands)	overall	880.1036	753.921	80.6	5406.4
	between		753.9834	82.68889	5193
	within		58.25414	498.6813	1349.026
Patent per Worker	overall	0.242729	0.2373976	0.0028511	1.278389
	between		0.228767	0.0052435	1.012365
	within		0.0659119	-0.0855488	0.5303019

Source: our elaborations on Eurostat data.

Table 3 - Econometric Estimation of Eq. (6)

Dep. Var: Log(Y)/Log(T)	
Intercept	0.032***
	(0.012)
Log(L)/Log(T)	0.006***
	(0.001)
Log(K)/Log(T)	0.565***
	(0.001)
D	0.576***
	(0.074)
D^2	-0.306***
	(0.056)
$R^2 = 0.98$	
N = 143	
n = 923	

Note: st. errors between parentheses. ***: p<0.01

Table 4 - Econometric Estimation of Eq. (8)

Dep. Var: g_Y / g_T	
Intercept	0.288
	(0.358)
g_L / g_T	0.212***
	(0.068)
g_K / g_T	0.227***
	(0.015)
D	2.843**
	(1.417)
D^2	-3.500***
	(1.691)
$R^2 = 0.26$	
n = 780	

Note: st. errors between parentheses.
***: $p<0.01$; **: $p<0.05$

Figure 1 – Technological Learning and Agglomeration

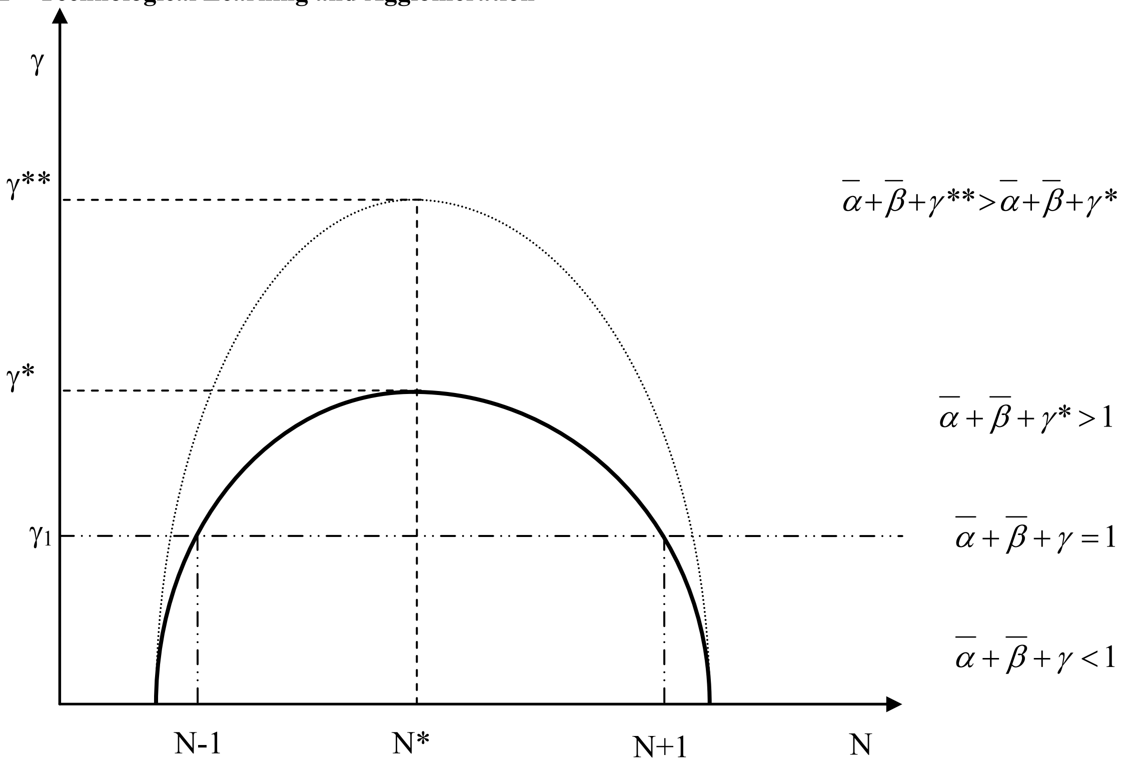

Figure 2 – Regional Distribution of Patent Applications (percentiles)

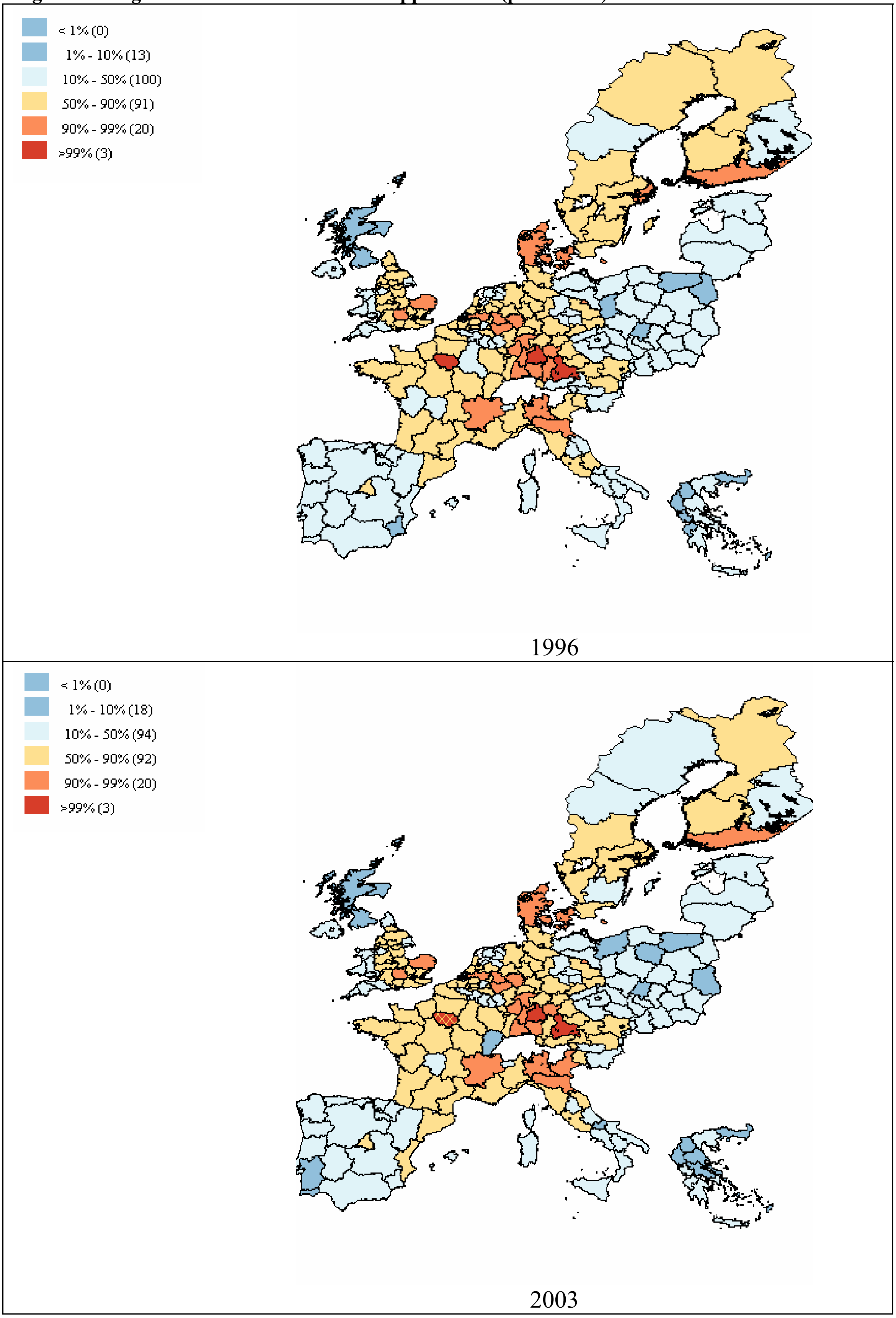

Figure 3 - Regional Distribution of Patent Applications per Worker (pecentiles)

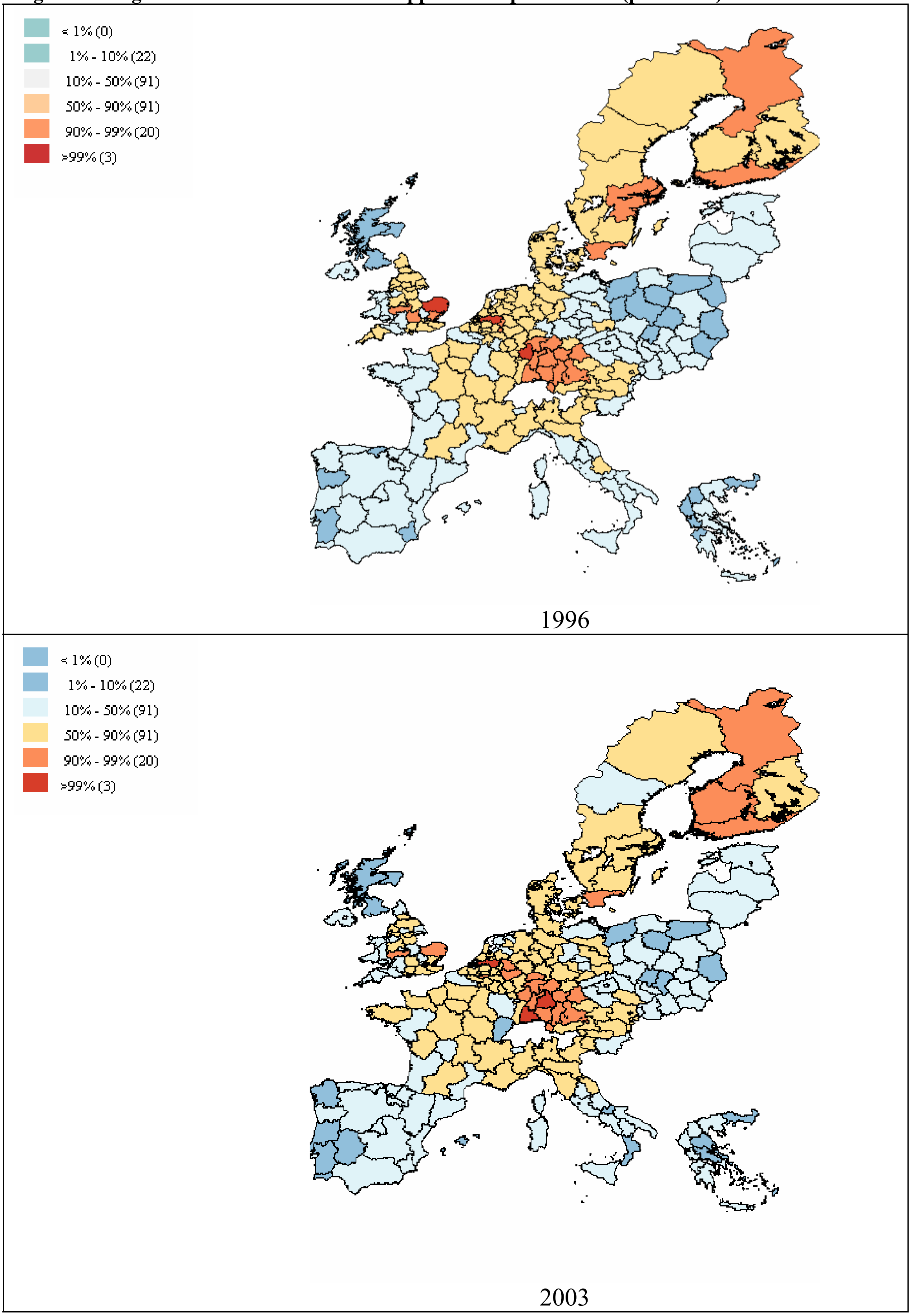

Figure 4 - Regional Distribution of Patent Applications per Million GDP (pecentiles)