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ABSTRACT

Innovation, Demand and Knowledge Spillovers: Theory and Evidence From European Regions*

The importance of innovation for the economic performance of industrialized countries has recently been heavily stressed by theoretical and empirical literature. Very few studies have, however, carefully considered the determinants of European innovation; the productivity of its R&D; and the existence of knowledge spillovers across regional boundaries. Here we develop a model which, by emphasizing 'the demand pull' as a key exogenous determinant of long-run innovation across regions, allows us to estimate the returns to regional R&D as a generator of innovation. We find that most of the cross-regional differences in innovation rates can be explained by their own R&D, even after correcting for the endogeneity bias. Moreover, significant spillovers are found among geographically close regions, especially if they are technologically similar.

JEL Classification: O3, R0, R1
Keywords: regional R&D, spatial spillovers, endogenous innovation

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NON-TECHNICAL SUMMARY

Technological innovation has been one of the most important factors in explaining labour productivity growth in this century. In the last decades innovation has become an even more important contributor to the economic well-being and the comparative advantage of industrialized countries, as the nations of the world economy are becoming increasingly open and interdependent. Openness fosters new ideas and their diffusion. Spillover benefits may spread through space, time and sectors.

This paper analyzes the importance of R&D and knowledge diffusion, as well as local demand, in shaping the geographical distribution of innovative activity using data on European regions: the regional dimension is particularly relevant at the European level, since their level of heterogeneity is still large. The first empirical issue to be addressed is how to measure the 'stock of knowledge'. We take patent count as a proxy for the increase in economically profitable knowledge. One patent is one new good and all of them give the same contribution to productivity, since they can be used as a measure of the increase in the stock of knowledge.

Data analysis confirms the clustering of the innovative activity in the European regions. The intensity of innovative activity is very different across space in the European regions: the top five patenting regions (Northrein-Westfalia, Bayern, Waden-Wurtenberg, Ile de France and East Anglia) are responsible for 50% of total patents as well as almost 50% of total R&D expenditure, while the bottom 11 regions had almost no patenting at all in the 1977–95 period.

How many of these disparities in innovative output are due to R&D intensity in the regions? A simple regression shows that average long-run R&D expenditure explains almost 73% of the cross-regional variation in long-run patenting intensity, and that the elasticity of patenting to R&D spending is significantly larger than one. The very high returns to regional R&D could be the sign of increasing returns to its own research but inter-regional spillovers might have a role in explaining the remaining variation in innovative activity. In particular some occasional examples tell us that the location of a region is significantly correlated with its productivity in innovation. By looking at two regions with the same average total spending in R&D, like Madrid and Hamburg, it is possible to realize that the peripheral region of Madrid produced about one-tenth of the patenting per worker than the central region of Hamburg, in the period 1985–95. Similarly, the peripheral region of Lazio (Italy) produced about one thirtieth of the patenting per worker than the central region of south-Netherland.

Are these example mere exceptions or is there a systematic effect of the neighbour regions on other regions' innovative activity? We know that knowledge is input in production that bears some peculiar properties: it is a non-rival input in the generation of new knowledge. The use of an idea to produce goods and services by an agent does not preclude any other person to build on it in order to generate a new one (Romer 1990).

This partial non-excludability of knowledge suggests that R&D may generate 'technological spillovers' and that these spillovers may nevertheless be restricted in space. Plausibly, ideas spread – first in the proximity of the place, where they have been generated, and only later in the rest of the world. In particular, when we consider applied and non-codified knowledge, the advantage of geographical proximity consists in the need of a face-to-face interaction to effectively learn from other people's ideas. Hence, while general information is more easily diffused, specific knowledge justifies the concentration of innovation in space, to take advantage of these 'externalities'.

But is this the whole story? Are knowledge spillovers a factor of first order importance in generating agglomeration of innovative activity? Data shows that innovation activity is highly correlated with local demand, which is here measured by the size of population. Innovation clusters where most of the European population is, and has been, for the last 100 years. The idea is that there exists a circular causation, in which R&D generates innovation, and technological growth which in turn generates profits and incentive to invest in R&D.

We use two different measures of 'market potential' of one region, i.e. local demand and local raw labour, as factors which increase the market potential for the intermediate patented goods, without affecting R&D productivity. We think that a good proxy for both variables is the population in a region and in its neighbour regions, with decreasing coefficients. We choose population at the beginning of the period (1980) to minimize concerns that the recent process of innovation might have affected its distribution. In determining the location of innovative activity, this extremely irregular distribution of population and market potential should play a role if local markets, both for intermediate and final goods, have an impact in determining profits for local innovators.

The results show that most of the cross-regional variation in patenting is due to differences in R&D. The spatial spillovers exist and are statistically significant for the R&D carried out within 200 kilometres of the region. The magnitude of these spillover effects, if not negligible, is not very large either: the elasticity of patenting to 'close' R&D is between 4 and 11%, while the elasticity to own R&D is in the range of 100–140%. This result suggests that spatial spillovers may be of 'second order' importance while clustering of R&D is of 'first order' importance.

We perform a number of different checks to test the robustness of the results. Since the benefit of ideas could spread more easily within countries than across, the effect of spillovers across distance may be simply capturing the fact that the positive and perfect spillovers may be capturing a border effect. To control for it we add the average level of R&D spending or employment in each of the eleven countries to our regressors. We find that the national R&D variable has a very strong and positive effect, but the elasticity to R&D of regions within a range of 100 kilometres is larger than 1%.

The natural question to ask is whether 'geographical space' is the most natural dimension in which regions innovate and in which spillovers happen. R&D and spillovers coming from regions which are close in the 'technological space' (produce and innovate in similar sectors) rather than in 'geographical space' could be more relevant. We construct an index of technological distance but we find that the purely spatial spillovers are more important than the purely technological ones.

Also, it may well be that the R&D performed in similarly specialized regions may be more important, at a given distance. To inquire into this we estimate again four spillover parameters, considering now only the regions within the 200-kilometre range from one's capital city. It clearly emerges, in all specifications, that the technologically closer regions among those in geographical proximity are by far the most important in generating R&D spillovers on innovative activity. The elasticity of innovation to R&D employment in these regions is around 0.10 and highly significant, while the effect of R&D in more different regions is not significant and often negative.

1. Introduction

Technological innovation has been one of the most important factors in explaining labor productivity growth in this century[1]. In the last decades innovation has become an even more important contributor to the economic well-being and to the comparative advantages of industrialized countries, as the nations of the world economy are becoming increasingly open and interdependent. Openness fosters new ideas and their diffusion. Spillover benefits may spread through sectors, space and time, affecting productivity and growth worldwide. Nevertheless even a cursory look at countries and regions in the world reveals large disparities in productivity and innovation rates[2]. To understand this phenomenon it is crucial to take a closer look at the process of diffusion of technology and in particular at the internal and external effect of research and development in generating innovation.

The aim of this work is to analyze the importance of research and development and of knowledge diffusion, via sector and spatial spillovers, in shaping the distribution of innovative activity in the long run. While the marginal cost of transferring information across geographic space has been made invariant by the tele-communications revolution, the marginal cost of transferring knowledge, especially tacit knowledge, rises with distance[3]. To test for the importance of spatial proximity and geography for the innovative activity we use data on European regions: the local as well as the regional dimension is particularly relevant at the European level, since regional heterogeneity is still large. Also, together with increasing returns to innovation and localization of knowledge, high market potential in densely populated European regions, might be relevant to explain the pattern of high concentration in innovation activity, since it affects the profitability of markets for innovation.

Our theoretical framework captures some of the characteristics of a regional economy: specialization in a range of products, responsiveness to the local conditions of the market, relatively high mobility of skilled worker but low mobility of unskilled workers (and of overall population) across regions. It provides us with a clear relation between R&D, knowledge spillovers and innovation activity, that we can estimate on European data. Unfortunately, the vast theoretical literature that combines a Schumpeterian approach in a general equilibrium set-up (see Aghion and Howitt (1998) for review of the literature and references) has not been accompanied by the

[1]Most quoted and popular reference: Solow (1957) but the introduction to the book Aghion and Howitt (1998) strongly argues on these lines as well .
[2] Quah (1996) among others makes this point.
[3] See D.B.Audretsch (1998)

development of an empirical literature of the same dimension[4]. More recently Caballero and Jaffe (1993) and Eaton and Kortum (1996) moving from the theoretical approach of the new growth theory have tried to assess the importance of R&D on innovation estimating a general equilibrium model for innovation in the US or across countries in the world. Jaffe (1986), Feldman(1994) and Audretsch and Feldman (1996) have modified the model of knowledge production function to include an explicit specification for the spatial dimension. Keller (1996,1999) and Branstetter(1996) measure intra-national versus international knowledge spillovers. The aim of our paper is to contribute to this literature testing empirically, using European Regional data, the existence of spatial spillovers of R&D as well as the importance of local demand as a determinant of innovation activity.

The structure of the paper is the following: in section 2 we review some empirical facts to show the relevance of the chosen topic and frame it, section 3 is devoted to some review of the related literature. In section 4 we present our model and in section 5 the econometric specification of the fundamental estimated equation. Section 6 presents the data and the empirical results. Section 7 concludes the paper.

2. Some Empirical Facts

[4] Certainly the difficulty of measuring innovation is part of the reason for this lag in the empirical implementation.

Data analysis confirm the clustering of the innovative activity. The intensity of innovative activity is very different across space in the European regions [5]: the top five patenting regions (Northrein-Westfalia, Bayern, Waden-Wurtenberg, Ile de France and East Anglia) are responsible for 50% of total patents[6] as well as almost 50% of total R&D expenditure, while the bottom 11 regions have almost no patenting at all in the 1977-1995 period.

Figure 1, figure 2 and figure 3 show the geographic concentration of R&D expenditure, patents and demand (population density) in Europe. It is easy to see how the central European regions, and in particular Germany and France, show the highest concentration as regards all three dimensions and how innovation is more concentrated than demand. The eye effect is confirmed by computing an Herfindhal concentration index of R&D for the 86 regions of our sample.

The H-index has a value of 0.17 while the value of the index, were R&D equally distributed among European regions, would be 0,011. The same computations for patenting gives us an H-index of 0,145. Production (GDP) and population although less concentrated (H-index has a value of 0,049 and 0,039 respectively) are concentrated in the same area.

How much of these disparities in innovative output is due to R&D intensity in the regions? A simple regression shows that average long run R&D expenditure explains almost 73% of the cross regional variation in long run patenting intensity, and that the elasticity of patenting to R&D spending is significantly larger than one[7]. Figure 4 documents these facts. We can therefore infer that :

1) The very high returns to regional R&D could be the sign of increasing returns to its own research. Within region spillovers might be responsible for this. Certainly differences in R&D expenditures explain the large part of heterogeneity in regional and country's innovation.
2) Inter-regional spillovers might have a role in explaining the remaining variation in innovative activity. In particular some occasional examples tell us that the location of a region could be significantly correlated with its productivity in innovation. By looking at two regions with the same average total spending in R&D, like Madrid and Hamburg (roughly sixty-four 1985-U.S. Dollars per worker), it is possible to realize that the peripheral region of Madrid produced about

[5] The same is true for the US. Also,few countries are the generators of most of the patenting that takes place world-wide Inventors from US, Japan, Germany, France and the UK advance 81% of the patent application at the European Patent Office

[6] in the paper expenditure in R&D is considered as an input in innovation activity whose output (innovation) is measured by patents. We are aware of all limitations and drawbacks of this measure of output. Neverthless we conform to the existing literature since we have no better measure to adopt.

[7] Elasticity = 1.12, standard error=0.05: This result is just a stylized fact, we will consider the endogeneity problem seriously in the empirical part.

one tenth of the patenting per worker than the central region of Hamburg, in the period 1985-1995. Similarly, the peripheral region of Lazio (Italy) produced about one thirtieth of the patenting per worker than the central region of south-Netherland[8]. The same is true for the central French region of Champagne-Ardenne that produces the same patenting per worker than the peripheral French region "Midi'-Pirennee" using less than one third of the R&D resources (28 US $ per worker versus 91).

Are these examples mere exceptions or is there a systematic effect of the neighbor regions on other region's innovative activity? We know that knowledge is an input in production that bears some peculiar properties. First it is a non-rival input in the generation of new knowledge. The use of an idea to produce goods and services by an agent does not preclude any other person to build on it in order to generate a new one (Romer 1990). Secrecy is certainly a way to prevent knowledge diffusion and it is often used by firms to exclude other people from the use of new ideas[9]: even in the case of a patent, which is made public, the research that leads to it and the background ideas may be kept known only to a restricted number of people, at least for a while.

This partial non-excludability of knowledge suggests that R&D may generate "technological spillovers" and that these spillovers may nevertheless be restricted in space. As Glaeser et al. (1992) put it " intellectual breakthroughs must cross hallways and streets more easily than continents and oceans". The mobility of workers through sectors, firms and space may be a way of spreading innovation; the local formal and informal communication may be another way. Plausibly, ideas spread first in the proximity of the place where they have been generated, and only later in the rest of the world. In particular, when we consider applied and non-codified knowledge, the advantage of geographical proximity consists in the need of a face-to-face interaction to effectively learn from other people's ideas[10]. Hence, while general information is more easily diffused, specific knowledge justifies the concentration of innovation in space, to take advantage of these "externalities"[11].

But is this the whole story? Are knowledge spillovers a factor of first order importance in generating agglomeration of innovative activity? Data shows that innovation activity is highly correlated with local demand: the size of the population explains 38% of the patenting (see figure 5). Innovation clusters where most of the European population is and has been for the last 100 years (see Figures 1,2 and 3). Also the percentage of workers in R&D is highly and positively correlated

[8] The definition of "central" or "peripheral" is relative to what is considered the economic center of Europe, roughly the triangle London, Paris, Bonn

[9] Secrecy is considered the best method for maintaining and increasing competitiveness of their innovation. See the Community Innovation Survey made by the European Commission .

[10] For an in depth analysis of the importance of face-to-face interaction in developing ideas see Gaspar and Glaeser (1996).

[11] The classic references of the importance of "ideas in the air" is, of course, Marshall (1890).

with the population of a region (measure of the market size) and about 25% of the cross regional variation in this percentage is explained by the size of the population[12]. We take this as evidence that the population of a region and its demand create incentives for investing in innovation, and as the spillovers of ideas remain local, this generates higher polarization of innovation. The marginal mobility of human capital tends to reduce the differences in wage that could arise, so that income per worker is less unequally distributed. Nevertheless, the variation in the intensity of innovation is an important determinant of the variation of the productivity per worker in Europe. It explains about 13% of the cross sectional variation of workers' productivity by itself. Compared, for example, with a measure of education, which is known to have an important impact on productivity, the fraction of college educated people in one region explains only 7% of the cross sectional variation of productivity per worker[13]. If determinants of research and innovation were to be "endogenous" to the economic system, they must be the profits that innovation generates: what better engine to generate innovation than a large local market for the new products or processes which innovation will bring to life?

If this is a mechanism that generates concentration of innovative activity, then spillovers and increasing returns to knowledge may further contribute to lock in the process and explain the higher concentration of innovation over demand. Understanding and measuring the importance of own and local research in generating innovation is an extremely important task as it may shed some light on the cross-regional differences in productivity.

3. Related literature

The literature that relates to our paper is twofold. On one hand people have studied agglomeration of production and innovation in space, measuring intranational versus international knowledge spillovers(Branstetter (1999), Coe and Helpman (1996), Keller (1996,1999)). On the other hand a few paper have related innovation and patenting to the dimension of the market demand. We consider local demand as a proxy for potential profits from innovation[14].

Audretsch and Feldman (1996) document the clustering of innovative activity, especially at the early stage of the life cycle of products, showing that in the initial stage local spillovers are

[12] . This is consistent with the known fact that, for example in the US, most of the innovation, happens in large urban centers (in SMSA, especially in PMSA, see Jaffe et al. (1993) and Feldman and Audretsch (1999)).
[13] The data on educational attainment per region are only available from national sources for Spain, Italy, Germany, France and the UK.
[14] The existence literature studies the relation between innovative activity and profitability, by concentrating the attention on the degree of competitiveness versus monopoly of a market. We will not address any discussion on the market structure of the market for innovation

particularly important. Glaeser et al. (1992), by looking at employment and wage data, suggest that externalities originate from having a local diversity of industries, generating the so called “Jacobs” (1969) externalities. There is a strand of research, on the other hand, that stresses more intra-industry spillovers as important contributors to innovation, as researching and working on similar things may benefit each other’s productivity (Griliches 1992).

The importance of specialization versus diversity is explicitly addressed also in our paper since we consider both spatial and sector spillovers, finding that technological similarity enhances technological externalities, once regions are close. A similar approach is followed by Jaffe (1986) who quantifies the effects on the productivity of firms’ R&D of an exogenous variations in the state of technology (technological opportunity) and on the R&D of others firms (spillovers of R&D). He finds evidence of spillovers of R&D from several indicators of technological success on the productivity of R&D. In particular he shows that firms whose research is in areas where there is much research by other firms have, on average, more patents per dollar of R&D. He obtains an estimate of firm's R&D elasticity of 0.875 that reaches the value of 1.1 when the effect of R&D from other firms is taken into account. These estimates are very close to ours, as in one region we are internalizing large part of inter-firm spillovers. Following a similar approach Branstetter estimates the impact of intranational and international knowledge spillovers on innovation and technological change at the firm level, using previously unexploited panel data from the US and Japan. He finds robust evidence that intranational spillovers are stronger than international spillovers. Keller (1999) examines the evidence on technology diffusion through trade in differentiated intermediates goods. Because intermediates are invented through costly research and development investment, employing imported intermediates implies an implicit sharing of the technology that was created in other countries. Again there is evidence that countries benefit more from domestic R&D than from R&D of the average foreign country. Also, conditional on technology diffusion from domestic R&D, the import composition of a country matters, but only if it is strongly biased towards or away from technological leaders.

As regards the European countries' experience the analysis developed by Eaton and Kortum (1996) appears particularly interesting. They estimate a general equilibrium model on cross-country data, which defines simultaneously the dynamics of innovation and productivity growth. Their specification of a patenting equation allows them to find a measure of the productivity of resources used in R&D in generating innovation. They find that technology diffusion between countries falls as the distance between them grows. Also, human capital raises the ability of a country to absorb technology and the elasticity of production of ideas with respect to research employment is estimated to be close to unity. Therefore technology diffusion is significant and proportional to the countries' ability to absorb innovation. These results confirm the existence of a spillover phenomenon and leave room for the study of the variation of spillovers in different geographical areas.

As regards the role played by demand factors in explaining R&D activity it is worth citing the work by Geroski, Walter and Van Reenen (1996)(GWV) and Hanson (1998). GWV studies the determinants of innovative activity. They find the production of innovation is more sensitive to demand pull pressures and less sensitive to supply pressure, like industry R&D spending, than patent. Hanson (1998) examines the spatial distribution of economic activity in the US to see to what extent demand linkages, strongly stressed by the new economic geography literature as determinant of agglomeration in production, are relevant empirically. In order to study this issue he expresses potential demand for goods produced in a location as the sum of purchasing power in all other locations, weighted by transportation costs that take care of distance. His results suggests that the combined effects of scale economies and expenditure share make geographic concentration a stable feature of the spatial distribution of economic activity. His results resemble ours in that he also finds that demand and knowledge spillovers, through space and technology, are the important determinant of clustering.

4.The Model

The following section describes a simple model inspired by the recent theory on patenting and innovation that guides the empirical analysis developed in this paper.

We consider an economy with N many regions, and a structure of production and innovation where a new good coincides with a new idea and increases the productivity of the region[15]. We assume perfect mobility of skilled workers both between production and research and across regions[16]. Also each regional unit experiences innovation and patenting which happens on the frontier of the region's technological level. We could think of N also as the number of aggregate goods (sectors) produced in our economy which would imply that each region specializes in only one sector.

[15] The framework is as in Romer (1990) and Jones (1996).
[16] In the appendix we show that relaxing this assumption the main implications of the model hold.

Each region innovates by adding further intermediate goods that increase the productivity of the region itself. In our model the arrival of an innovation and patent does not destroy the profitability of the existing patents in the region, as the extreme effect of “creative destruction” does in the Aghion and Howitt (1992) model. Instead, if we think that the patented goods compete for the local market, then a new patent will certainly squeeze the profitability of the existing patents. We know from a series of studies (e.g. Eaton and Kortum 1996) and from survey evidence (The Community Innovation Survey by Eurostat and DGXIII) that most of the patenting is done to protect inventions on the local market and to keep or increase the market share of one firm.

We allow for the possibility of spillovers in the level of knowledge across regions. In particular there may be a catch-up process, which prevents regions' productivity to grow increasingly apart or a diffusion of knowledge across regions which binds them together. Two stylized facts make us more comfortable in describing the situation in European regions in the period 1978-1995 as captured by a balanced growth path (BGP) distribution of productivity-levels growing at a common rate rather than diverging over time. First GDP per capita in the European regions has grown at an average annual rate of 0.038 in the period 1978-1992, with an average standard deviation across regions of 0.012, very stable over time. Second, in a regression of convergence of per capita growth levels, the “β” coefficient of growth rates on initial levels turns out to be equal to -0.12[17].

In our approach we are close to the spirit of the “endogenous growth” literature since we consider, as determinants of growth, the incentives to innovate, which endogenously arise from the markets. The existence of some regions where the profits for innovation are larger than in others, due to demand or technological reasons, is one of the important determinant of R&D allocation. In particular the idea that some characteristics of the regional markets affects the profits from innovating in that region, while they do not affect the productivity of R&D in the region, is the crucial assumption which allows us to identify and estimate the parameters of the “innovation” function.

4.1 Production and Innovation

[17] Similarly we do not adopt the specification proposed by Segerstrom (1998), where different R&D soending is compatible with different GDP growth as it would have the implausible implication (in the cross section) of equal rate of patenting in different regions.

The production of output in each region depends on the use of intermediate capital goods and on the level of other local inputs used, mainly unskilled workers. The intermediate capital goods, whose variety is increased by innovation, are produced by skilled workers[18]. The local demand is mainly directed to locally produced goods and services (due to transport costs[19]). We may therefore represent, as reduced form of the GDP produced in the region, the following expression:

$$Y_{it} = D_i L_{i,t}^{1-\alpha} \int_{s=0}^{A_i} x_{it}^{\alpha}(s) ds \qquad \text{where } \alpha<1 \tag{1}$$

A_{it} is the number of intermediate patented goods in the region, each of which is produced in amount $x_{I,t}$ by a monopolistic firm. $L_{I,t}$ is the amount of unskilled labor (not mobile) used in production, while D_i is the price of the regionally produced GDP, which differs, due to different demand, in different regions. D_i is an increasing function of the population in the region, not involved in production but consuming (retired, people not in the labor force, children), whose behavior is not explicitly modeled. If we think of this population as unevenly distributed across regions, and consuming more of the locally produced composite good, they will contribute to determine the "price" of the local good. Therefore the term D_I may be interpreted as the "price" of the local composite good Y_{it}. Each monopolistic producer of an intermediate capital good will earn profits, which in equilibrium are equal to the rent from innovating and therefore to the reward to the innovator. These profits will be increasing in L_{it} and D_{it}, as these factors increase the local demand for intermediates (via final demand or demand from producers).

Innovation, in a region is generated by the amount of resources employed in R&D as well as by the intensity of spillovers from inside and outside generated knowledge. We represent this features in the following function which describes how new knowledge is generated:

$$\dot{A}_{it} = \lambda(n_{it}) f_1\left(A_{it}\right) f_2(A_{it}^s), \quad \lambda' > 0, \quad f_1' > 0 \quad f_2' > 0 \tag{2}$$

λ is an increasing function of n_{it}, the amount of labor employed in R&D, capturing the productivity of R&D in generating innovation. We will define its elasticity as ε_λ. f_1 is the

[18] One unit of capital goods requires one unit of skilled labor as input.

contribution of the local existing knowledge to the creation of new knowledge and f_2 is a function which captures the effect of spillovers from other regions' knowledge. A_{it} is the stock of knowledge of region i at time t, while A_{it}^S is the average stock of knowledge in the regions which have a spillover effect on region i. More precisely, A_{it}^S is a geometric average of other regions' stock of knowledge, where the exponent weighting knowledge of region j, is a measure of the intensity of the knowledge spillovers from region j to region i, (see appendix for a formal definition). It can be shown that under the condition of decreasing return on total knowledge spillover ($1-\varepsilon_{f1}-\varepsilon_{f2}>0$, where ε_{f1} and ε_{f2} are the elasticities of the function f_1 and f_2), the system of N differential equations in (2) admits a balanced growth path, which is locally stable. The common rate of growth of the regions will be $\frac{\varepsilon_\lambda g_H}{1-\varepsilon_{f1}-\varepsilon_{f2}}$, where g_H is the growth rate of the skilled labor force, and the relative innovating rate, namely the growth rate of the relative stock of knowledge $a_{it}=\frac{A_{it}}{A_t}$, could be expressed, in compact vector notation, as:

$$\text{(3)} \qquad \log(\dot{\underline{a}}) = \underline{c} + \tfrac{\varepsilon_\lambda}{(1-\varepsilon_{f1})}\left(I-\varepsilon_{f2}M\right)^{-1}\log(\underline{n})$$

Equation (3) is the key equation for the empirical implementation of the model. Each underlined variable is an Nx1 vector of regional variables, while I and M are NxN matrices. The equation states that in BGP the flow of new knowledge (which we will capture with the patenting rate of a region), depends on the level of resources spent in R&D in the region and in all the other regions, via the "spillover matrix" M. The M_{ij} element of such matrix, captures the spillover of knowledge from region j into region i, as described in the definition of A_{it}^S. A linearized version of equation (3) is estimated in the empirical section.

4.2 The issue of endogeneity

[19] We choose to model demand only via the easy shifter in the production of the aggregate output, and not to develop a fully specified economic geography model. Chapter 5 of the Fujita,Krugman and Venables (1999) provides a model which could be the foundation of this reduced form production function.

Equation (3), derived from the innovation-generating equation, in BGP is one of the two key equilibrium relations. It states that, the more resources are spent in R&D, the more innovation is generated, directly or via spillovers. Nevertheless the model provides us also with another important equilibrium relation. In fact, the amount of the resources allocated by the regional economy to innovation is not exogenous, but it is determined by the perspective profits accruing to the innovation, which are the innovator's rent. The wage differential between the R&D and the production sector is the incentive which drives resources (Human Capital) into R&D and away from production. In particular the value of a patent increases with the profits it commands, which in turn depend positively on the size of the local market (demand from "out of the labor force" and from unskilled workers), while productivity of R&D increases with the existing stock of knowledge. Therefore the number of employed in R&D in equilibrium depends positively on the total size of the local market (D and L), and on the level of productivity of R&D (captured by a). The exact equilibrium relation, derived in the appendix, shows that $\underline{n}$, the vector of regional employment in R&D depends log-linearly on $\underline{a}$, the vector of relative stock of knowledge, $\underline{L}$ the vector of local unskilled labor force and $\underline{D}$ the vector of local demand.

$$(4) \quad \log(\underline{n}) = \underline{c_1} + \log(\underline{a}) + \tfrac{1}{1-\alpha}\log(\underline{D}) + \tfrac{1}{1-\alpha}\log(\underline{L})$$

Equation (4) clearly shows the channel through which endogeneity of R&D operates. The stock of knowledge cumulated in one region affects the amount of employment in R&D so that to estimate the productivity of R&D in innovation in BGP, we cannot simply apply OLS to equation (3). However, this same relation identifies the instrument we need to correctly estimate the productivity of R&D in innovation. All the variables which affect the profits, via the demand for the new product, but do not affect the productivity of R&D, are determinants of $\underline{n}$ and not (directly) of $\underline{a}$ and could, therefore, be used as instruments. That can be the case of all the variables that capture the size and extent of the local market without affecting directly the productivity of research. We take care of defining them explicitly in the next section.

5. Empirical specification and the structure of the spillovers

As said in the previous section, we will empirically implement the relationship expressed by (3). This expression is non linear in the parameter ε_{f2} and all the spillovers parameters M_{ij} enter via the inverse matrix in square brackets. Although in principle we could estimate the parameters directly from this specification using a non linear method, we would have to do an inversion of a matrix and obtain extremely non linear function of the parameter, with extremely hard estimation problems. What we could do is to re-write the matrix in braces, linearizing it around the point where the parameter ε_{f2}=0. We apply the Taylor formula for a vector equation and terminate it after the first term.The linear expression we find is:

$$(5)\quad \log(\dot{\underline{a}}) \approx \underline{c} + \tfrac{\varepsilon_\lambda}{(1-\varepsilon_{f1})}\left(I + \varepsilon_{f2} M\right)\log(\underline{n})$$

Equation (5) is a general relation between regional innovation rate and regional resources used in R&D that can be estimated using IV , once we find the right instrument for R&D employment. The interpretation of (5) is rather intuitive. It says that the determinants of innovation in a region are two factors:

1) The R&D done in the region itself,
2) The R&D done in all the other regions, filtered by a coefficient capturing the overall spillovers (ε_{f2}) and a matrix which identifies the intensity of spillovers across space (as M_{ij} will depend on the distance between region i and region j).

The coefficient on the term log($\underline{n}$) will capture the total returns to own R&D in generating new knowledge. It is a combination of two factors: the productivity of R&D in the innovation equation (ε_λ) and the intensity of spillovers from own knowledge stock (ε_{f1}). The coefficient of the term M*log($\underline{n}$), on the other hand, is a measure of the intensity of the effect of other regions' R&D on one region's innovation and will be considered as a measure of the intensity of the spillovers.

As first approach we do not want to impose any parametric structure on the intensity of the spillovers (M_{ij}) allowing only that they vary with distance (in the geographic or in the technological space). Therefore we decompose the matrix M as follows:

$$(6)\qquad M = \beta'_1 M_1 + \beta'_2 M_2 + \ldots + \beta'_K M_K$$

To construct M_i we have grouped the regions in K classes of distance, including in each class the couple of regions whose distance d_{ij} is in the interval [x_{k-1}, x_k] units. Each entry ij of the

M_k matrix has a value of 0 when the distance between region i an j does not fall in the k-th class. The entry is equal to $(1/n_i)$, where n_i is the size of the k-th class for region i, if the distance between i and j falls in that class. Hence we obtain K, Markov M_k matrices, multiplied by a β'_k coefficient that captures the intensity of the spillovers from the regions in that class of distance which we can estimate. It is then possible to assess the effect of the inter-regional spillovers of R&D on innovation, and to identify the rate of decay of spillovers with geographical or technological distance. The system that we can estimate is, in matrix notation, as follows:

$$(7) \qquad \log \dot{\underline{a}} = \underline{C} + \beta_0 \log \underline{n} + \beta_1 M_1 \log \underline{n} + \beta_2 M_2 \log \underline{n} + ... + \beta_K M_K \log \underline{n}$$

β_0 gives a measure of the BGP elasticity of innovation to own research while (β_K / β_0) is a measure of the relative importance of the knowledge spillovers coming from regions at distance k from region i.

The theoretical analysis developed in the previous section tells us that the expression (7) is a linear approximation of the exact BGP relation between knowledge stock and its determinants. In particular this relation is only a part of the BGP conditions and we need to account for endogeneity of log($\underline{n}$).

The amount of resources employed in R&D, in fact, depends importantly on the profits that innovation generates, once implemented. Regional characteristics, influencing the demand for new products, but not the productivity of research, appear in the term D_i of equation (5) and not in (4) and are therefore good instruments to estimate the β's. We think that the issue of valid instruments to estimate the effect of R&D and of the spillovers on innovation is a crucial one, not addressed by the recent empirical literature. If innovation is endogenous to the economic system, it arises for the profits that the innovation generates. There is a circular causation, in which R&D generates innovation, and technological growth (equation (5)), which in turn generates profits and incentive to invest in R&D (equation (4)). Most of the empirical literature, which considers the cross-country implication of R&D on growth (Eaton and Kortum 1996, Bayoumi, Coe and Helpman 1999), assumes the exogeneity of the R&D expenditure (much as the classic growth literature assume as exogenous the countries' savings rates, Mankiw, Romer and Weil (1992)). This is in contrast, we think, with the whole theory of endogenous growth.

We are going to use two different measures of "market potential" of one region, i.e. local demand and local raw labor, as factors which increase the market potential for the intermediate patented goods, but do not affect R&D productivity. We think that a good proxy for both variables is the population in a region and in its neighbor regions, with decreasing coefficients. The population within the region and in the neighbor contributes to create local demand for final and intermediate goods, shifting relation (4) but not affecting relation (5). We choose population as close to the beginning of the period (1980) as we have data for, to minimize concerns that the recent process of innovation might have affected its distribution. It is with the industrial revolutions that the process of urbanization took place and the large differences in regional population developed. Since then (certainly in the last 50-100 years) this distribution has not changed significantly (Bairoch 1988). Paul Krugman (1991) tells us that the best predictor of concentration of economic activity today is economic activity 100 years ago, in the US as well as in Europe. This is certainly true for population as well. Therefore, in determining the location of innovative activity, this extremely irregular distribution of population and market potential should play a role if local markets, both for intermediate and final goods, have an impact in determining profits for local innovators.

The second instrument we use is the age structure of population. Due to life cycle and to family structure, people at different age may have different levels of demand (in particular in presence of liquidity constraints). In particular, the share of population in the central part of their life (30-50) should exhibit higher demand compared to the extremely young or the extremely old. Therefore this could also be a good instrument to proxy demand and to estimate return to R&D and spillovers. As we will describe in the empirical part, these two sets of instruments do relatively well in capturing the cross-sectional variation of the intensity of R&D (R&D employed as percentage of the labor force), in fact they jointly explain around 37% of such variation. Population by itself explain about 25% of the cross sectional variability of R&D intensity.

6. Empirical Results

The first empirical issue to be addressed is how to measure the "stock of knowledge". If a new patented good can be considered as a new intermediate and a new idea, as in Romer (1990) and Jones (1995), the patent count can be used as a measure of increase in the stock of knowledge. In Aghion and Howitt (1992), Eaton and Kortum (1996) and in all the models based on a "quality ladder" and vertical innovation, the "count of patents" cannot measure the relevant stock of knowledge: both the frequency and the "size" of innovations matter. Also, since the new patents substitute and do not complement the existing ones, all that really matters in those models is to establish the “degree of knowledge” set by the last generation of patents in each sector.

The shortcoming of this approach is that we have only extremely coarse and noisy measures of the “size” of one patented innovation and an even worse understanding of which sector is relevant for patenting purposes. Moreover as the region, rather than the sector, is the unit of our analysis it seems plausible to consider a new patent produced within the region as a complement rather than a substitute of the existing ones. Therefore we take patent count as a proxy for the increase in economically profitable knowledge. One patent is one new good and all of them give the same contribution to productivity. We attribute a patent to the region of residence of its first inventor, as we want to capture the spillovers from ideas to generate new ideas, and therefore the location of the inventor is the location where the idea has been developed.

With these assumption, and considering that the economy will be on average on the balanced growth path, in the 18 years period we consider[20], we are able to estimate equation (20). In particular, equation (7) has a direct translation in terms of patents, which is:

$$(8)\quad \log(\underline{Pat}) = \underline{C_0} + \beta_0 \log \underline{n} + \beta_1 M_1 \log \underline{n} + \beta_2 M_2 \log \underline{n} + ... + \beta_K M_K \log \underline{n}$$

Equation (8) is the basic specification of our empirical estimates. The average yearly amount of patents’ application , in each region (in the period 1977-1995) is considered as the measure of BGP intensity of patenting[21]. This in turn, is assumed to depend, on the number of workers employed in R&D (average in the 1977-1995)[22] in the region itself and in the other regions, if there are any cross-regional spillovers of knowledge. The coefficients $\beta_1, \beta_2, ...\beta_K$ are a measure of the intensity of cross-regional spillovers that depends on the distance between regions. Hence, the cross sectional variation of the employment in R&D in the other regions, assuming that these spillovers vary with distance, allow us to identify the relative intensity of the spillovers. β_0, on the other hand, captures the elasticity of innovation to own R&D employment. Intuitively, if the different intensities

[20] 18 years could be a short period of time if we believe in the low estimate of convergence by Barro and Sala (1991). Nevertheless stylized facts and new estimates of the speed of convergence from panel data (Canova and Marcet 1995, De la Fuente 1996, DeLa Fuente 1998) lead us to believe that western Europe is close to its BGP since the 70’s.

[21] For the 11 regions with 0 patents’ application, we attribute a rate of patenting equal to 0.04 per year, which would not have given even one patent in 18 years, on average.

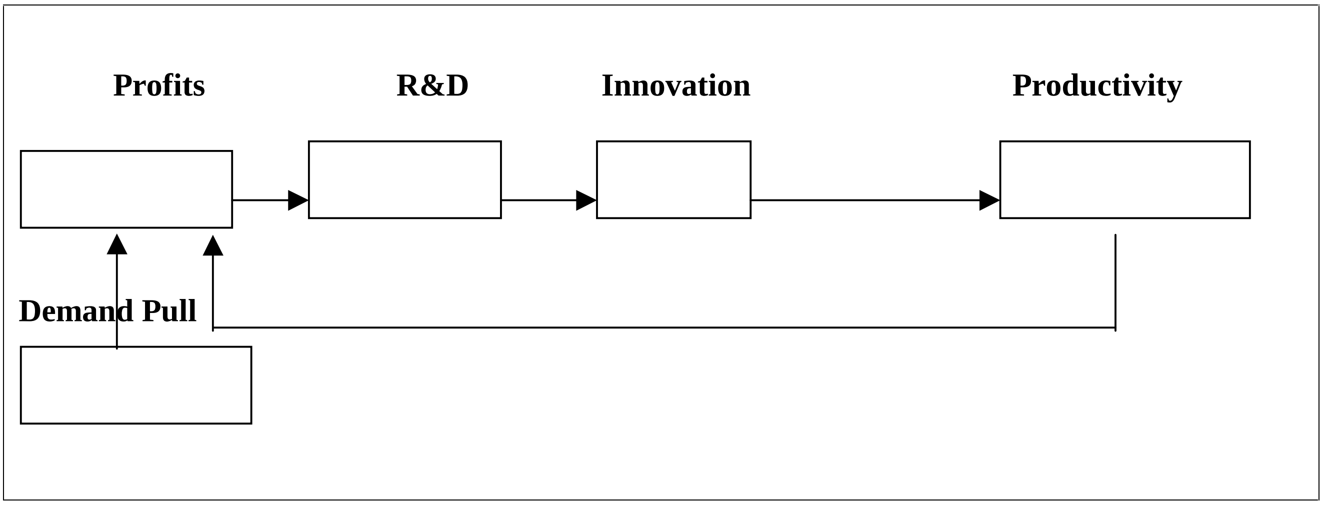
[22] All the variables included in the regression are in their average value in the conisdered period (1977-1995). In some cases not each annual value is available in the series, and in this case the average has been computed using only the available years in the period.

of R&D get translated into a more polarized distribution of innovation, as the data suggest, then the parameter β_0 should be (as in most of the estimates) larger than one.

The problem of estimating equation (8) is, as described at length in the last section, the endogeneity of the employment in R&D. The circular causation illustrated in figure 1, between R&D, productivity and profits will bias upward the OLS estimates of the β's. The "market size", affecting the incentive to innovate only through demand allows us to find consistent estimates eliminating the bias. Comparing the OLS and the IV estimates, we realize that the second procedure gives always lower point estimates of the elasticity of innovation to R&D.

Figure I

Scheme of causation



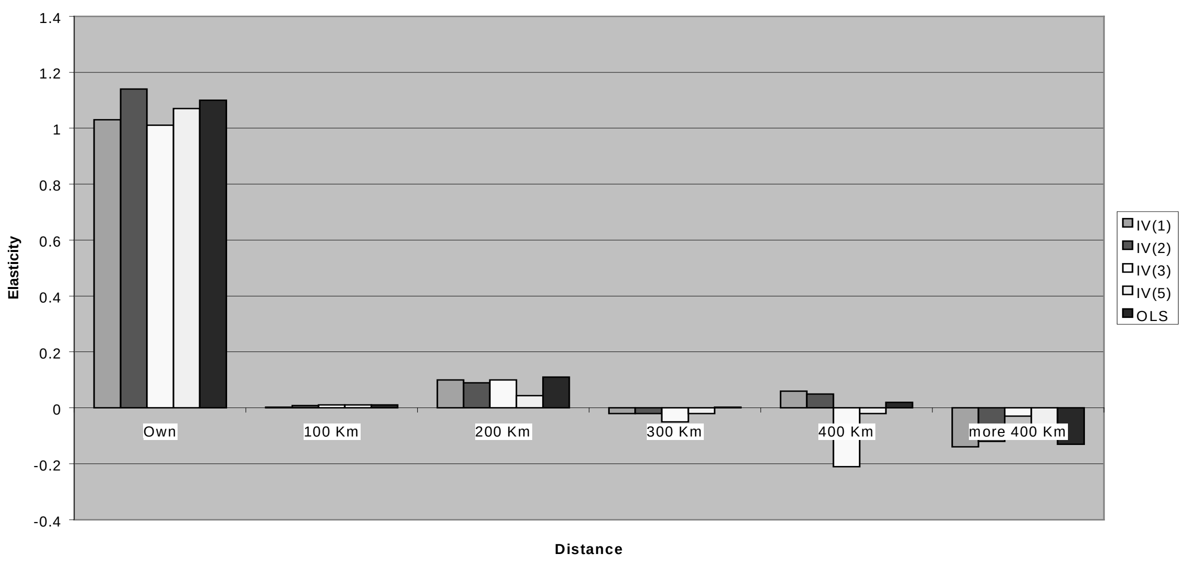
6.1 The basic model with geographical spillovers

In the empirical implementation of equation (12) we have an important issue to address, namely how many space intervals for each variable to introduce in order to have a reasonable trade-off between explained variance and precision of the estimates. We also have to decide the size of a space interval within which to consider different observations at the same distance. The first problem is made much more severe by collineariety of the variables. Including variables which capture average R&D employment in regions farther away, results in including variables that can be highly collinear. The collinearity arises because the relative "change" in environment every 100 Kilometers decreases with the size of the group included (which increases with distance). The std. deviation of the average R&D employment remains stable, at one third of its mean, when distance increases. The result is that, if we include 10 variables for the intervals from 0 to 1000 Km's, by 100, and one for all the distances larger than 1000 km, we have a coefficient of correlation in the order of 0.95-0.9 among the last 5-6 variables out of 10. This will make the estimates totally unreliable, and the std. errors very large. We use, therefore the following procedure: we start with the smallest distance and we keep adding space intervals in R&D employment as long as the correlation coefficient between the last two added variables is smaller than 0.80 (see Table 1a and Table 1b for the correlation between R&D real expenditures in different space intervals).

In this way we are able to include four intervals (from 0 to 400 Km by 100) in the case of 100 Km cells and 2 intervals (from 0 to 400 Km by 200) in the case of 200 Kms Cells. The rest of the spatially lagged R&D employment are included as an average variable (whose coefficient in the tables is denoted as β^{4+} or β^{2+} depending on the cell's length. This "average variable", capturing the effect of average R&D employment more than 400 Kilometers away, has a correlation coefficient with each of the R&D in each space interval, at a distance larger than 400 Km's, larger than 0.92. Therefore it conveys the same information as each of the other "spatially lagged" variables and controls for the "average R&D in the rest of Europe. We perform weighted OLS and IV estimates of the coefficients of the basic regression (12) with the chosen length of spatial lags[23]. The weighting is made because, due to different size of regions the size of the measurement errors could be different across them. The full results are reported in Table 2a and 2b, in the first case using R&D employment and in the second real R&D spending as explanatory variable . Table 3a and 3b, contain the same regression results, but with 200-Km's distance cells to capture the spillover of R&D. In the figure of the following page we have summarized the relevant information conveyed in those tables, as we have reported the point estimates of elasticity of the innovation function to R&D at different distances, so that we may eyeball the decreasing effects of R&D via spillovers.

[23] All regressions include a constant, which depends on the common growth rate.

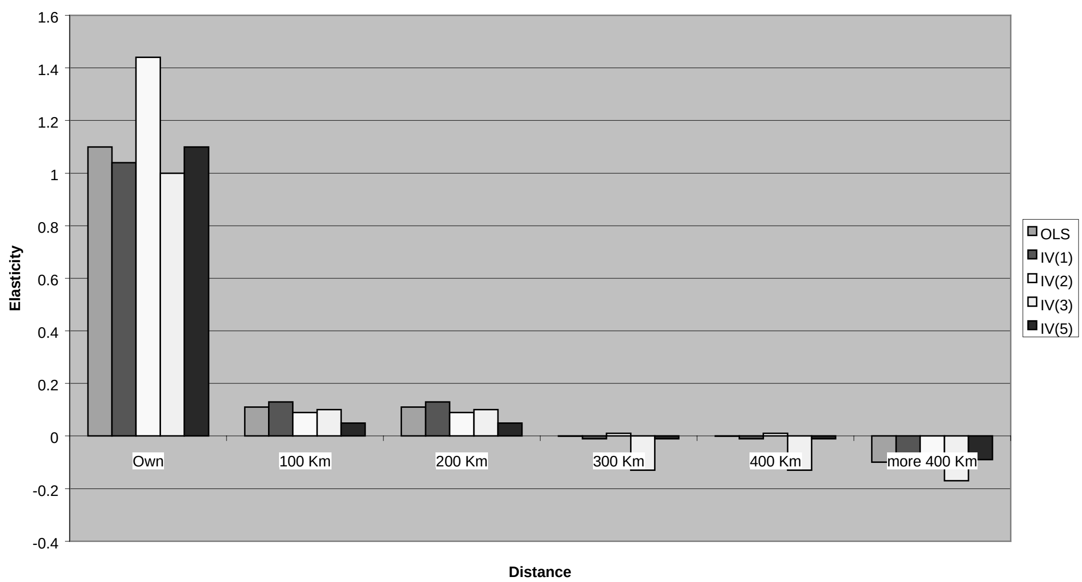
Elasticities of Innovation to R&Destimated with 100 Kms cells



Let’s concentrate on the basic specification estimated with local population as IV (regression IV(1) in all tables), as all the other specifications include some other variables to check the robustness of the results. Two things emerge clearly and consistently:

1) The coefficient on R&D (employment or spending) is always very significant and most of the time equal or close to one. Most of the cross-regional variation in patenting is due to differences

Elasticities of Innovation to R&D, estimated with 200 Kms cells



in R&D.

2) The spatial spillovers exist and are statistically significant for the R&D done within 200 Km’s from the region. In particular when we sub-divide the interval in 100 Km’s cells the most

significant and consistently positive elasticity is that on R&D in the 100-200 Kms range. This is probably due to the fact that, in the closest 100 Km's from a regional capital, there are very few other capitals (in the case of large regions none at all). This dilutes the effect of the first variable. The magnitude of these spillovers effects, if not negligible is not very large either: the elasticity of patenting to "close" R&D is between 4 and 11%, while the elasticity to own R&D is in the range of 100-140%. This result, suggests that spatial spillovers may be important but not "first order" in determining the BGP differences in innovation rates across regions.

Hence, there is a difference between the effect of own R&D and that of R&D from closer regions of one order of magnitude. We can infer that the spatial concentration of R&D (probably for market reasons) creates incentive for innovation to cluster while spillovers are important but second order of importance.

We perform a number of different checks to test the robustness of the results:

1. In regressions IV(2) we have re-scaled the variables to have them in "per worker" terms. This measures patenting per worker (a measure of intensity in innovation) as a function of R&D per worker (a measure of R&D intensity). The results do not change significantly to demonstrate that it is not the size of a region that drives the results.

2. In regression IV (3) and IV(4) we have included some controls, to check that the omission of some variables, potentially spatially correlated, is not responsible for the results.

In IV(3) we have included a measure of human capital in the region, i.e. the fraction of workers with education equal or more than college[24], which could be an important input of innovation process and that can be correlated across regions. Including this variable, which appears always highly significant, does not reduce the estimates of the spillovers effect. In IV(4) we have considered the importance of local infrastructure in increasing productivity of research.. We have used a measure of the density of roads and other way of transportation in the region to capture the quality of communication infrastructures. Again this variable enters with a positive (not significant) coefficient, and does not substantially change the estimates of the spillovers.

National R&D and Parametric Specifications

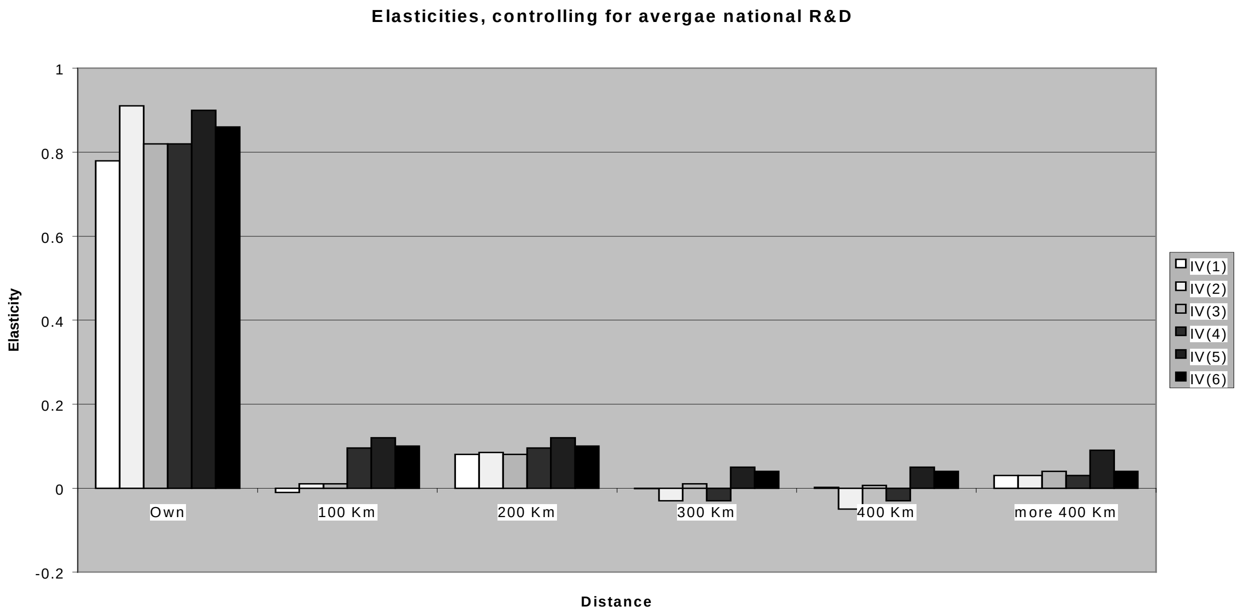
We have devoted particular attention to the effect of national R&D. Certainly the benefit of ideas could spread more easily within countries than across, even in absence of any barrier, due to the common language and similar educational background of the skilled workers. Therefore the

[24] See Data appendix for the sources. We only had data for 71 of the 86 regions on the education variable

effect of spillovers across distance may be simply capturing the fact that we have positive and perfect spillovers within a country while zero spillovers across. To distinguish this case from one in which, distance still matter, after we consider the national component of R&D we add to our regressors the average level of R&D spending or employment in each of the eleven countries. If one region receives benefits just from being in a high R&D country, uniformly from the whole country, this variable will be significant and R&D of regions in the neighborhood will not matter any longer. The results of including this variable, together with the usual controls and using both 100 and 200 KMs cells, are reported in table 4. The national R&D variable has a very strong and positive effect, but the elasticity to R&D of regions in the vicinity remains almost unchanged and mostly significant. We tend to believe that this is the best specification of our model. It reveals strong evidence that within country spillovers matter, and it generates the usual feature of decaying spillovers over space, without the undesirable feature of negative values[25] for the spillovers from farther regions (see figure in the following page that summarizes these results). Again, the visual impression, confirmed by the data, indicates that only the two closest groups have significant effects, but of one order of magnitude smaller than the effect of own R&D.

In this specification the pattern of the spillovers exhibit a decay of the elasticity towards 0, as the distance increases. Moreover, in this case, an F test of significance of the sum of all coefficients capturing externalities ($\beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_{4+} = 0$) rejects the null at the standard levels of significance confirming the hypothesis of existence of externalities.

[25] we are not the only one to obtain negative spillovers effect of R&D on patents. In different set-ups both Jaffe(1986) and Branstetter(1996) argues that if technological rivalry with other firms is intense enough and the scope of intellectual property rights conferred by patents is broad enough, firms may simetimes find themselves competing for a limited pool of available patents--a patent race. For this reason the positive externality is potentially confounded with a negative effect of other firms' research due to competition. Because of this the spillover coefficient might be negative. This might even be more true for distant regions or firms.



The results obtained so far only use the first 400 Km's in distance from each region (as we had to eliminate the other variables due to collineariety). At the cost of specifying a functional form for the dependence of spillovers on distance, we may parametrize this decay and use all the data on R&D at any distance to estimate only one parameter that captures this dependence.

We specify three different functional forms for the decay of spillovers with distance: exponential ($e^{\lambda(dist)}$), power ($\lambda^{(dist)}$) and inverse ($\frac{1}{\lambda(dist)}$). We still divide the regions in 100 Km's cells, but now we use as dependent variables the average R&D weighted for the parametric function. We use the 86 regions to estimate the parameter λ, using non linear instrumental variables.

The results, reported in table 5a reveal that, although there is a significant amount of noise, all three methods estimate parameters which imply spillovers quickly decreasing with distance. The best fit is obtained with the exponential specification, which delivers also the fastest rate of decay. With any method, however, only R&D in the regions within a range of 100 Kms has an impact larger than 1% on innovation (see simulation in table 5b). These effects, obtained imposing parametric forms seems somewhat smaller than those obtained using non-parametric methods, although broadly consistent in terms of tendency and order of magnitude. The parametric specification forces a smooth behavior, which does not seem supported by the data.

6.2 Spillovers in purely technological space

The natural question to ask is whether “geographical space” is the most natural dimension in which regions innovate and in which spill-overs happen. R&D and spillovers coming from regions which are close in the “technological space” (produce and innovate in similar sectors) rather than in “geographical space” could be more relevant. To shed some light on this point, i.e. on the importance of spillovers coming from region technologically similar we may construct a distance which is a metric in the technological space. In particular two regions will be close if they share many sectors (of production), while they are far if they specialize in different sectors. Once we have defined an index of “distance” we proceed as described in section 3 to define cells into which the value of this index falls and to construct the matrices M_1 , M_2 …M_K and to estimate the β's.

The index of distance we use is the index of bi-lateral specialization for two regions. After having defined 9 manufacturing sectors[26] we calculate the following value for each couple of regions (k,l): $\sum_i \left| sh_{ik} - sh_{il} \right|$. Sh_{ij} is the share of total value added in manufacturing in region j, produced by sector i. The index will be 0 in case of exactly identical composition of value added, and 2 in case of exact complementarity. In our sample of 86 EU regions we have that the index range from 0.3 (very similar regions) to 1.2 (dissimilar ones). Regions which have a very different productive specialization of the manufacturing sector will be distant in this metric and may receive small spillover from each other, even if they are geographically close. We identify 4 class of distance, each covering an interval equal to 0.3 in the metric of the specialization index and ranging from 0.3 to 0.12. The estimates of specification (21), using this metric on the “external effects” of R&D are reported in Table 6. Although the point estimates are positive for β_1 and β_2 while negative for β_3 and β_4 (i.e. decreasing with distance) they are not significant in almost any specification. This suggests that considering regions as innovative units, the metric induced by their productive specialization is not appropriate to capture R&D spillovers, or actually that the purely spatial spillovers are more important than the purely technological ones.

6.3 Spillovers in Technological space for close regions

In the previous section we have considered a purely technological metric for the space in which regional spillovers take place. Nevertheless, we may suspect that technological similarity is not irrelevant, but has an effect only on those regions which are geographically close. In particular geographical space could be an important determinant of technological spillovers (as shown before), but, at a given distance may be more important the R&D performed in similarly specialized regions. To inquire into this we estimate again four spillover parameters, considering now, only the regions within the 200 Kms range from one's capital city. We group these regions into the four cells, in decreasing order of production-sectors proximity, and construct the four spillover matrices. The effect of outside R&D on regional patenting is estimated in the regressions of Table 7. First let us point out that most of the (geographically) "close" regions are also technologically similar: the vast majority of technological distances for these regions fall in the first or second cell of the "technological distance". Second it clearly emerges, in all specifications, that the technologically closer regions among those in geographical proximity, are by far the most important in generating R&D spillovers on innovative activity. The elasticity of innovation to R&D employment in these regions is around 0.10 and highly significant, while the effect of R&D in more different regions is not significant and often negative for the most different ones. It appears that the importance of R&D in neighboring regions for one's own innovation is enhanced by the similarity in the productive structure of the regions.

7.Conclusions

While there is an increasing consensus on the importance of technological innovation for the economic performance of the European Union, few studies have considered the geography of innovation in Europe, in relation to its determinants and to the productivity of R&D. Eaton et al. (1998) point the finger to the European disappointing performance in innovation and identify in the small size of the local market for innovation the main cause of this failure. This paper take seriously the geographical relation between the size of the market and the innovative activity and uses it to determine what part of the innovation is due to own (market driven) research and development and what part could be attributed to inter-regional spillovers. The findings indicate that own R&D has an effect on innovation about 10 times larger than other regions' R&D, in balanced growth path, but nevertheless inter-regional spillovers exist, are significant and decrease rather quickly with distance. Moreover if physical proximity is what allows the spillovers, technological proximity enhances them, as among close regions those more similar in the productive structure are also the more effective in influencing the innovation.

[26] Metals, non metallic minerals, chemicals, machinery, means of transportation, food, textiles and leather, paper, Others

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Tables

Table 1a

Correlation Coefficient between Space Intervals of R&D: 100 Km. cells

R&D Employment	Correlation
[own]-[0-100]	-0.17
[0-100]-[100-200]	0.60
[100-200]-[200-300]	0.73
[200-300]-[300-400]	0.75
[300-400]-[400-500]	0.81
[400-500]-[500-600]	0.84
[500-600]-[600-700]	0.89
[600-700]-[700-800]	0.83
[700-800]-[800-900]	0.87
[800-900]-[900-1000]	0.96

Table 1b

Correlation Coefficient between Spatially Lagged R&D: 100 Km. cells

R&D Employment	Correlation
[own]-[0-200]	-0.12
[0-200]-[200-400]	0.75
[200-400]-[400-600]	0.87
[400-600]-[600-800]	0.84
[600-800]-[800-1000]	0.96
[800-1000]-[1000+]	0.97

Table 2a[27]**:**

Indep. Variable Log(R&D Employed), cell length: 100 Km (Geographical distance)

Standard errors in parenthesis

Dep. Var: log (Patents)	Weighted OLS	Weighted IV(1)	Weighted IV (2), per capita	Weighted IV(3),with college +	Weighted IV(4), with infrastr.
β_0	1.10***	1.03***	1.14***	1.01***	1.07***
	(0.08)	(0.19)	(0.44)	(0.09)	(0.08)
β_1	0.01	0.003	0.008	0.02	0.01
	(0.02)	(0.03)	(0.03)	(0.03)	(0.015)
β_2	0.11***	0.10***	0.09**	0.10***	0.043**
	(0.04)	(0.04)	(0.047)	(0.04)	(0.022)
β_3	-0.003	-0.02	-0.02	-0.05	-0.028
	(0.07)	(0.07)	(0.07)	(0.09)	(0.03)
β_4	0.02	0.06	0.05	-0.21	-0.02
	(0.07)	(0.07)	(0.09)	(0.13)	(0.04)
β_{4+}	-0.13	-0.14	-0.12	-0.03	-0.078
	(0.09)	(0.09)	(0.12)	(0.16)	(0.05)
R^2	0.75	0.68	0.34	0.74	0.79
Tot. Observations	86	86	86	71	86

Table 2b:

Indep. Variable Log (Real R&D spending), cell length: 100 Km (Geographical distance)

Standard errors in parenthesis

Dep. Var: log(Patents)	Weighted OLS	Weighted IV(1)	Weighted IV (2), per capita	Weighted IV(3), with college +	Weighted IV(4), with infrastr.	Weighted IV(5) with country-R&D
β_0	1.11***	1.01***	1.43***	1.05***	1.17***	1.12***
	(0.05)	(0.07)	(0.032)	(0.07)	(0.08)	(0.10)
β_1	0.01	0.016	0.01	0.03***	0.017	0.03
	(0.01)	(0.02)	(0.03)	(0.014)	(0.015)	(0.02)
β_2	0.04**	0.046**	0.075*	0.038**	0.043***	0.05**
	(0.02)	(0.02)	(0.040)	(0.022)	(0.02)	(0.025)
β_3	0.05	0.01	-0.01	0.004	0.02	-0.002
	(0.03)	(0.04)	(0.07)	(0.05)	(0.02)	(0.052)
β_4	-0.008	-0.01	0.02	-0.12	-0.02	0.01
	(0.04)	(0.04)	(0.08)	(0.08)	(0.04)	(0.052)
β_{4*}	-0.11**	-0.08	-0.08	-0.05	-0.07	-0.15**
	(0.05)	(0.05)	(0.11)	(0.10)	(0.05)	(0.07)
R^2	0.86	0.68	0.41	0.80	0.79	0.72
Tot. Observations	86	86	86	71	86	86

[27] *significant at 10% level, ** significant at 5% level, *** significant at 1% level

Table 3a:

Indep. Variable Log(R&D employment), cell length: 200 Km (Geographical distance)
Standard errors in parenthesis

Dep. Var: log (Patents)	Weighted OLS	Weighted IV(1)	Weighted IV (2), per capita	Weighted IV(3), with college +	Weighted IV(4), with infrastr.	Weighted IV(5) with country-R&D
β_0	1.10***	1.04***	1.44***	1.00***	1.10	0.82***
	(0.08)	(0.09)	(0.17)	(0.09)	(0.05)	(0.10)
β_1	0.11***	0.13***	0.09	0.10**	0.055*	0.096
	(0.04)	(0.06)	(0.06)	(0.05)	(0.030)	(0.058)
β_2	-0.001	-0.01	0.01	-0.13	0.01	-0.03
	(0.07)	(0.11)	(0.10)	(0.20)	(0.06)	(0.11)
β_{2*}	-0.10	-0.11	-0.07	-0.17	-0.09	0.03
	(0.07)	(0.08)	(0.10)	(0.21)	(0.06)	(0.09)
R^2	0.74	0.67	0.43	0.71	0.75	0.70
Tot. Observations	86	86	86	71	86	86

Table 3b:

Indep. Variable Log(Real R&D spending), cell length: 200 Km (Geographical distance)
Standard errors in parenthesis

Dep. Var: log(Patents)	Weighted OLS	Weighted IV(1)	Weighted IV (2), per capita	Weighted IV(3), with college +	Weighted IV(4), with infrastr.	Weighted IV(5) with country-R&D
β_0	1.08***	0.99***	0.96***	1.00***	1.05***	1.10***
	(0.05)	(0.069)	(0.24)	(0.07)	(0.072)	(0.09)
β_1	0.03	0.05**	0.05	0.06**	0.043	0.055*
	(0.02)	(0.024)	(0.03)	(0.03)	(0.25)	(0.03)
β_2	0.06	0.04	0.04	0.05	0.03	0.03
	(0.04)	(0.05)	(0.05)	(0.13)	(0.05)	(0.06)
β_{2+}	-0.11***	0.10*	0.11	-0.22	-0.08	-0.15
	(0.03)	(0.055)	(0.06)	(0.14)	(0.05)	(0.08)
R^2	0.86	0.77	0.48	0.79	0.77	0.69
Tot. observations	86	86	86	71	86	86

Table 4:

Preferred Specifications: Indep. Variable Log(R&D employment)
Standard errors in parenthesis

Dep. Var: log (Patents)	Weighted IV(5)with country employment in R&D	Controlling for regional share of College +	Controlling for regional density of transport infrastructures	As in first column with 200 Km cells	As in second column with 200 Km cells	As i colum 200 K
β_0	0.78***	0.91***	0.82***	0.82***	0.90**	0.86**
	(0.11)	(0.11)	(0.11)	(0.10)	(0.10)	(0.10)
β_1	-0.01	0.01	-0.01			
	(0.03)	(0.3)	(0.03)	0.096	0.12**	0.10
β_2	0.08**	0.085**	0.08**	(0.058)	(0.06)	(0.06)
	(0.04)	(0.04)	(0.04)			
β_3	-0.001	-0.03	0.01			
	(0.07)	(0.10)	(0.08)	-0.03	-0.05	0.04
β_4	0.002	-0.05	0.007	(0.11)	(0.25)	(0.12)
	(0.08)	(0.13)	(0.08)			
β_{4+}	0.03	0.03	0.04	0.03	0.09	0.04
	(0.10)	(0.17)	(0.10)	(0.09)	(0.25)	(0.10)
Average Country	1.05***	0.62***	1.04***	1.01***	0.60***	1.00**
R&D	(0.17)	(0.21)	(0.18)	(0.17)	(0.20)	(0.18)
R^2	0.71	0.74	0.71	0.70	0.73	0.70
Tot. Observations	86	86	86	86	86	86

Table 5a:

Parametric Estimates: NL Instrumental Variables, Std. errors in parenthesis
The distance is expressed in hundredths of Km's

Dep. Var: log(Patents)	Exponential Decay $e^{\lambda_a (dist.)}$	Power Decay $\lambda_b^{(dist)}$	Inverse Decay $1/(dist*\lambda_c)$
β_o	0.97*** (0.11)	0.83*** (0.10)	0.82*** (0.10)
λ_a	-3.9*** (1.1)		
λ_b		0.017 (0.01)	
λ_c			87.1 (100)
Country R&D	0.87 (0.50)	0.21 (0.20)	0.24 (0.26)
R^2	0.55	0.50	0.53
Tot. observations	86	86	86

Table 5b:

Point Estimates of elasticities, in percentage of innovation to R&D, Using the parameters' estimate from Table 5a.

Method/Distance	own	[100 Km]	[200 Km]	[300 Km]	[400 Km]	[more than 400 Km]
Exponential Decay	97%	2%	0.04%	0.00%	0.00%	0.00%
Inverse decay	83%	1.2%	0.5%	0.3%	0.2%	0.1%
Power decay	82%	1.7%	0.02%	0.00%	0.00%	0.00%
Non-Parametric, 100 Kms cells	91%	1%	8.5%	-3%	-5%	3%
Non-Parametric, 200 Kms cells	90%	9.6%	9.6%	-3%	-3%	3%

Table 6:

Indep. Variable Log(R&D Employment), cell length: 0.3 units (technological distance)
Standard errors in parenthesis

Dep. Var: log(Patents)	Weighted OLS	Weighted IV(1)
β_0	1.12***	1.03***
	(0.08)	(0.09)
β_1	0.07	-0.03
	(0.04)	(0.04)
β_2	0.31	0.23
	(0.20)	(0.22)
β_3	-0.21	-0.18
	(0.20)	(0.22)
β_4	-0.08	-0.02
	(0.13)	(0.15)
R^2	0.73	0.64
Tot. observations	86	86

Table 7

Only regions in the 0-200 Km range. Indep. Var log (R&D Employment)
cell length: 0.3 units (technological distance)
Standard errors in parenthesis

Dep. Var: log(Patents)	Weighted OLS	Weighted IV(1)	Weighted IV (2), per capita	Weighted IV(3), with college +	Weighted IV(4), with infrastr.
β_0	1.02***	0.94***	0.73**	0.88***	0.97***
	(0.08)	(0.09)	(0.36)	(0.10)	(0.10)
β_1	0.09***	0.10***	0.10***	0.13***	0.11***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
β_2	0.001	0.01	0.01	0.03	0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
β_3	-0.02	-0.02	-0.03	-0.01	-0.01
	(0.03)	(0.03)	(0.03)	(0.035)	(0.03)
β_4	-0.11	-0.13**	-0.15	-0.15	-0.13**
	(0.06)	(0.06)	(0.08)	(0.08)	(0.06)
R^2	0.78	0.72	0.44	0.74	0.72
Tot. observations	86	86	86	71	86

Appendix A: The model

A.1:Profits for intermediate goods

Given the production function in equation (1) the demand curve for each intermediate will be $p_{it}(s) = D_{it}\alpha L_{it}^{1-\alpha} x_{it}^{\alpha-1}(s)$ where p_{it}(s) is the price of the s-th intermediate good in region i at time t. The demand for skilled labor by one producer of intermediate good s is:

$$(1a) \qquad x_{it} = \left(\frac{w_t}{\alpha^2 L_{it}^{1-\alpha} D_{it}} \right)^{\frac{1}{\alpha-1}}$$

where we have assumed perfect mobility of labor across regions and therefore a unique wage. The profit of each monopolist in the i region is:

$$(2a) \qquad \pi_{it} = \frac{1-\alpha}{\alpha} w_t x_{it} = \frac{1-\alpha}{\alpha} w_t \left(\frac{\alpha^2 L_{it}^{1-\alpha} D_{it}}{w_t} \right)^{\frac{1}{1-\alpha}}$$

A.2: Derivation of the balanced growth path

The relevant knowledge for catch-up spillovers is defined as A_{it}^{S} equal to:

$$(3a) \qquad A_{it}^{S} = \prod_{j=1}^{N} A_{jt}^{M_{ij}} \quad \text{where} \quad \sum_{j=1}^{N} M_{ij} = 1$$

The M_{ij} is a weight which captures the contribution of region j knowledge on the creation of region i new knowledge.

If we call g_x the rate of change of the variable x, then we can take the rate of change on each side of expression (2) in the text, and we have:

(4a) $$\dot{g}_{A_i} = g_{A_i}\left[\varepsilon_{\lambda} g_H + (1-\varepsilon_f) g_{\bar{A}} - \varepsilon_f g_{A_i}\right] \qquad \text{for i= 1,2…N}$$

It is easy to see that it exists a BGP, where all sectors' technology grows at a constant and equal rate. The common rate of growth is:

(5a) $$g_A = \frac{\varepsilon_{\lambda} g_H}{1-\varepsilon_{f1}-\varepsilon_{f2}}$$

Expression (5a) says that the average rate of growth will depend on the growth rate of the skilled labor force, amplified by the productivity of R&D in innovation, and by the spillovers from existing knowledge. The result, that the growth rate depends only on the growth of human capital and not on the investment in R&D (which, as we will see, determines relative innovation intensities), is a consequence of the assumption of decreasing returns in the innovation-production function, which makes the model similar to Jones (1996). If we log-linearize expression (2) around the BGP we have that the system can be written in vector form as:

(6a) $$\underline{\dot{g}_A} = \left[\varepsilon_{f2} M + (\varepsilon_{fi} - 1) I\right](\underline{g_A} - \underline{\overline{g_A}})$$

where the underlined variables are vectors, M is an NXN matrix with $\tau_{i,j}$ as entries in each position and I is the identity matrix. As M is a Markov matrix it admits all characteristic roots smaller than or equal to one in absolute value, while the identity matrix admits N characteristic roots equal to 1. The characteristic roots of the matrix in square brackets, which are the sum of the characteristic roots of the two matrices, are therefore negative (given the conditions on the elasticities) and the differential system of equations (6a) is stable[28]. If we define with $\bar{A} = \prod_{1}^{N} A_i^{1/N}$, the geometric average of the patented goods in different regions, we can express the relative level of knowledge in a region as::

[28] hence the BGP exists for such a system and is locally stable.

(7a) $$a_{it} = \frac{A_{it}}{A_t}$$

Therefore around the BGP, denoting with ε_λ the elasticity of the λ function with respect to n, the following log-linear equation will hold:

(8a) $$\log(g_A) = c + \varepsilon_\lambda \log(n_i) + (\varepsilon_{f1} - 1)\log(a_i) + \varepsilon_{f2} \sum_{j=1}^{N} M_{i,j} \log(a_i)$$

which, in matrix notation and solved for log($\underline{a}$) gives:

(9a) $$\log(\underline{a}) = \underline{c} + \tfrac{\varepsilon_\lambda}{1-\varepsilon_{f1}} \left(I - \varepsilon_{f2} M\right)^{-1} \log(\underline{n})$$

Finally, recall that in BGP the flow of new knowledge is just proportional to the stock of exiting knowledge, so that we get :

(3) $$\log(\dot{\underline{a}}) = \underline{c}' + \tfrac{\varepsilon_\lambda}{1-\varepsilon_{f1}} \left(I - \varepsilon_{f2} M\right)^{-1} \log(\underline{n})$$

where the vector of constants $\underline{c}$' is equal to $\underline{c}$ + log(g_A), which represents the relative patenting of one region with respect to the average.

A.2: Equilibrium allocation of Human Capital

In order to determine the value of a patent, which will provide the input to calculate the reward to R&D workers, we consider the system along its BGP. In this situation the average productivity and the single region's productivity all grow at the same rate g_A , defined by (5a). The value of a patent is the present discounted stream of profits, which are generated by the invention. Using (2a) as the expression of profits for a typical producer in region i at time t, we obtain the following expression as value of the patent in region i:

(10a)

$$V_{it} = \int_{s=0}^{\infty} e^{-rs} \pi_i(t) ds = \int_{s=0}^{\infty} e^{-rs} \left(\frac{1-\alpha}{\alpha} \right) w(s)^{\frac{\alpha}{\alpha-1}} \left(D_i \alpha^2 \right)^{\frac{1}{1-\alpha}} ds =$$

$$\frac{1}{r + \frac{\alpha}{1-\alpha} g_A} \left(\frac{1-\alpha}{\alpha} \right) w(t)^{\frac{\alpha}{\alpha-1}} \left(D_i \alpha^2 \right)^{\frac{1}{1-\alpha}}$$

The return from innovation (value of a patent) is the present discounted value of a firm's profits using the market rate r. Also a faster pace of innovation in the sector squeezes the profits of a firm, which will face more intense competition, as it is clear from the term g_A in the denominator. The assumption of perfect mobility of skilled workers across regions and between production and R&D, implies that wages, in equilibrium, should be equal. Hence, the marginal productivity of a skilled worker in R&D, is the same as the productivity of a worker in production in BGP. The wage earned by a worker in R&D is the value of the innovation times the productivity of innovations per worker in the unit of time $(\dot{A}/n_i)$. Using (10a) and the BGP condition for the flow of innovation, the equilibrium condition on the labor market is:

$$\text{(11a)} \quad w(t) = \left(\frac{g_A a_i \bar{A}}{n_i} \right) \frac{1-\alpha}{\alpha} w(t)^{\frac{\alpha}{\alpha-1}} \left(\frac{1}{\left(r + \frac{\alpha}{1-\alpha}\right)} \right) \left(D_i \alpha^2 \right)^{\frac{1}{1-\alpha}}$$

Solving (11a) for n_i and taking logs, we can re-write this equilibrium condition in vector form obtaining equation (4) in the text.

A.4:Equilibrium growth rates in BGP

We can easily characterize the growth rate in BGP of the model. We already know the growth rate of A_i, the stock of knowledge (and of intermediate patented goods) in each region. We use the two following equilibrium conditions, in order to find the growth rate of output and wages, given zero growth in human capital (skilled employment).

$$\text{(12a)} \quad \sum_{i=1}^{N} n_i + \left(\frac{\alpha^2}{w(t)}\right)^{\frac{1}{1-\alpha}} \sum_{i=1}^{N} A_i(t) D_i = H$$

The first condition, which must hold for the aggregate of the economy, says that the total number of employed skilled workers in the R&D sectors plus the total number of employed skilled workers in production, must equate the total number of skilled workers (H). From (12a), as n and H in BGP both grow at the rate g_H and their difference will grow at the same rate, equation (12a) will provide in equilibrium the following relation among growth rates:

$$\text{(14a)} \qquad g_A - \frac{1}{1-\alpha} g_w = g_H$$

which can be solved to give:

$$g_w = \frac{\varepsilon_\lambda + \varepsilon_1 + \varepsilon_2 - 1}{1 - \varepsilon_1 - \varepsilon_2} g_H$$

Using the symmetry of profits per intermediate good (2a) and of wages paid, and the production function, we have the condition:

$$Y_{it} = L_{it}^{i-\alpha} C A w^{\frac{\alpha}{\alpha-1}}$$

which in terms of growth rates, assuming zero growth of labor, gives:

$$g_A + \tfrac{\alpha}{\alpha-1} g_w = g_Y$$

The last $g_w = g_Y$. The growth rates of regional income and of wages are equal and they are proportional to the growth rate of varieties of goods.

Appendix B: the case of permanent effect of R&D on growth

Using the same structure of the innovation function as in (2), but specifying it differently we may find a model in which the common growth rate of regional innovation and productivity, depends on the investment in R&D of the regions, but still there is convergence towards a BGP. In particular in this case the spillovers of knowledge across regions are interpreted as catch-up of one region technology versus those of the regions it has interaction with. In particular we can specify the change in knowledge as:

$$\text{(1b)} \quad \frac{\dot{A}_{it}}{A_{it}} = \lambda(n_{it})\, f\left(\frac{A^{S}{}_{i,t}}{A_{i,t}}\right) \qquad f\,' > 0$$

The variables are defined as before, but now the rate of growth of knowledge depends on R&D employment and on a function f, of technological "catch-up" relative to the regions whose knowledge spills into region i. Assuming zero growth of the skilled labor force, and defining with ε_f the elasficity of function f, the dynamics of knowledge are given by:

$$\text{(2b)} \qquad \dot{g}_{A_i} = g_{A_i}\left[\varepsilon_f\, g_{\bar{A}} - \varepsilon_f\, g_{A_i}\right] \qquad \text{for i= 1,2…N}$$

It is easy to see that it exists a BGP, where all sectors' technology grows at a constant and equal rate. The common rate of growth can be written as:

$$\text{(3b)} \quad \overline{g_A} = \lambda(\bar{n})\bar{a}^{(\bar{\tau}-1/N)}$$

where $\bar{n} = \prod_1^N n^{1/N}$ and $\bar{a}^{(\bar{\tau}-1/N)} = \prod_1^N a_i^{\overline{\tau_i}-1/N}$ and $\overline{\tau_i} = \sum_{j=1}^{N} \tau_{j.i}$.

Expression (5a) says that the average rate of growth will depend on the average resources employed in R&D in the different regions and also on the distribution of spillovers. Note that if the spillovers are perfectly symmetric $\bar{\tau}_i = 1/N$ or all the regions are the same then the common growth rate will simply become $\lambda(\overline{n})$. If we log-linearize the expression (5) around the BGP we have that the system can be written in vector form as:

$$\text{(4b)} \qquad \dot{\underline{g_A}} = \varepsilon_f (M - I)(\underline{g_A} - \underline{\overline{g_A}})$$

which is very similar to (6a). The characteristic roots of the matrix (M-I), which are the differences of the characteristic roots of the two matrices, are therefore negative and the differential system of equations (6) is stable.

In BGP will therefore hold the following condition:

$$\text{(5b)} \qquad \log(g_A) = \log(\lambda) + \varepsilon_\lambda \log(n_i) + \varepsilon_f \log(a_i) - \varepsilon_f \sum_{j=1}^{N} \tau_{i,j} \log(a_i)$$

which, in matrix notation and solved for log(a̲) gives:

$$\text{(6b)} \qquad \log(\underline{a}) = \underline{c} + \tfrac{\varepsilon_\lambda}{\varepsilon_f}\left(I - M\right)^{-1} \log(\underline{n})$$

Finally, in BGP :

$$\text{(7b)} \qquad \log(\dot{\underline{a}}) = \underline{c}' + \tfrac{\varepsilon_\lambda}{\varepsilon_f}\left(I - M\right)^{-1} \log(\underline{n})$$

This last expression is rather similar to (3), except that we have imposed that the coefficient of I and of M are the same, as the relevant term for the spillovers is simply the ratio of outside and inside knowledge. We consider this as a special case of our more general specification, which we estimate.

Appendix C:

An extension, Lack of cross-regional Mobility of Skilled workers

The mobility of European workers across regions and countries is rather low [29]. Let's assume the absence of mobility of the skilled workers across regions. In this case the relevant labor market is the regional market and the equilibrium conditions are modified as follows:

$$w_i(t) = \left(\frac{g_A a_i \bar{A}}{n_i}\right)\frac{1-\alpha}{\alpha} w_i(t)^{\frac{\alpha}{\alpha-1}} \left(\frac{1}{\left(r+\frac{\alpha}{1-\alpha}\right)}\right)\left(D_i \alpha^2\right)^{\frac{1}{1-\alpha}} \tag{1c}$$

$$n_i + \left(\frac{\alpha^2}{w_i(t)}\right)^{\frac{1}{1-\alpha}} A_i(t) D_i = H_i \quad \text{for } i = 1,2 \ldots N \tag{2c}$$

The wage becomes region-specific, and the condition which determines it, namely the clearing of the labor market, differs for each region. If we solve for $w_i(t)$ in (1b) and substitute into (2b) we get:

$$w_i(t) = \left(\frac{H_i - n_i}{\left(A_i(t) D_i \big/ \alpha^2\right)}\right)^{\alpha-1} \tag{3c}$$

$$\frac{n_i}{H_i - n_i} = \left(\frac{g_A a_i \bar{A}}{n_i}\right)\frac{1-\alpha}{\alpha}\left(\frac{1}{\left(r+\frac{\alpha}{1-\alpha}\right)}\right)\left(D_i \alpha^2\right)^{\frac{1}{1-\alpha}} \tag{4c}$$

Condition (3b) shows that the wage in region i depends positively on the number of skilled workers in R&D and on the technological level of the region: higher technological level and lower employment in production increase the productivity of skilled labor. Condition (4b) introduces this further channel of equalization in the equilibrium condition for returns in R&D and production. Higher level of knowledge (technology) and demand across regions determine higher employment

[29] See Eichengreen (1993), Decressin and Fatas (1995) among others

in R&D, but this effect is less pronounced than before. Smaller movements of employment in R&D offset the differences in regional profitability in BGP.

Data Appendix

Patent Data: The data on Patents are taken from the CD ROM of the European Patent office, Ed. 1995 which contains all the patent applications received by the patent office from 1977. Each record contains several pieces of information, including the city and region of residence of the inventor(s) which we use to localize the patent. Also the International Patent Classification codes, relative to the patent have been grouped into 30 sectors, and 5 macro-sectors following the classification elaborated by the French patent office and the Observatoire des Sciences and des Techniques described in Breschi 1998. We list the sectors and the macro grouping at the end of this appendix. The value used in the regression is the average number of patents per year in the considered period, as the BGP patenting rate of the region.

Data on Education: The data on education at the regional level come from national sources. They are the share of the labor force in 4-6 educational groups from which we were able to recover for all the regions the fraction of the population with college or more education. They refer to the period 1985-1990. We gratefully acknowledge Antonio Ciccone for providing us with the data. The sources that he quotes (Ciccone 1998) are the following:

French data- Pissarides and Wassmer 81997)

German data- Volkstzahlung (1987) and Seitz (1995)

Italian Data- Censimento generale della popolazione (1991)

Spanish data -Perez (1996)

United Kingdom- Labor Force Survey (1996).

Data on VA per manufacturing Sector: The regional data on value added per sector have been kindly provided by the Italian Confindustria, from Eurostat sources and for Germany they have been kindly collected from the landers by the German statistical office.

Other Data: Data on R&D spending and employment, GDP, population, population in age cohorts, employment, roads, are from the "Regio" data set, edited by the Eurostat. We used various issues (from 1980 to 1996). As real GDP we used the regional GDP in national currencies, deflated with the national GDP deflators and converted in US. Dollars 1985.

Technological Groupings in the Patent Classification:

I. Electric Engineering

1. Electric Machinery and apparatus
2. Audio-Visual technology
3. Telecommunications
4. Information Technology
5.Semiconductors

II Instruments

6. Optics
7. Measurement Control
8. Medical Technology

III Chemistry, Pharmaceuticals

9. Organic fine chemistry
10. Macromolecular chemistry
11: Pharmaceutical cosmetics
12. Biotechnology
13. Materials metallurgy
14. Food chemistry
15. Chemicals and Petrol industry

IV Process engineering

16. Chemicals Engineering
17. Surface Technology and Coating
19. Thermal processes and apparatus
20. Environmental Technology

V Mechanical Engineering

21. Machine Tools
22. Engine, Pumps, Turbines
23.Mechanical elements
24. Handling, Printing
25. Agricultural and Food Processing
26. Transport
27. Nuclear Engineering
28. Space technology
29. Consumers' Goods and equipments
30. Civil Engineering

List of the EU Regions Considered

Belgium (3):
Bruxelles
Wllaams gewest
Regione Wallonne

Luxemburg (1)

Denmark (1)

Germany (11, only west):
Baden-Wurtenberg
Bayern
Berlin
Bremen
Hamburg
Hessen
Niedersachsen
Northrein-Westfalia
Rheinland-Pfalz
Saarland
Schleswig-Holstein

Greece (4):
Voreia ellada
Kentriki Ellada
Attiki
Nisia Aigaiou, Kriti

Spain (7):
Noroeste
Noreste
Madrid
Centro
Este
Sur
Canarias

France (22):
Ile de France
Champagne-Ardenne
Picardie
Haute Normandie
Centre
Basse Normandie
Bourgogne
Nord-Pas-de-calais
Lorraine

Alsace
France Comte
Pays de la Loire
Bretagne
Poiteau Charentes
Acquitaine
Midi-Pirenees
Limousin
Rhone Alpes
Auvergne
Languedoc
Provence cote d'Azur
Corse

Ireland (1)

Italy (20):
Piemonte
Val d'Aosta
Liguria
Lombardia
Trentino
Veneto
Friuli
Emilia Romagna
Toscana
Umbria
Marche
Lazio
Abruzzi
Molise
Campania
Puglia
Calabria
Basilicata
Sicilia
Sardegna

The Netherlands(4)
Noord netherland
Oost netherland
West Netherlands
Zuid netherlands

Portugal (1)

Great Britain (11):
North
Yorkshire and Humbershire

East midlands
East Anglia
South West
South east
West Midlands
North west
Wales
Scotland
Northern Ireland

Figure 1[30]

Population density (quintiles in decreasing order)

[30] black: top
blu second
red third
green fourth
yellow fifth.

Figure 2

Intensity of R&D (spending in real terms) Quintiles

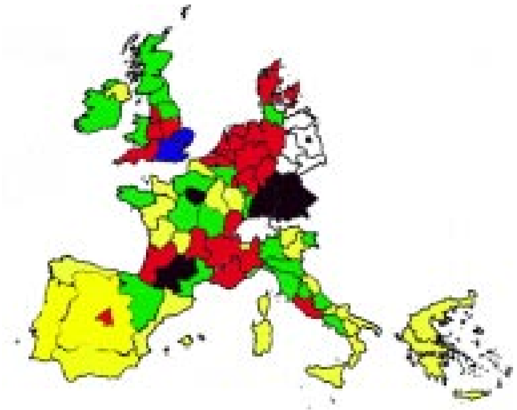
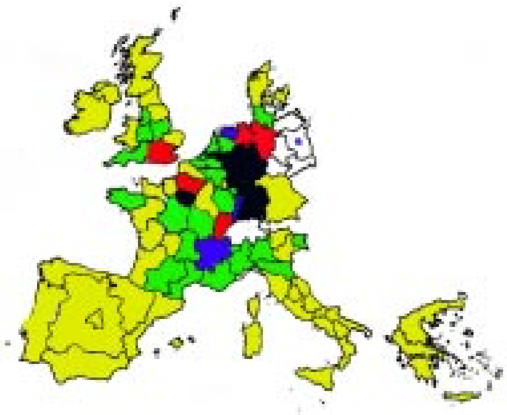


Figure 3

Intensity of Patenting (Patents per year) Quintiles



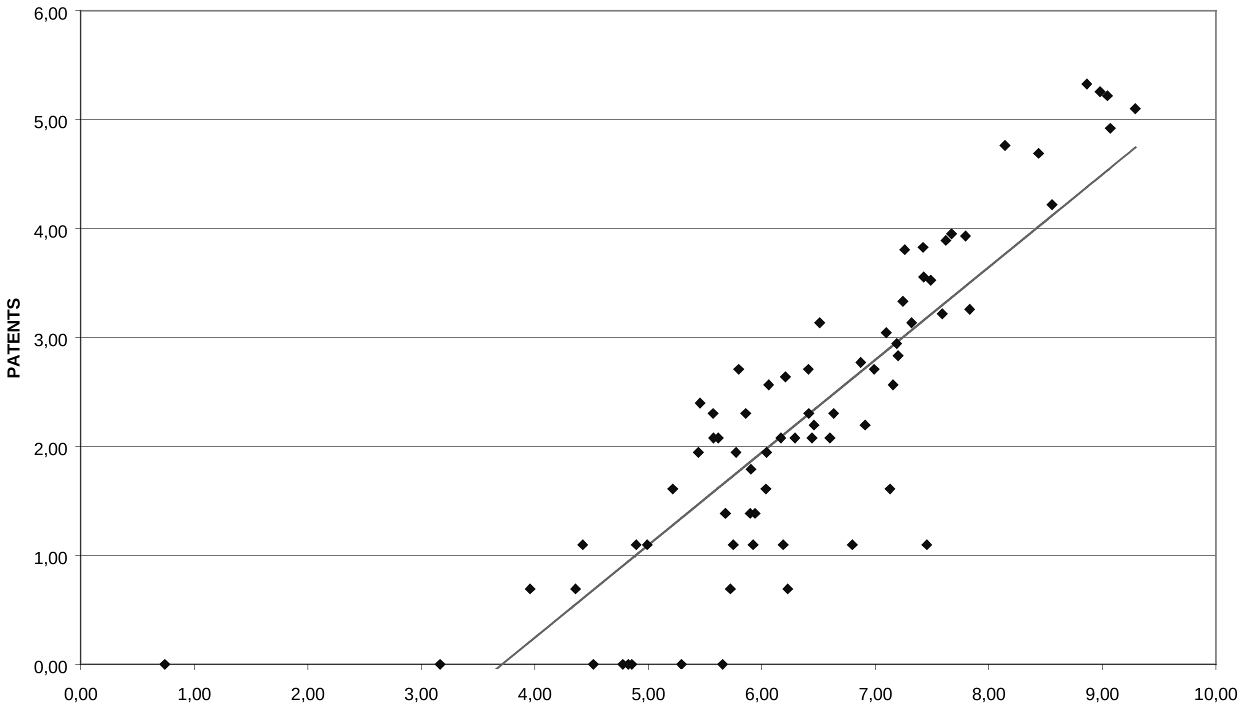


Figure 4. R&D EXPENDITURE AND PATENTS

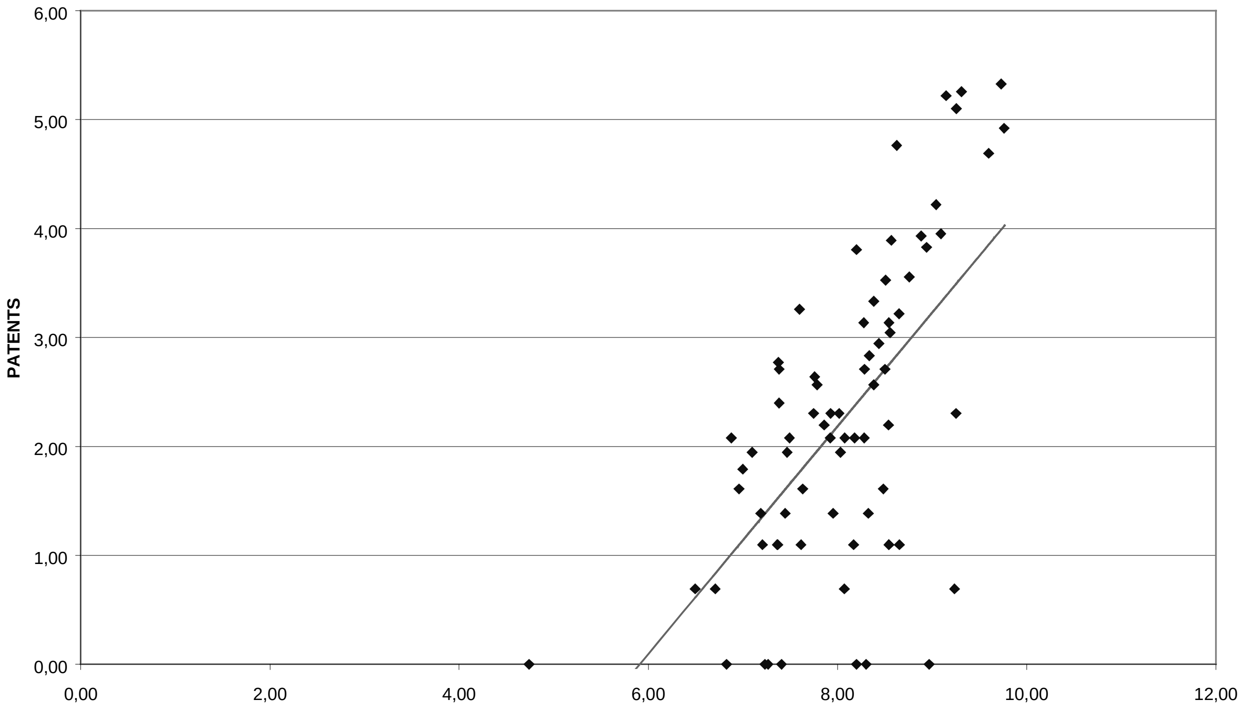


Figure 5. POPULATION AND PATENTS