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INNOVATION AND SPILLOVERS: EVIDENCE FROM EUROPEAN REGIONS

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Abstract

The importance of innovation for the economic performance of industrialized countries has been largely stressed recently by the theoretical and empirical literature. Moreover the intensity of knowledge externalities in generating innovation, is the key parameter in determining sustained growth in a model with endogenous technological change. This paper takles the extremely important task of identifying and estimating a "production function" of innovation for European regions using Patent and R&D data, 1977-1995. After correcting for the endogeneity bias we find that the elasticity of innovative output to R&D employment is around 1, while knowledge externalities exist, are geographically localized in an area of 200 kms and are significant. Nevertheless these externalities are not strong enough to generate sustained growth, and therefore European regions' innovative activity is better represented by a model as Jones (1995) than by one as Romer (1990). Knowledge spillovers could be due to the similar technological specialization of close regions, as we find significant spillovers also in technological space.

Keywords: Regions, R&D, spillovers, demand pull, endogenous innovation

JEL Classification: O3, R0, R1

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1. Introduction

Innovation does not fall as manna from heaven. It feeds on the existing stock of knowledge and on R&D expenditure on one side, and contributes to the creation of new knowledge on the other (see Romer (1990), Aghion and Howitt (1992), and Jones (1995)). In an open economy the inputs to innovation production are domestic as well as foreign. Openness and integration foster the diffusion of ideas and knowledge spillovers may spread through sectors and space, affecting productivity and growth worldwide. Nevertheless space and localization still matter, as a cursory look at countries' and regions' productivity reveals[1].

The aim of this work is to identify and estimate the effect of research and of knowledge externalities, across sectors and space, in generating innovation. We do so by looking at the European Regions, for the 1977-1995 period using data on patents as a measure of innovative output. The original contributions of the paper are three:

To estimate, correcting for endogeneity, the reduced form of the "production function" of innovation.

To identify from these estimates, using a model of endogenous technological growth, the key parameters of the "structural production function" of innovation.

To measure in "geographical" space as well as in "technological" space, the scope of the externalities generated from the stock of technological knowledge created in a region.

The first contribution concerns the estimation of the "reduced form" of a "production function of innovation". Here an issue of endogeneity arises. If an increase in resources devoted to R&D fosters innovation, it is also true that an increase in innovative output increases the productivity and the profitability of further research for innovation and induces higher expenditure in it. Any cross sectional regression of innovative output on research inputs will suffer from this endogeneity bias. To cope with this issue our empirical approach distinguishes between variables that affect the productivity and those that influence the profitability of R&D. We use the first as control variables that explain how local characteristics of a region, together with expenditure in R&D, determine the production of innovation. We use the second as instruments to solve the endogeneity problem. In this respect we believe that an important role, in determining R&D profitability, is played by local market potential. On one side, a large local market means a higher R&D competition since a higher

[1] Quah (1996) among others makes this point.

number of competitors can be accomodated by the larger market[2]. On the other, since firms identify the market potential before launching innovative projects[3], a large local market is an incentive to innovate. Previous studies on innovation activity in Europe find that European countries do not differ in terms of research productivity with respect to Japan and USA, but they do in terms of research expenditure. Eaton and Kortum (1996) and Eaton et al.(1998) conclude that the absence of a large local market outlet for innovative products is the factor that is considered crucial to understand the stagnant research activity in Europe[4].

The second contribution of this paper, i.e. the development of a simple model of endogenous technological change which incorporates the "production function" of innovation, allows us to interpret the estimated parameters as elasticity of innovation to R&D and to the existing stock of knowledge. In particular, we find that externalities to innovative activity exist, are positive and significant but they are not strong enough to sustain "endogenous" growth, as in the Romer (1990) model[5]. Our results offers supports to a model a' la Jones (1995) that lead to the convergence of growth rates of innovation across European regions.

Finally, our third contribution is to measure in "geographical" space as well as in "technological" space, the scope of the externalities generated from the stock of technological knowledge of a region. It has been widely documented[6] that clustering of innovative activity takes place especially at the early stage of the life cycle of products, showing that at the initial stage local spillovers are particularly important. Also robust evidence has been produced showing that intranational spillovers are stronger than international spillovers. Our estimates reveal relevant and localized externalities. Within the 200 Km's range from a region the "external" effect of R&D on innovation is about 10% of the direct effect of local R&D. Similarly, if we arrange regions in a technological space, only R&D in those regions which are technologically closest have an impact of innovation.

[2] Through this channel we could also have a negative effect known as the "business stealing effect" which might increase in regions where demand is larger.

[3] See the "chain-linked" model by Kline and Rosemberg(1986)

[4] An indirect piece of evidence in favor of the importance of the domestic market for the development of an innovative firms in Europe, comes from the information on the firms listed on the recently created New Stock Markets. Firstly European highly innovative firms choose to be listed mainly on their domestic stock markets. Secondly, on their financial prospectus, firms cite as competitors mostly firms that operates on their domestic local market. Lastly, financial prospectuses are mostly written in the domestic language and are clearly directed to the local investors.

[5] Knowledge created in the rest of the world is considered an exogenous factor that affect identically growth of all European regions.

6 Jaffe (1986), Feldman (1994) and Audretsch and Feldman (1996) have used a knowledge production function that includes an explicit specification for the space dimension. Keller (1996,1999) and Branstetter(1996) measure intra-national versus inter-national knowledge spillovers.

Three strands of the existing literature are related to our work. The first is the empirical analysis of models with endogenous technological change. The best known is Jones (1995b) which uses R&D as input of the innovative activity and total factor productivity as a measure of technological progress. More recently, in the same spirit, Dinopulos and Thompson (2000) estimate in a cross-country analysis the parameters of the innovation generating function. The second strand is a series of models estimating a "patent generating equation" within a general equilibrium context, such as Eaton and Kortum (1996) and Eaton et al (1998). Finally the third strand includes works which estimate cross-regions or cross-countries externalities in production or innovation, exploiting the geographic structure and spatial correlation of the data[7], such as Ciccone (1999) four US counties and Coe and Helpman (1995) for R&D spillovers across countries. Our work is the first, to our knowledge, to specify and test an innovation-generating equation for European Regions, allowing for spatial spillovers and correcting for endogeneity bias.

A final remark on the use of regions as units of analysis. When considering Europe, the regional dimension is particularly relevant. Heterogeneity among countries (difference in their legal systems, in product standards, subsidies to R&D, taxation) would in fact limit the power of the analysis. Moreover, as European countries give up some of their privileges in favor of the EU on one hand and of the regions on the other it might become more important to consider regions as the relevant units for economic analysis.

The rest of the paper is organized as follows. In section 2 we present some empirical facts and some evidence suggestive of knowledge spillovers. Section 3 presents the "production function" of innovation, derives the equation that is estimated and clarifies the relevant issues on externalities and endogeneity. Section 4 develops the theoretical model of which the "production function of innovation" is a building block. Section 5 is devoted to the empirical estimation and robustness checks. Section 6 concludes.

2. Stylized Facts and the importance of Spillovers

[7] Another strand of research, using patent data (Jaffe et al. 1993, Jaffe and Trajtenberg 1999, among others) has exploited the "citations" rather than the spatial correlations to infer spillovers and their geographical scope. On the virtues and limits of these approach see Jaffe et al (2000).

Data analysis confirms the clustering of the innovative activity as its intensity is very different across space in the European regions [8]: the top five patenting regions (Northrein-Westfalia, Bayern, Waden-Wurtenberg, Ile de France and East Anglia) are responsible for 50% of the total number of patents[9] 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 and Figure 2 show the intensity of R&D expenditure and patents in Europe. It is easy to see that the central European regions, and in particular Germany and France, show the highest intensity for both variables. 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 0.017 and of 0.0145 for R&D expenditure and patenting respectively while the value of the index, were these two variables equally distributed among European regions, would have been 0,011.

How much of these disparities in innovative output is due to different R&D intensity in the regions? A simple scatterplot (Figure 3) and a regression show 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[10].

These facts suggest that :

a. Within region spillovers might be responsible for the very high returns to regional R&D.
b. Inter-regional spillovers might have a role in explaining the remaining variation in innovative activity. For instance, the peripheral region of Madrid, potentially exposed to little knowledge spillovers from close regions, produced about one tenth of the patenting per worker than the central region of Hamburg with the same amount of R&D spending (roughly sixty-four 1985-U.S. Dollars per worker). Similarly, the peripheral region of Lazio (Italy) produced about one thirtieth of the patenting per worker than the central region of South-Netherland, with comparable amount of R&D spending. 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).

[8] 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

[9] 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. Nevertheless we conform to the existing literature since we have no better measure to adopt.

[10] 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.

The two regional inputs we consider as determinants of the rate of innovation, are the resources used in R&D (employment and spending) and the stock of knowledge present in the region. Knowledge 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. 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 "technology 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[11]. Hence specific knowledge justifies the concentration of innovation in space, to take advantage of these "externalities"[12].

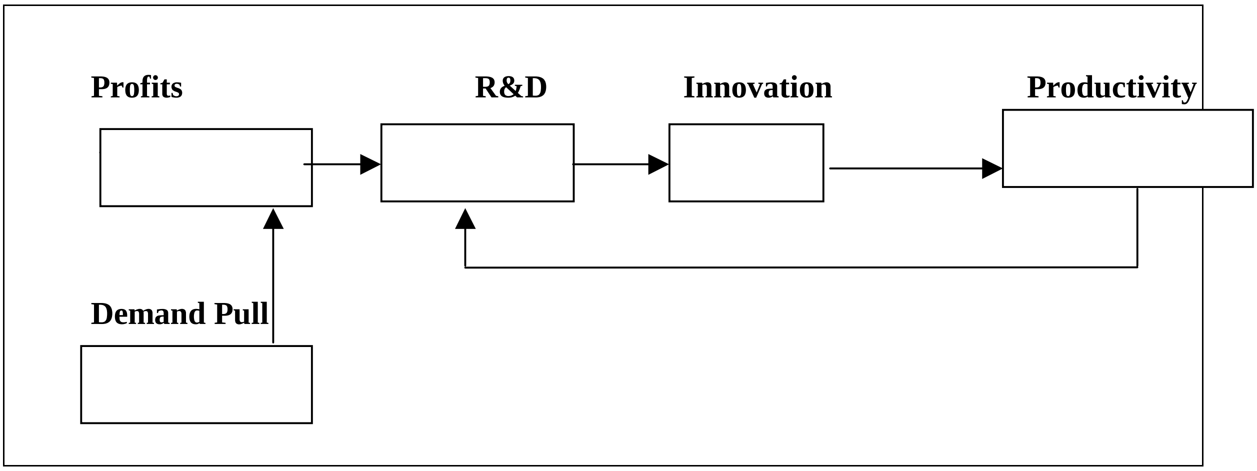
The problems in identifying and estimating the contribution of the stock of knowledge in producing new knowledge are two. The first is that there is not a good measure of the existing stock of knowledge in a region. The second is that a problem of circularity (endogeneity) between knowledge and resources invested in R&D arises. Box 1 below shows the circular causation: R&D generates innovation, and innovations increase the stock of knowledge making further R&D more productive and generating incentives to invest in R&D[13]. Most of the empirical literature, which considers the cross-country implication of R&D on growth (Eaton and Kortum 1996, Coe and Helpman 1995), assumes the exogeneity of the R&D expenditure. Here instead we consider that an important determinant of innovation is, as shown in the scheme, the potential profit generated from it. Therefore an unequal spatial distribution of demand, which may affect profits in different locations provides the "exogenous" determinant of R&D and becomes the instrument to correct for the

[11] For an in depth analysis of the importance of face-to-face interaction in developing ideas see Gaspar and Glaeser (1996).
[12] The classic references of the importance of "ideas in the air" is, of course, Marshall (1890).
[13] There is a temporal delay in this sequence, but as we are forced to use long run averages (especially for the bad quality of R&D data) we cannot exploit the time dimension

endogeneity. A measure of market potential might play this role[14] while the accumulation of the stock of knowledge and localized spillovers further contribute to lock in the process and explain the high concentration of innovation.

Box 1

Scheme of causation



3.The Production Function of Innovation

3.1 The structural "innovation-generating function"

Innovation, in a region, could be represented as an aggregate process, whose most important inputs are R&D employment (spending) and the existing stock of technological knowledge[15]:

$$New\ Knowledge = f(R\,\&\,D, Stock\ \ of\ \ \ Knowledge)$$

We assume that knowledge generated within the region and the one generated in other regions have a different impact in generating innovation. We synthesize these

[14] Market potential, we will see, is a valid instrument in balanced growth path. Out of balanced growth path we need a slightly different instrument which is "historical" market potential.

[15] It is easy to allow for a depreciation rate of the stock of knowledge. It would not change any of our relevant results.

described features in the following innovation-generating function or "production function of innovation"(Romer (1990),Jones (1995a)) :

$$\dot{A}_{it} = \lambda(n_{it}) f_1(A_{it}) f_2(A^s_{it}), \qquad \lambda' > 0, \quad f_1' > 0 \quad f_2' > 0 \qquad (1)$$

where A_{it} is the stock of knowledge generated in region i up to time t, and $\dot{A}_{it}$ is its time derivative. A^S_{it} is the average stock of knowledge generated in other regions, which, through diffusion, is available in region i. n_{it} is the amount of labor employed in R&D in region i and the function $\lambda(.)$ captures its contribution in generating innovation. We are assuming that the knowledge generated in the rest of the world is equally accesible to all the regions and therefore contributes to generating innovation via a constant that we standardize to one. f_1 captures the contribution of the locally generated knowledge to the creation of new knowledge and f_2 captures the effect of knowledge generated in other regions on innovation. More precisely we assume:

$$f_2(A^S_{it}) = \left(\prod_{j \neq i} A_{jt}^{m(d_{ij})} \right)^{\varepsilon_2} \qquad (2)$$

where $m(d_{ij})$ are weights that depend on distance between region i and j: when decreasing with distance the knowledge generated further away has smaller impact on innovation. To identify ε_2 as the elasticity to outside-generated knowledge we assume that for each i the sum of the weights over j is equal to one ($\sum_j m(d_{ij}) = 1$). We call ε_λ the elasticity of the function λ, and ε_1 is the elasticity of the function f_1. It can be shown that under the condition of decreasing return to total knowledge spillover ($\varepsilon_1+\varepsilon_2<1$)[16], the system of N differential equations in (1) admits a balanced growth path (BGP), which is locally stable[17]. The common rate of growth of the regions in BGP is $g = \frac{\varepsilon_\lambda g_n}{1-\varepsilon_1-\varepsilon_2}$, where g_n is the growth rate of the employment (expenditure) in R&D. If, as in the model of section 4, skilled workers are mobile across regions, the growth rate of employment in R&D is equal to the growth rate of the total skilled

[16] We assume that for each region j the sum of the spillover elasticities is a constant. This is equivalent to assuming that the structure of spillover across space is equivalent for each region (although the amount may differ due to different R&D of other regions).

[17] Details of this derivation in appendix A2

labor force[18]. Taking logs, using the BGP condition $\dot{A}_i = gA_i$, and in vector notation, we derive from (1) the following regional innovation-generating equation:

$$\log(\underline{\dot{A}}) = \underline{c} + \tfrac{\varepsilon_\lambda}{(1-\varepsilon_1)} \left(I - \frac{\varepsilon_2 M}{1-\varepsilon_1} \right)^{-1} \log(\underline{n}) \qquad (3)$$

where M is the matrix whose elements are $m(d_{ij})$ and they capture the spillover of knowledge from region j into region i, as described in the definition of A^S_{it} .. Equation (3) is the key equation for the empirical implementation of the model (we will estimate an approximation of it). Each underlined variable is an Nx1 vector of regional variables: $\underline{\dot{A}}$ is the vector of "regional innovation", $\underline{c}$ is a vector of constant capturing all the common terms affecting regional innovation[19], $\underline{n}$ is the vector of employees in R&D (or expenditure in R&D). I is the identity matrix.

3.2 Empirical specification of the reduced-form "innovation-generating function"

The equation which provides guidance to our empirical estimation is an approximation of (3), after linearizing the term in brackets around $\varepsilon_2=0$:

$$\log(\underline{\dot{A}}) = \underline{c} + \frac{\varepsilon_\lambda}{1-\varepsilon_1} \log(\underline{n}) + \frac{\varepsilon_2}{(1-\varepsilon_1)^2} \Sigma \log(\underline{n}) + \underline{u} \qquad (4)$$

where -$\underline{u}$- is a vector of uncorrelated random errors. The interpretation of (4) is intuitive. It says that two factors are the determinants of innovation of a region on its balanced growth paths:

a. The R&D done in the region itself, which affects innovation directly and via the spillover effect of the locally generated stock of knowledge.
b. The R&D done in all the other regions, filtered by a matrix which weights them depending on distance from region i.

Equation (4) can be considered as the "reduced-form" production function of innovation, and is an interesting relation per se, when correctly estimated, as it may provide a measure for the spatial impact on innovation of changes in R&D.

Since the behavior of spillovers in space is one of the issue we want to inquire we do not want to impose any parametric structure on the diffusion of knowledge in

[18] We report in appendix A4 the growth rates of all variables in BGP

[19] To get this vector we are using the property: $\Sigma\underline{c}=c\underline{1}$ therefore $\Sigma^{-1}\underline{c}=c\underline{1}$.

space (be it geographic or technological). Hence we define the weighting function as $m(d_{ij}) = \sum_k m_k \frac{d(i,j)}{n_j(i)_k}$ where m_k is the weight to the ideas generated at distance "k" from region i, while d(ij) is a dummy whose value is 1 if region j is at distance k from region i, and 0 elsewhere. Finally $n(i)_k$ is the number of regions at distance "k" from region i, and it is true that $\sum_j \frac{d(i,j)}{n_j(i)_k} = 1, \quad \forall k$. Therefore in matrix notation we construct the sequence of (NxN) matrices $D_{[1]} \ldots D_{[K]}$, by grouping all the regions in K classes of distance, including in each class the couple of regions whose distance d_{ij} is in the interval $[h_{k-1}, h_k]$ units[20]. Hence we obtain K-many Markov $D_{[k]}$ matrices that multiplied by log(n) select, for each region , the average R&D done in the regions j at distance k from i. The system that we estimate is, in matrix notation, as follows:

$$\log \dot{\underline{A}} = \underline{C} + \beta_0 (\log \underline{n}) + \beta_1 (D_{[1]} \log \underline{n}) + \beta_2 (D_{[2]} \log \underline{n}) + \ldots + \beta_K (D_{[k]} \log \underline{n}) + \underline{u} \qquad (5)$$

The relation between the estimated parameters and the parameters in the structural production function of innovation are : $\beta_0 = \frac{\varepsilon_\lambda}{1-\varepsilon_1}$, $\beta_k = \frac{m_k \varepsilon_2}{(1-\varepsilon_1)^2}$ and $\sum_k \beta_k = \frac{\varepsilon_2}{(1-\varepsilon_1)^2}$. We cannot identify directly the original elasticities from these estimates but we can check the conditions for endogenous growth and the spatial scope of the spillovers.

3.3 Endogeneity and "out of BGP" Bias

Two relevant problems arise when estimating equation (5): an endogeneity problem, discussed in the previous paragraph, which bias OLS estimates in balanced growth path, and the potential correlation between contemporaneous instruments and residuals out of the balanced growth path which may cause inconsistency of the IV estimates. We analyze them separately and, with the help of our theoretical model, we propose a solution.

The endogeneity bias is illustrated by the scheme in box 1. In Balanced growth path (BGP) the correlation beteween R&D and innovation is due to the direct effect of higher production of ideas where investment in R&D is large, but also to a reverse effect of higher R&D investment where there is larger stock of local knowledge. Because of the perfect correlation between the stock and the flow of knowledge in

[20] Each entry ij of the $D_{[k]}$ 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 $(1/n_j(i)_k)$, if the distance between i and j falls in that class.

balanced growth path, estimation of (5) will suffer such endogeneity bias. Therefore in BGP we need an instrument that affects the amount of R&D done in each region but not its productivity in finding new ideas. Variables which affect the profitability of innovation rather than R&D productivity, and are unevenly distributed across regions, are excellent candidates for this role. This is the case of population (and therefore of local demand) since the determinants of population distribution in Europe have been exogenous to the process of generation of innovation and mainly determined by historical factors. In the empirical section various measures of local market potential are used as instruments.

The other source of bias in our estimation is due to the potential correlation between the residuals and the instruments, out of the balanced growth path. This point becomes clear when we log-linearized expression (4), around the balanced growth path:

$$\log \dot{\underline{A}} = \underline{c}' + \frac{\varepsilon_\lambda}{1-\varepsilon_1}\log \underline{n} + \frac{\varepsilon_2}{(1-\varepsilon_1)^2} M \log \underline{n} + (\varepsilon_1 + \varepsilon_2 M)(\log \underline{A} - \log \overline{\underline{A}}) + o(\log \underline{A}) \tag{6}$$

where the term $(\varepsilon_1 + \varepsilon_2 M)(\log \underline{A} - \log \overline{\underline{A}})$ is the first derivative of the function $\log \dot{\underline{A}}$ calculated in the balanced growth path, time the deviation of the vector of $\underline{A}$ from it[21]. In this case the error term –u- in equation (5) is equal to the last two terms of espression (6). Hence if the population of a region is also correlated (due to out of the BGP shocks) to its current stock of ideas it is also correlated with the residuals and can not be used as instrument[22]. Nevertheless, this will not be the case when we use the historical population of European regions, as IV. In this case, as $\underline{A}$ converges towards its steady state, the correlation between the population and the deviation of $\underline{A}$ from its balanced growth path vanishes.

The speed of convergence of $\underline{A}$ towards its balanced growth path, derived in the appendix A3, is simply $-\varepsilon_\lambda g_n$[23]. Assuming g_n=0.05 per year (which is the average growth rate of the employed in R&D in Europe, derived from our data set and very close to the estimates in Jones (1995b)), and ε_λ=1, we have that in 50 years the deviations from BGP are reduced to less than 8% of their original value. Hence, using population in the 30's as instrument, in the calculation of market potential for European regions, we are able to eliminate almost completely the potential bias.

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[21] Also $\underline{c}' = \underline{c} + \log(g)$.

[22] For instance a negative shock, temporarily affecting productivity of a region and inducing out-migration ,will induce correlation between the instrument (population) and the residuals and will bias the estimates.

[23] We are assuming symmetric convergence to the balanced growth path, and the speed calculated is an approximation in the vicinity of the BGP.

This procedure will enable us to obtain consistent estimates of the parameters without knowing the current stock of regional knowledge. By comparing the estimates using current population as IV and historical population, we see that this kind of bias is not particularly relevant after all. This remarkable fact, illustrated in Figure 6, is explained by the extremely high correlation of historical (1930) regional population in Europe to regional population in 1980. The spatial distribution of population in Europe (and therefore of demand) was already established, as it is today, in 1930: 85% of the current variance of regional population is explained by variance in 1930!

4. The Model of the Economy

Although we leave the analytical derivation of the model to the Appendix a brief look at the rest of the economy might be useful to understand the theoretical idea which is behind our empirical approach.

Our economy has 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 manufacturing sector of the region[24]. We assume perfect mobility across regions of skilled workers, who take part into the production of innovative goods and that might be employed in R&D. Unskilled workers (L) participate in the production of the final manufacturing good. In each region new intermediate goods (x_{it}) are invented and put at work, increasing the productivity of its manufacturing sector (y_{it}). One unit of each intermediate good requires one unit of skilled labor to be produced, and we assume that new intermediate goods are produced using local patents[25]:

$$y_{it} = L_t^{1-\alpha} \int_{s=0}^{A_i} x_{it}^{\alpha}(s)ds \quad \text{where } \alpha<1 \qquad (7)$$

where A_{it} is the number of intermediate patented goods. In each region there is also a perfectly competitive sector, producing services (Z_{it}) with Cobb-Douglas technology, using labor (S_{it}) and the composite manufacturing goods inputs:

$$Z_{it} = S_i^{\gamma} y_{it}^{1-\gamma} \qquad (8)$$

[24] The framework of our manufacturing sector is very similar to Romer (1990) and Jones (1996).

[25] This implies rather strongly that not only intermediates are non-traded but also patents for intermediates. This assumption makes the results more clear-cut. In the empirical implementation we allow for all regions (not only the one where it is invented) to affect the demand of an intermediate.

We assume that workers in this sector are specific to it, and their distribution across region is exogenous. All agents in a region are similar in terms of their utility function and in the aggregate they generate the demand for the goods and services produced in the region[26]. Although our analysis focuses on the manufacturing sector, which is the one where innovation and productivity growth takes place,the service sector is relevant because might have different size in different regions and could affect the demand for the manufactured good determining therefore its price. Being exogenous to the process of innovation, employment in services provides an excellent instrument for our empirical analysis.

As already mentioned, 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 in the Aghion and Howitt (1992) model. There is not a real "business steeling" effect, as goods are not substitutes, but there is a "business squeezing" due to the fact that more goods compete for a local market: Profits are increasing in local demand (and therefore S_{it}), and decreasing in the total number of cumulated innovations (A_i) which squeeze the market for the marginal innovation.

4.2 BGP determinants of R&D

By solving the model (see Appendix A1 and A2), we derive the following relation between regional R&D, stock of knoweldge and demand.

$$\log(\underline{n}) = \underline{c_1} + (1-\gamma\alpha)(1-\gamma)\log(\underline{A}) + \gamma(1-\alpha\gamma)\log(\underline{S}) \qquad (9)$$

which clarifies the issue of endogeneity we have previously discussed. This relation expresses the endogeneity of $\underline{n}$ in BGP, as that variable depends on $\underline{A}$. From the above espression we can infer that, in BGP, it exists a positive relationship between the level of knowledge and the amount of resources which are devoted to research. This relation combines a negative effect, which is the "business squeezing effect" which is larger the larger the number of intermediates $\underline{A}$, and a positive effect of increased productivity of R&D as $\underline{A}$ grows. The net effect of $\underline{A}$ on $\underline{n}$ in our model is positive. Regions which are more productive as they have cumulated more knowledge, devote more resources to innovation. Therefore OLS estimates of equation (4) suffer from an endogeneity bias. Nevertheless equation (9) provides the

[26] This assumption does not necessarily imply that the economies are closed but that transportation costs and market segmentation lead regions to consume more of the locally produced goods and services.

potential instruments to fix this endogeneity problem. The size of the service sector[27] (S_l), and in general of the local demand (direct and indirect), affects the amount of resources devoted to R&D while, not entering equation (4), does not affect the productivity of R&D in BGP. Variables proxying demand and the size of the service sector have an uneven spatial distribution across European regions and can be used as instrumental variable in the estimates of the productivity of R&D and of its spillovers.

5. Estimation and Robustness checks

In the empirical implementation of equation (5) we take as measure of the flow of profitable innovation the yearly patenting rate of each region in the 1977-1995 period. We are assuming that one patent is one new good and all of them give the same contribution to productivity[28]. The data on R&D used, are the average total R&D employment and spending (in ECU) for the period 1977-1995, from the Eurostat Regio data-set[29].

If the western European regional economies have been on average on the balanced growth path, in the 18 years period we consider[30] we can effectively use contemporaneous variables such as population and local demand as instrument. As we are worried of potential correlation of the instruments (population) and the error term out of the BGP, we check the robustness of our estimates using historical population, i.e. population in 1930, as IV.

Equation (5) has a direct translation in terms of patents, which is:

$$\log(\underline{pat}) = \underline{C} + \beta_0(\log \underline{n}) + \beta_1(D_{[1]} \log \underline{n}) + \beta_2(D_{[2]} \log \underline{n}) + ... + \beta_K(D_{[k]} \log \underline{n}) \quad (10)$$

The vector pat measures the average yearly number of patents for the 1977-1995 period. For those regions with 0 patents' application, we attribute a minimal rate of patenting equal to 0.04 per year, which would not have given even one patent in 18

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[27] Service industries are heavy users of information technologies, and the bulk of information technology investment is actually used by services (80% circa in US and UK).There is also increasing evidence that service sectors heavily invest in human resources, which are increasingly recognized as a key competitive element of firms' innovative strategies.
[28] For a dicussion of the advantages of this convention in locating patents see Jaffe et al (1993) among others.
[29] See data appendix for details.
[30] Stylized facts and new estimates of the speed of convergence from panel data (Canova and Marcet 1995, De la Fuentes 1996, De La Fuentes (1998) lead us to believe that western Europe is close to its BGP since the 70's.

years, on average. The vector n measure total employment in R&D (or in some specification total real spending inn R&D) averaged over the 1977-1995.

The coefficients $\beta_1, \beta_2, ...\beta_K$ measure the intensity of spillovers in R&D at distance 1,2…K while β_0 captures the elasticity of innovation to own R&D employment in BGP.

5.1 The basic model with spillovers in geographical space

In the empirical implementation of equation (10) we have two important issues to address, namely the number and the length of the "space" intervals for each explanatory variable in order to have a reasonable trade-off between explained variance and precision of the estimates. The first problem is made much more severe by the possibility of collinearity between variables. The inclusion of variables that capture average R&D employment in regions far away might give rise to a collinearity problem. If we include 10 variables for the intervals from 0 to 1000 Km's[31], increasing by 100 Km, and one for all those regions farther than 1000 km, we have a coefficient of correlation of the order of 0.8-0.95 among the last 5-6 variables out of 10. This will make the estimates totally unreliable, and the standard 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 Km's Cells. The R&D employment for longer distances is included as an average variable, (whose coefficient in the tables is denoted as β^{4+} or β^{2+} depending on the cell's length), aimed at capturing the effect of average R&D employment more than 400 Kilometers away. We perform weighted OLS[32] (results in Table 2) and IV estimates of the coefficients of the basic regression (10). The first regression (I) in Table 2 allows the elasticity (and therefore the coefficients) to change every 100 Km's while the second regression (II) allows them to change only every 200. Similarly in the following tables 3a, 3b, 4, 5 and 6.

[31] Distance between two regions is calculated as distance between their capital cities.
[32] The weighting is made because, due to different size of regions the size of the measurement errors could be different across them

All the results are reported in Tables (3 (a, b)). We use R&D[33] employment as a measure of research inputs and a proxy of local market potential, as instrumental variable. We approximate market potential simply with regional population in 1980 and by the population of the other regions, weighted at an exponentially decreasing rate. The market potential is determined by a region's access to markets for its goods[34] and following the work of Hanson (1998), which estimates the impact of demand at increasing distance, we use exponential decay to determine the impact of the size of the market on local demand. For each region, we add own and other region's weighted population with an exponential rate of decay with coefficient –0.03 on distance in thousands of Kilometers (Table 3a). In Table 3b the coefficient of decay is lower and equal to –0.01. Due to the robustness of our estimates to this choice we have decided in favor of -0.03 rate of decay for all the subsequent estimates[35].

Since the benefits of ideas could spread more easily within countries than across them, due to the common language and similar educational background of the skilled workers, we take care of a "country" effect by adding the average national level of R&D spending or employment to our regressors. If one region receives benefits just from being in a high R&D country his "country" variable would be significant and R&D of regions in the neighborhood should be insignificant[36].

In Table 4 we use real R&D spending as explanatory variable while Table 5 and 6 differ from Tables 3a only for the variable used to measure local market potential. Employment in services (which according to our model should be a good instrument) and demand for manufacturing as intermediates goods are used respectively in those estimates. The demand for manufacturing as intermediates is calculated by applying the national input-output matrix to the industrial employment of the regions. All the variables used are an average for the 1977-1995 period.

The relevant estimated coefficients, using population-based market potential, are also drawn in Figure 4 which is particularly useful to eyeball the decreasing effects of R&D via spillovers. In that figure only the β's are drawn, leaving out the coefficients on the control variables, and all the estimates (under different specifications) are shown together. The roman number relative to each estimate refers to the estimating specification in Table 3a. It is possible to spot immediately how the

[33] These results are obtained using total R&D. We have also run the regressions distinguishing between private and public R&D. The results do not change significantly: the elasticity of patenting to private or to total R&D remains almost unchanged. The results could be severely affected by the quality of the data on private R&D available at regional level.
[34] Harris (1954)
[35] We also used simply regional Population as IV obtaining similar results, see Bottazzi and Peri (1999).
[36] The estimates of the other coefficients increase only slightly if we eliminate the average R&D for the country.

coefficient estimates are similar across specifications and drop with distance and how they are no longer significant for distance larger than 200 Kms.

INSERT FIGURE 4, HERE

Figure 5 compares the estimates of the significant β's (β_0 and β_1) using OLS and the basic IV estimation of Tables 3a, 5 and 6. The pattern shows that the potential endogeneity (upward) bias of β_0 fades away when we use instruments which are likely to be more and more exogenous, moving from the demand for manufacturing goods as intermediates towards the employment in services and to the total population. Therefore, as it also passes a Sargan test of exogeneity at the 5% level, we concentrate on population-based market potential as the most reliable instrument.

INSERT FIGURE 5

Let's concentrate on the basic specification (regression I and V in tables 3A), whose main findings are confirmed by most of the other specifications. This regression is estimated using current-population-based market potential (rate of decay –0.03) as IV (Tables 3a, 3b). Three things emerge clearly and consistently:

1. The coefficient on R&D employment is always very significant and most of the time close to one. Most of the cross-regional variation in patenting is due to differences in R&D.
2. Spillovers through space exist and are statistically significant for the R&D done within 200 Km's from the region (see Figure 4). 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) potentially because large cities tend to arise at some distance from each-other. This effect is larger when estimated using employment rather than spending in R&D.
3. The magnitude of these spillovers effects, if not negligible, is not very large either: the elasticity of patenting to "close" R&D employment (0-200 Km) is between 8 and 10%, while the elasticity to own R&D ($\beta_0 = \varepsilon\lambda/ 1- \varepsilon_1$) is in the range of 90-100%. These results suggest that spatial spillovers may be important but not "first order" in determining the BGP differences in innovation rates across regions. 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 5% significance level, confirming the hypothesis that total R&D spillovers are significant in

determining innovation in one region. Nevertheless the only significant coefficient is, in all specification, the one for R&D within 200 Km's.

4. The national R&D variable has a very strong and positive effect.

The results show that 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 creates incentive for innovation to cluster while spillovers towards close regions are important but second order of importance.

The estimates using market potential based on population in 1930 as IV are extremely close to those obtained using market potential based on 1980 population as IV. Table 8 provides these estimates for the same specification as Table 3a. We can see that both the own effect (in the range 0.86-0.95) and the spillover effect (in the range 0.08-0.12) are close to the estimates in Table 3a. The estimates of the other specifications using historical population rather than 1980 population are reported in table 1A and 2A in the Appendix. The similarity of the estimates confirms the idea that the balanced growth path approximation for European regions in the 1977-1995 period is a good one as there do not seem to be an out-of-BGP bias.

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

In regression II and III of table 3-6 we have included some controls, to check that the omission of some variables, potentially spatially correlated, is not responsible for our finding of the spillovers. In II we have included a measure of human capital in the region, i.e. the fraction of workers with education equal or more than college[37]. This could be an important input of the innovation process and can be correlated across regions. Including this variable does not reduce the estimates of the spillovers effect while it appears always highly significant. In III 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. The irrelevance of infrastructures to explain geo-concentration of innovative firms in confirmed in Midelfart-Knarvik et al.(2000).

In regressions IV of table 3(a,b) 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 elasticity to own research is here higher than in the other specifications, while the spillovers estimates are lower. In this specification the use of total market potential

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

(measured by population) as instrument for R&D per worker is not very good as it was in explaining total R&D in the region.

5.2 Parametric specification

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 collinearity). At the cost of specifying a functional form for the dependence of spillovers on distance, we may parametrize this decay and use the data on R&D at any distance to estimate only one parameter that captures the speed of decay of spillovers with distance.

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 least squares.

The results, reported in table 7a 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. The percentage impact of R&D at various distances implied by the estimated coefficients can be read in Table 7b. 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. We think that the differences are due to the fact that the parametric specification forces a smooth behavior, which does not seem supported by the data. For this reason we stick to the non-parametric estimates.

5.3 Spillovers in technological space

The natural question to ask is whether "geographical space" is the most relevant dimension to consider: 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, we construct a distance in the technological space. First we define an index of "distance", then we proceed as described in section 3.2 to define cells into which the value of this index falls and to construct the matrices $D_{[1]}$, $D_{[2]}$ …$D_{[k]}$ and to estimate the β's.

Technology spillovers have been measured following different methodologies in the literature. An extensive review of the existing measurement methods is offered by Los (2000). We therefore leave aside any discussion on the pro and the cons of the different approaches. We follow Jaffe (1986) and we construct a measure of technological distance between regions, on the basis of the distribution of regions' patenting activities over technological fields.

Let's define F technological classes, using the International Patent Codes matched with the NACE classification. This procedure generates 30 classes[38]. Then each region i could be represented by a vector of dimension 30, say $\underline{f_i}$ which contains as k-th entry, f_{ik} the share of patents in that technological class . The distance in technological space, between region i and j (actually decreasing as the index increases) will be:

$$\omega_{ij} = \frac{\sum f_{ik} f_{jk}}{\sqrt{(\sum_{k=1}^{F} f_{ik}^2 \sum_{k=1}^{F} f_{jk}^2}} \qquad (11)$$

This is, technically, a correlation (cosine) coefficient between vectors consisting of the shares of the patents in each technological class in the two regions. If the two regions have patented exactly in the same classes the cosine will be one, if the patenting activities are perfectly complementary the cosine will be zero.

In our sample of 86 EU regions we have that the index range from 0 to 0.92. We identify 3 classes of distance: [0-0.2], [0.2-0.4], [0.4-1]. The estimates of specification (10), using this metric on technology and obtained by using historical (1930) population-based market potential as IV, are reported in Table 9.

Even in this case the effect of the own region R&D is highly significant and consistent with the results previously obtained. As for the other coefficients, only β_1 that measures the spillovers received from regions specialized in most similar technology fields, appears significant.

One final caveat. The two distances (geographical and technological) which we have defined certainly do not belong to "orthogonal" spaces. The positive effect of geographically close regions might be due to the fact that they are also technologically similar. The correlation between the two distances in the sample is 0.35, and when we

[38] The classes and the matching of the codes are available from the authors upon request.

regress geographical distance[39] on technological distance only 12% of the variance of the first is explained by the second. These two spaces are not particularly collinear although a certain degree of correlation can not be excluded[40]. The analysis, considering both the dimensions provide a complete picture of spillovers in Europe.

5.4 Structural parameters and implications for growth

Our estimates of the elasticities of innovation to R&D employment and spending provide an important measure of the productivity in the innovative sector in Europe. Nevertheless, due to our very general and non-parametric approach, we stop just short of identifying the structural parameters of our model, notably $\varepsilon_\lambda, \varepsilon_1$ and the ε_2. We can identify, nevertheless, two key results which have implication on the convergence behavior of the regional economies. Considering only the parameters significantly different from 0 in the specification with 200 Km's cells, we consistently find estimates that significantly satisfiy the following inequalities:

$$\beta_0 = \frac{\varepsilon_\lambda}{1-\varepsilon_1} > 0,$$

$$\beta_{[0-200]} = \frac{\varepsilon_2}{(1-\varepsilon_1)^2} < 1$$

From the first condition, if $\varepsilon_\lambda>0$ we derive $\varepsilon_1<1$. From the second, if $\varepsilon_1>0$ after some manipulations we get $(\varepsilon_1+\varepsilon_2)<1$[41]. These two conditions are exactly the restrictions needed to ensure convergence of the endogenous innovative process to a BGP in which the stock of knowledge (and therefore of productivity) of regions grow at the same rate, while their level differ, depending on the distribution of demand. Our estimates confirm that a model a' la Jones (1995) or a' la Dinopulos and Thompson (2000) provide a good representation of European regional technological change in the last 20 years.

6. Conclusions

While there is an increasing consensus on the importance of technological innovation for the economic performance of the European Union, few studies have

[39] It has been standardized to be a "correlation coefficient", between 0 and 1 and increasing as distance decreases

[40] We cannot estimate the two kind of spillovers at the same time for lack of IV's.

[41] In particular we get $(\varepsilon_1+\varepsilon_2)<1-\varepsilon_1(1-\varepsilon_1)$.

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 estimate the innovation generating function in regions. We find that spillovers of R&D activity across regions exist, are significant , decrease rather quickly with distance. The elasticity of innovation to them is around 0.1 while it is 1 the elasticity of innovation to own R&D employment. In a model of endogenous technological change these estimates are very important as they provide support for regional convergence in innovation rates (and productivity, if innovation is a key determinant of it).

Our results support the idea of spatially localized spillovers, already proposed by other authors, and use the geographical correlation of innovative activity and R&D in Europe to infer the existence of such spillovers. We think that the analysis of technological growth in Europe, at the onset of its economic integration, could be a key issue for policy makers.

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Appendices

A.1 Manufacturing and Services

Each region produces one composite manufactured good using intermediate goods and raw labor. The total production of the composite manufactured good in region i is as follows:

(1a) $$y_{it} = L_t^{1-\alpha} \int_{s=0}^{A_i} x_{it}^{\alpha}(s)ds \quad \text{where } \alpha<1$$

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_t is the amount of unskilled labor used in production (assumed w.l.o.g. to be equal across regions). The production function of the service sector is a Cobb-Douglas combination of Service-specific labor (S_i), which is not mobile across regions, and the output of the manufacturing sector.

(2a) $$Z_{it} = S_i^{\gamma} y_{it}^{1-\gamma}$$

The demand generated by this sector on the manufacturing sector is $(1-\gamma)S_{it}^{\gamma} y_{it}^{1-\gamma}$. Each agent has a utility function which is Cobb-Douglas, and for simplicity we assume, w.l.o.g., of the same γ parameter as (2a). She, therefore, divides her income into a fraction γ spent to purchase the manufacturing composite (y_{it}) and a fraction (1-.γ) spent in purchasing services (Z_{it}).

Equating the local demand and supply for the manufacturing sector we find the expression of the corresponding prices:

(3a) $$P_{it} = \frac{(1-\gamma)(1+\gamma)}{\gamma} S_i^{\gamma} y_{it}^{(1-\gamma)}$$

Given the production function in equation (1a) the demand curve for each intermediate is $p_{it}(s) = P_{it}\alpha L_{it}^{1-\alpha} x_{it}^{\alpha-1}(s)$ where p_{it}(s) is the price of the s-th intermediate good in region i at time t. The optimal pricing rule is:

(4a) $$p_{it} = \frac{1}{\alpha} w_t$$

We assume perfect mobility of skilled workers across regions and therefore a unique wage w_t for all regions. The demand for the single firms:

$$(5a) \qquad x_{it} = \left(\frac{w_t}{\alpha^2 L^{1-\alpha} P_{it}} \right)^{\frac{1}{1-\alpha}}$$

and the profit of each monopolist in the i-th region, therefore is:

$$(6a) \qquad \pi_{it} = \frac{1-\alpha}{\alpha} w_t x_{it}$$

Now consider the production function of the composite manufacturing good. A share (1-α) of the total value added is paid to unskilled worker while the remaining share α is paid as wage to the skilled workers and as profits to the producers of intermediates. Therefore:

$$(7a) \qquad \int_0^{A_i} \pi_{it} di + \int_0^{A_i} w_{it} x_{it} di = \alpha P_{it} y_{it}$$

Using (6a) and the fact that all firms are similar we get:

$$(8a) \qquad \pi_{it} = \frac{\alpha(1-\alpha) P_{it} y_{it}}{A_{it}}$$

In equilibrium, as all firms have the same size, we may write the manufacturing output as:

$$(9a) \qquad y_{it} = L^{1-\alpha} A_i x_{it}^{\alpha}$$

using (5a) and (9a) we can solve for x_{it} and we get:

$$(10a) \; x_{it} = C_x w_t^{\frac{1}{\alpha-1}} S_i^{\gamma} A_i^{-\gamma}$$

where we have collected all constant terms into the term C_x . Using (10a) and (9a) to solve (8a) the expression of profits becomes:

$$(11a) \qquad \pi_{it} = C_{\pi} w(t)^{\frac{\alpha(1-\gamma)}{1-\alpha}} A_i(t)^{(1-\gamma\alpha)(1-\gamma)-1} S_i^{\gamma(1-\gamma\alpha)}$$

In order to determine the value of a patent we consider the present discounted stream of profits, which are generated by the invention. Using (11a) as the expression of profits for a typical producer in region i at time t, collecting all the constant and using the fact that all variables grow at constant exponential rate in BGP we obtain the following general expression as value of the patent in region i:

$$V_{it} = \int_{s=t}^{\infty} e^{-r(s-t)} \pi_i(s)\, ds =$$

$$= C_v w(t)^{\frac{\alpha(1-\gamma)}{1-\alpha}} A_i(t)^{(1-\gamma\alpha)(1-\gamma)-1} S_i^{\gamma(1-\gamma\alpha)} \qquad (12a)$$

The return from innovation (value of a patent) is the present discounted value of a firm's profits using the market rate r. A larger relative number of firms in the local market (A_I) squeezes the profits of a firm and therefore the value of a patent, while a larger local demand (S_i) will increase the profits of a firm and therefore the value of a patent.

A.2: Derivation of the balanced growth path

Let us call with g_x the rate of change of the variable x. We can take the rate of change on each side of expression (1) in the text to get:

(13a) $$\dot{g}_{A_i} = g_{A_i}\left[\varepsilon_\lambda g_H - (1-\varepsilon_1) g_A + \varepsilon_2 M g_{\bar{A}}\right] \qquad \text{for i= 1,2…N}$$

where M is a the markov matrix of weights.

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

(14a) $$g_A = \frac{\varepsilon_\lambda g_H}{1-\varepsilon_1-\varepsilon_2}$$

Expression (14a) 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 (ε_λ) , and by the spillovers from existing knowledge (ε_1+ε_2). The result, that the growth rate depends only on the growth of human capital (employed in R&D) and not on the level of investment in R&D, is a consequence of the assumption (ε_1+ε_2<1). which makes the model similar to Jones (1995). If we log-linearize expression (1) around the BGP we have that the system can be written in vector form as:

(15a) $$\underline{\dot{g}_A} = [\varepsilon_2 M + (\varepsilon_1 - 1) I](\underline{g_A} - \underline{\overline{g_A}})$$

where the underlined variables are vectors, M is an NxN matrix with $m(d_{ij})$ as entries in each position and I is the identity matrix. The characteristic roots of the matrix in square brackets are all negative (exploiting a property of the markovian matrices) and therefore the differential system of equations (15a) is stable[42].

In BGP, substituting $\dot{A}_i = \frac{A_i}{g_A}$, taking logs on both sides and collecting all the constant in an initial term we can re-write (1) as:

$$\text{(16a)} \quad \log(\dot{A}_i) = c + \varepsilon_\lambda \log(n_i) + \varepsilon_1 \log(\dot{A}_i) + \varepsilon_2 \sum_{j=1}^{N} m(d_{ij}) \log(\dot{A}_i)$$

which, in matrix notation, and solved for $\log(\dot{A})$ gives the equation in the text:

$$\text{(3)} \qquad \log(\underline{\dot{A}}) = \underline{c} + \tfrac{\varepsilon_\lambda}{1-\varepsilon_1} \left(I - \tfrac{M\varepsilon_2}{1-\varepsilon_1}\right)^{-1} \log(\underline{n})$$

A.3: Speed of Convergence to BGP, in the symmetric case

It is easy to calculate the speed of convergence to the BGP in the case of equal deviation from the BGP of all regions. This is the case we consider as reference, knowing that if shocks are not identical, there will be a linear combination of the shocks approaching the BGP at the same speed.

In this case, let's define as g_i the growth rate of A_i, and $\bar{g} = \frac{\varepsilon_\lambda g_n}{1-\varepsilon_1-\varepsilon_2}$ is the BGP level of g_i. The function describing the change in g_I derived from (1) is:

$$\dot{g}_i = g_i \left(\varepsilon_\lambda g_n + (\varepsilon_1 + \varepsilon_2 - 1) g_i\right) \qquad \text{(17a)}$$

to find the speed of convergence we should take the linear approximation of this function around its steady state, and the coefficient of the linear term would be the speed of convergence. Applying a linearization around the steady state to (17a) we get;

$$\dot{g}_i = -\varepsilon_\lambda g_n (g_i - \bar{g}) \qquad \text{(18a)}$$

and solving the function:

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

$$g(t) = (1 - e^{-\varepsilon_\lambda t})\overline{g} + e^{-\varepsilon_\lambda g_n t} g(0) \qquad (19a)$$

any shock will disappear at the exponential rate $\varepsilon_\lambda g_n$ if it affects the regions' growth rate in the same way. If shocks to growth rates are different there is nevertheless a linear combinations of these shocks that converge at the steady state at the above speed.

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. Taking growth rates of (3), (9a) and (10a) wand solving we are able to find the growth rates of wage and manufacturing output as a function of the growth rate of A:

$$g_y = \frac{1}{1-\gamma} g_A$$

$$g_w = \frac{(\alpha - 1)[1 - (1-\gamma)(1-\gamma\alpha)]}{1-\gamma} g_A$$

Also it is easy to derive that the growth rate of the service output is:

$$g_z = (1-\gamma) g_y = g_A$$

Data Appendix

1.Data on patents

The Data on Patents are a random extraction, based on the application number, from the European Patent office Data relative to patents whose application was advanced between 1977 and 1995. The total number of patents used to build the $\dot{A}_i$ variable is 6057. Not having any data on citation we have simply counted each patent as one innovation, aware of the potentially unequal content of innovation in each patent. Being the regions relatively large so that most of them have a large number of patents we rely on the averaging to smooth errors.

The data on R&D are the values of total employed in R&D sectors, and total real spending in R&D from the Eurostat Regio data set. The period of coverage for these data is, in general, 1984-1996. We have reconstructed the regional series by interpolating, where observations were missing and we have considered the average value over the period as the approximation of regional BGP Employment or Spending in R&D. Similarly population, per capita GDP, and employment in different sectors have been taken from the Regio dataset, by considering the longest span of data available for the 1977-1995 period and averaging them.

The data on education (Human Capital) in european regions have been kindly provided by Antonio Ciccone. See Ciccone (1998) for the sources.

The National Input-Output Matrices to calculate the potential demand in Manufacturing from a region and to proceed from there to calculate the market potential in a region are taken from the OCSE-STAN database for a year in the interval considered as close to the beginning of the period as possible.

2. Data on Historical population

We have collected the population of the 86 european regions from data of national censuses . In particular:

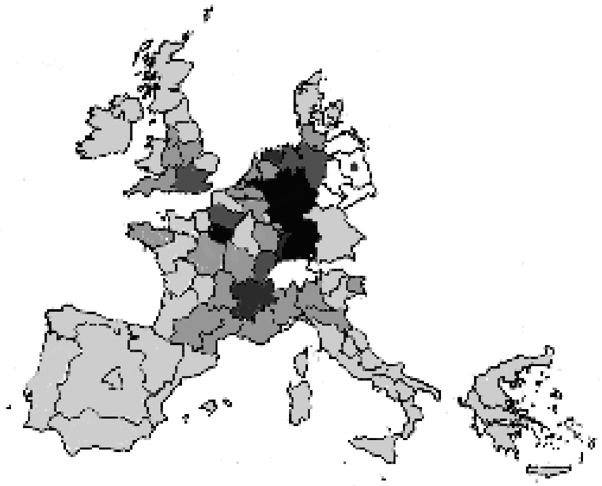
Belgium: "Population par Arrondissement Administratif- Situation au 31 Decembre 1930", Institut National de Statistique
Denmark: Statistical Office.
France: "Recensements de 1891 à 1962",INED Documentation.Data are from the 1931 Census and are derived from Table V.B "Population legale par departement circonscription d'action regionale. Recensement de 1891 à 1962"
Germany: " Statistiches Jahrbuch fuer das Deutche Reich 1931: Laender und Landsteil and Laender und grossere Verwaltungsberichte".Also " Verwaltungsgrenzen

in der Bundesrepublik Deutchland selt Beginn des 19. Jahrhunderts (Veroeffentlichungen der Akademie fuer Raumforschung und Landesplanung-Forschungs-und Sitzungsberichte,Band 110)", Hannover 1977, ISBN 3-507-91408-5 and "Statistiches Reichsamt: Statisik des Deutschen Reiches, Band 451: Die Bevolkerung des Deutschen Reichs nach den Ergebnissen der Volkszahlung 1933, heft 1: stand, entwicklung und siedlungsweise der Bevolkerund des Deutschen Reichs", Berlin 1935.
Greece: "Population de fait d'apres les Recensements de 1839 à 1923 par Departements", Table I, Data are for the year 1928.
Ireland: Census of the Population of Ireland, Central Statistical Office. Data are from the Census in 1936
Italy: "Cento Anni di statistiche sulle Regioni d'Italia"- SVIMEZ Associazione per lo sviluppo dell'industria nel Mezzogiorno. Data are for the year 1931.
Netherlands: "Aantal inwoners van de provincien en Nederland (1830-1946)". Statistics Netherlands. Data are fior the year 1930.
Portugal: Population in 1930 is derived from the "Censo da Populacao de Portugal", no Ide dezembro de 1930, Direccao Geral de Estatistica.
Spain: "Censos de Poblation", cuadro 2.20:"Poblacion de Espana por Comunidades Autonomas,1787-1981. Poblation de hecho". Data have been kindly provided by Antonio Ciccone and are for the year 1930.
UK: "Census of Population"- Table (A: Census Populations, density and intercensal Changes 1911-1931. England and Wales, Urban and Rural, Aggregates and Regions, Counties, County Boroughs and Metropolitan Boroughs.- National Statistics. Data are for the year 1931.

Particularly difficult has been the reconstruction of the population by region for Greece, Germany and UK. For these three countries have been necessary to map the old definition of region to the actual definition, using data at counties level and aggregating. We are particularly grateful to the German Statistical Office that has guided our reconstruction and in particular to Dr. Thomas Helmcke .

Figure 1

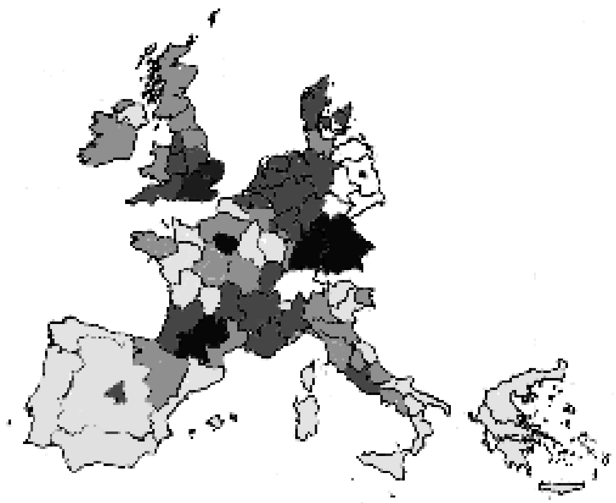
Intensity of Patenting (Patents per year) Quintiles



[1] black: top; blue: second; red: third; green: fourth ; yellow fifth.

Figure 2

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



[1] black: top; blue: second; red: third; green: fourth ; yellow fifth.

Figure 3. R&D EXPENDITURE AND PATENTS

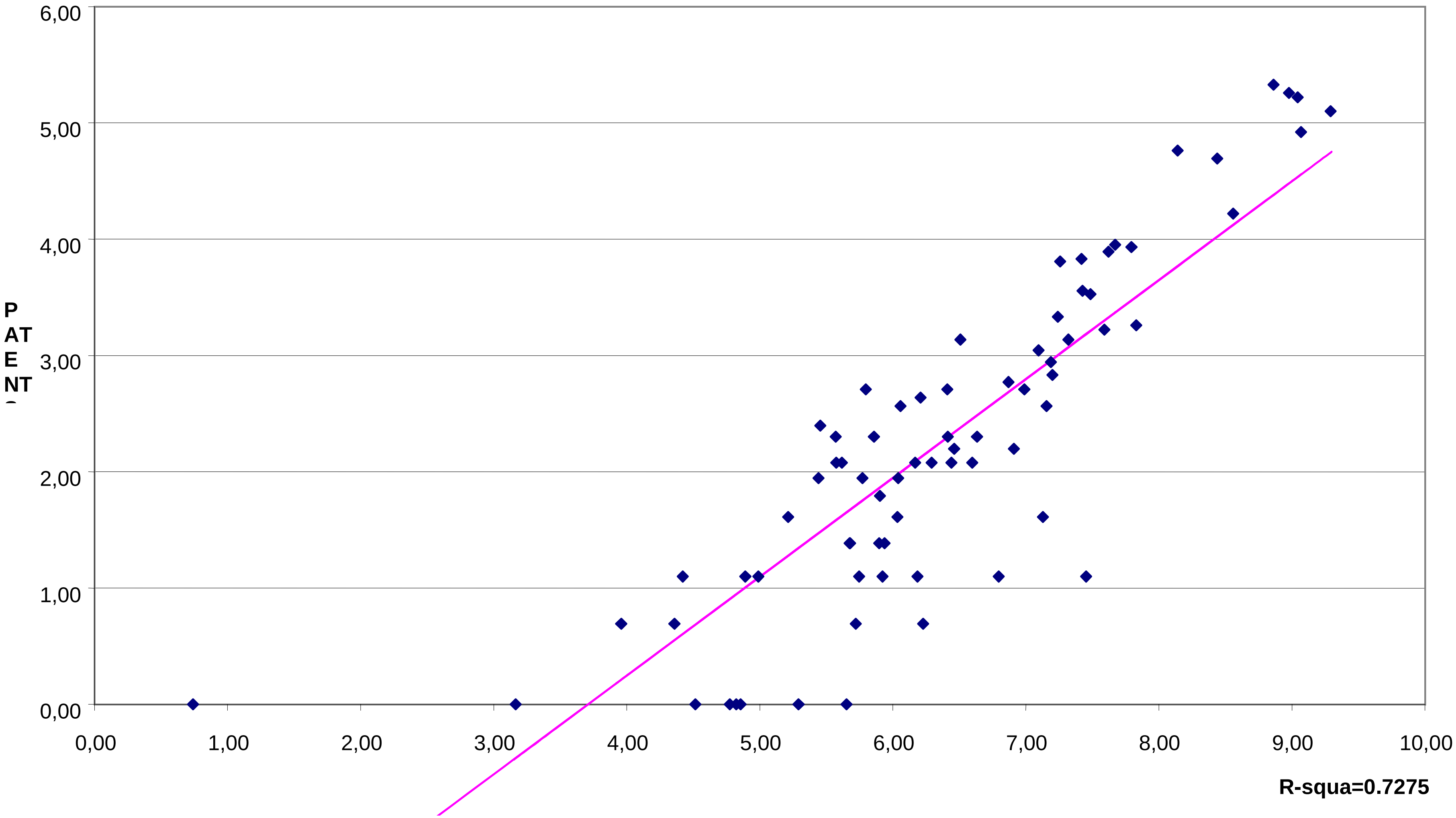
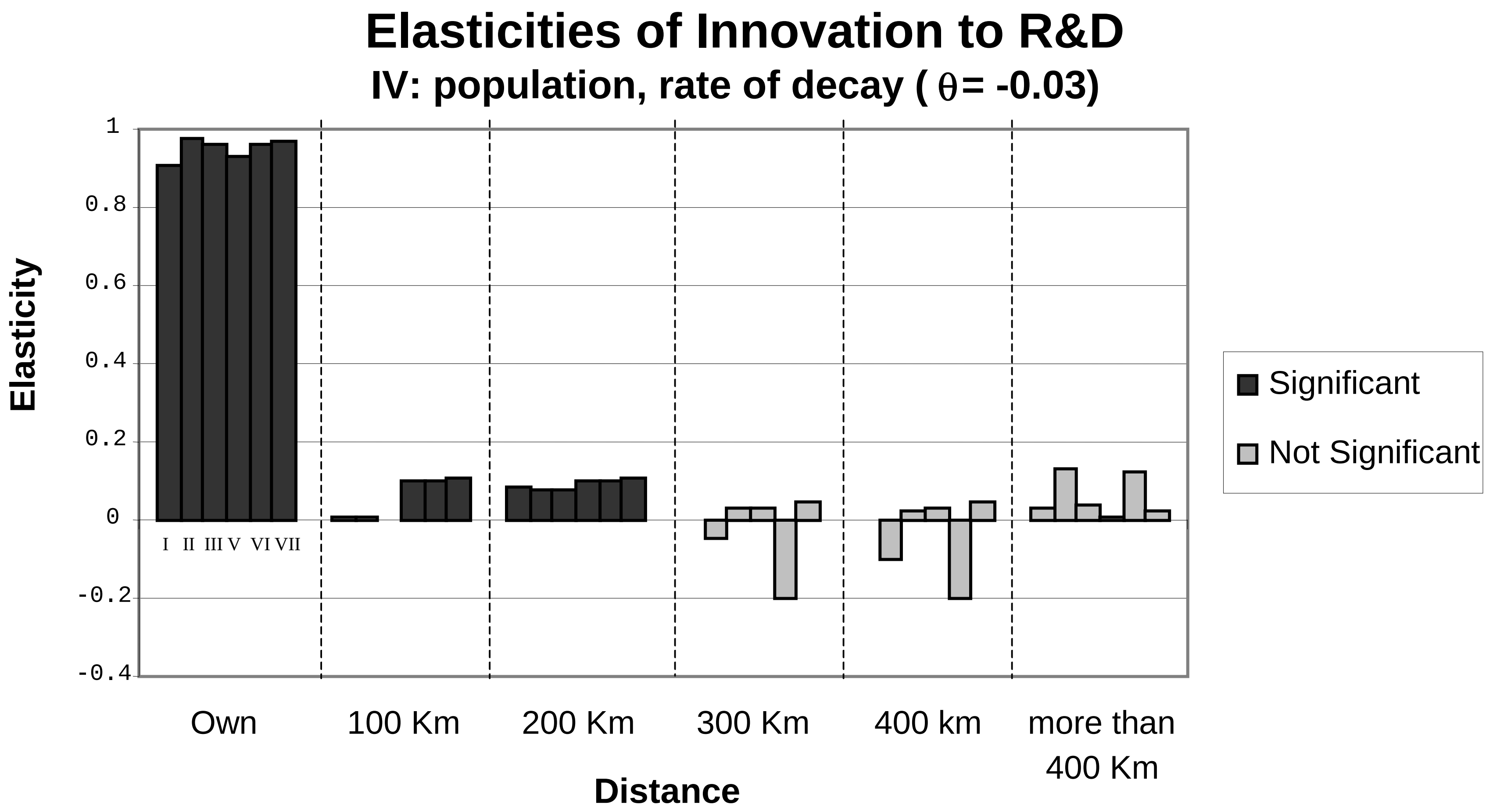


Figure 4



Elasticities of Innovation to R&D
IV: population, rate of decay (θ= -0.03)
Elasticity
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
I II III V VI VII
Own
100 Km
200 Km
300 Km
400 km
more than 400 Km
Distance
Significant
Not Significant

Figure 5

Elasticities of Innovation to R&D (100 Km cells)

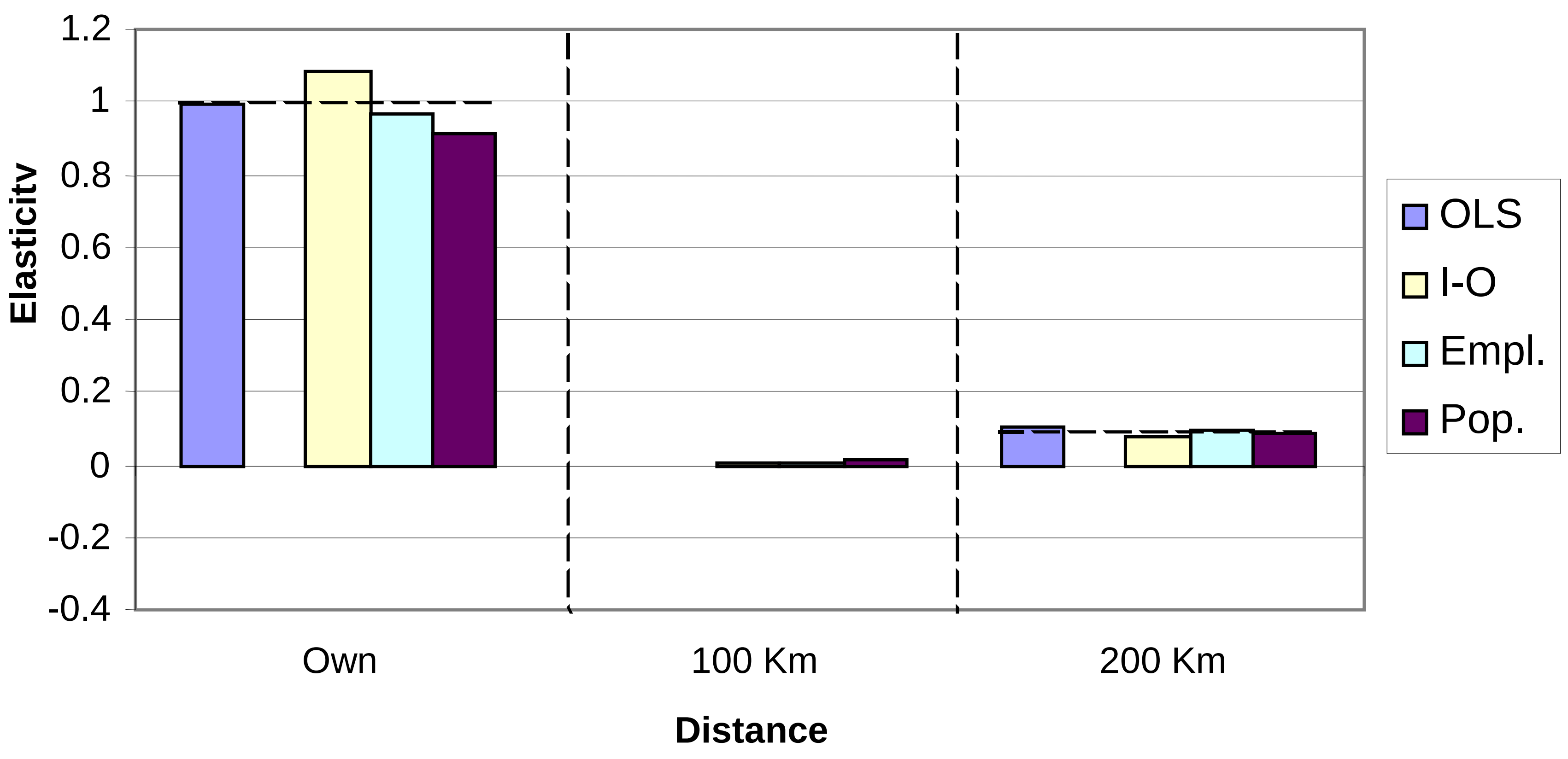
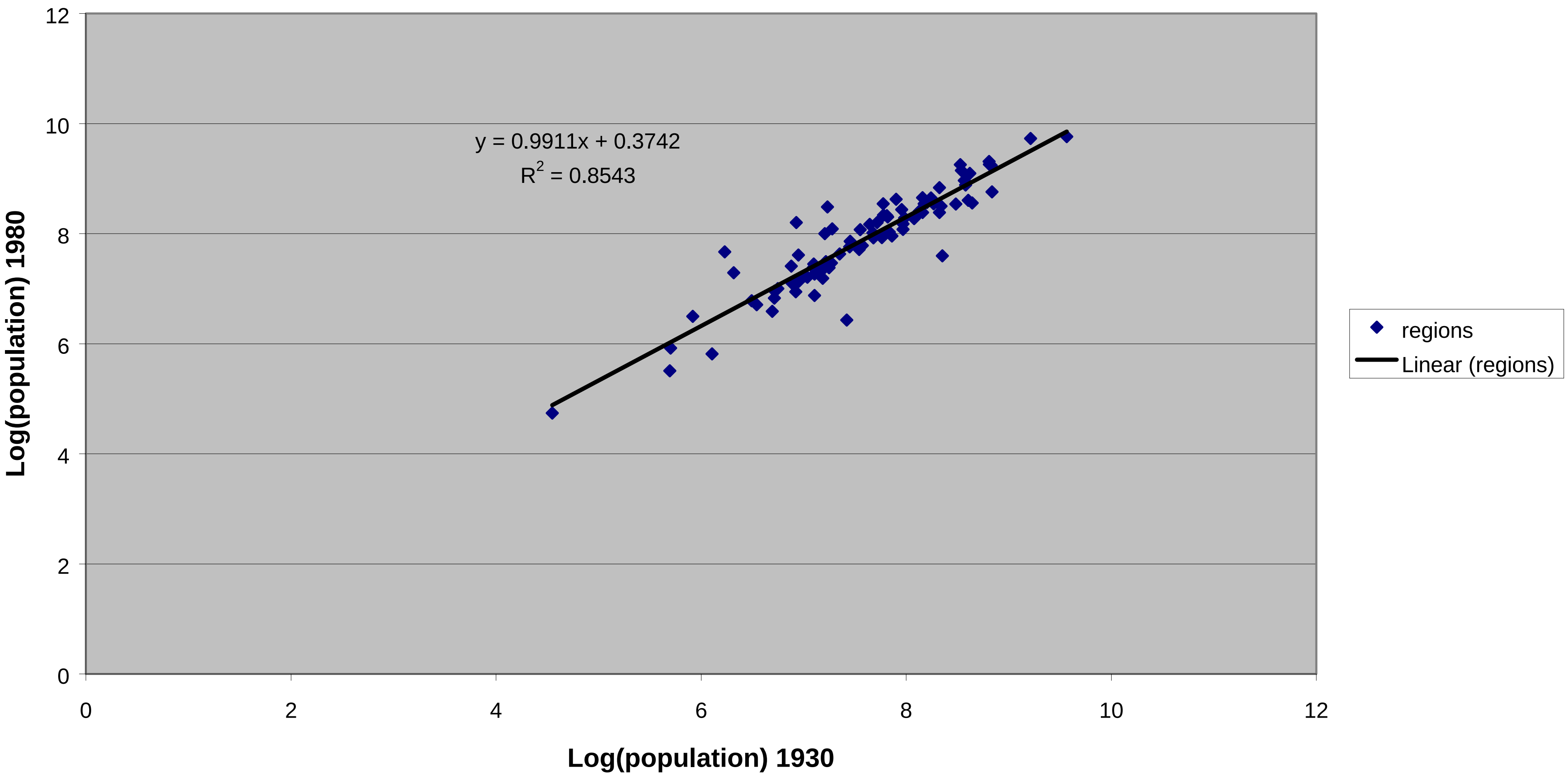


Figure 6:
Population in regions



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 2: Ols Estimates

<table>
<tr><th>Dep. Var:
log (Patents)</th><th>I (100 Km cells)
Basic</th><th>II:As in I
(200 Km cells)</th></tr>
<tr><td>β_0</td><td>0.99***
(0.09)</td><td>0.99***
(0.09)</td></tr>
<tr><td>β_1</td><td>0.00
(0.03)</td><td rowspan="2">0.09***
(0.04)</td></tr>
<tr><td>β_2</td><td>0.10***
(0.04)</td></tr>
<tr><td>β_3</td><td>0.00
(0.07)</td><td rowspan="2">0.00
(0.07)</td></tr>
<tr><td>β_4</td><td>0.01
(0.07)</td></tr>
<tr><td>β_{4+}</td><td>-0.05
(0.09)</td><td>-0.05
(0.07)</td></tr>
<tr><td>Average
Country R&D</td><td>0.43***
(0.19)</td><td>0.42***
(0.17)</td></tr>
<tr><td>R^2</td><td>0.76</td><td>0.77</td></tr>
<tr><td>Observations</td><td>86</td><td>86</td></tr>
</table>

Table 3a: Indep. Var.: Log(R&D Employment), Geographical distance

Method of Estimation: weighted IV estimation: Instruments= Local Market potential[1], **with –0.03 exponential rate of decay**

Standard errors in parenthesis

Dep. Var: log (Patents)	I (100 Km cells)	II[2]	III[3]	IV[4]	V (200 Km cells)	VI (200 Km cells)	VII (200 Km cells)	VIII (200 Km cells)
β_0	0.91***	0.98***	0.96***	1.28**	0.93***	0.96***	0.97***	1.05***
	(0.10)	(0.11)	(0.11)	(0.36)	(0.19)	(0.10)	(0.10)	(0.27)
β_1	0.01	0.01	0.00	0.00	0.101**	0.10**	0.11**	0.084*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.051)	(0.053)	(0.05)	(0.05)
β_2	0.081**	0.08**	0.08**	0.05				
	(0.040)	(0.04)	(0.04)	(0.04)				
β_3	0.001	-0.05	0.03	-0.01	0.03	-0.20	0.05	0.04
	(0.07)	(0.09)	(0.08)	(0.07)	(0.10)	(0.20)	(0.11)	(0.11)
β_4	0.001	-0.10	0.02	-0.08				
	(0.07)	(0.13)	(0.08)	(0.08)				
β_{4+}	0.03	0.13	0.04	0.08	0.009	0.12	0.02	-0.05
	(0.09)	(0.17)	(0.09)	(0.09)	(0.07)	(0.20)	(0.09)	(0.11)
Country R&D	0.79***	0.53***	0.77***	0.71***	0.74***	0.54***	0.72***	0.66**
	(0.17)	(0.20)	(0.18)	(0.19)	(0.17)	(0.20)	(0.18)	(0.18)
High Educated		6.30***				7.4***		
		(3.00)				(3.3)		
Infrastr. Density			0.38				0.38	
			(0.25)				(0.25)	
R^2	0.72	0.75	0.72	0.53	0.72	0.72	0.73	0.51
Observations	86	86	86	86	86	86	86	86

[1] Local Mkt Potential is calculated as the population of the region plus the population of other regions multiplied by an exponentially declining factor (with coefficient of decay –0.03 or –0.01).

[2] Controlling for Human capital (= the share of workers in the region with college degree)

[3] Controlling for infrastructures (= the density in the region of roads and railways)

[4] Variables are in per capita terms

Table 3b: Indep. Var.: Log(R&D Employment), Geographical distance

Method of estimation: weighted IV estimation: Instruments= Local Market potential, **with –0.01exponential rate of decay** Standard errors in parenthesis

Dep. Var: log (Patents)	**I (100 Km cells)**	**II[5]**	**III[6]**	**IV[7]**	**V [8] (200 Km cells)**	**VI (200 Km cells)**	**VII (200 Km cells)**	**VIII (200 Km cells)**
β_0	0.95*** (0.10)	0.99*** (0.11)	0.98*** (0.11)	1.39*** (0.34)	0.95*** (0.10)	0.96** (0.10)	0.98*** (0.10)	1.08*** (0.30)
β_1	0.01 (0.03)	0.00 (0.03)	0.01 (0.03)	0.02 (0.04)	0.12** (0.06)	0.11** (0.056)	0.13*** (0.06)	0.13*** (0.07)
β_2	0.08** (0.04)	0.08** (0.04)	0.08** (0.04)	0.05 (0.04)				
β_3	0.01 (0.07)	-0.01 (0.09)	-0.01 (0.08)	0.01 (0.08)	0.04 (0.09)	-0.10 (0.22)	-0.05 (0.09)	0.14 (0.16)
β_4	0.00 (0.07)	-0.15 (0.16)	0.01 (0.08)	-0.07 (0.09)				
β_{4+}	0.00 (0.09)	0.03 (0.16)	0.01 (0.09)	0.01 (0.10)	0.01 (0.09)	-0.06 (0.22)	0.00 (0.09)	-0.26 (0.15)
Country R&D employed	0.76*** (0.17)	0.56*** (0.20)	0.76*** (0.18)	0.55** (0.20)	0.72*** (0.17)	0.53*** (0.20)	0.71*** (0.18)	0.50** (0.18)
High Educated		5.56** (3.00)				7.17*** (3.20)		
Infrastr. Density			0.31 (0.24)				0.30 (0.25)	
R^2	0.73	0.72	0.72	0.50	0.72	0.71	0.72	0.53
Observations	86	86	86		86	86	86	86

[5] Controlling for Human capital (= the share of workers in the region with college degree)

[6] Controlling for infrastructures (= the density in the region of roads and railways)

[7] Variables are in per capita terms

Table 4: Indep. Var.: Log(R&D real Spending in Ecu), Geographical distance

Preferred specification, weighted IV estimation: Instruments= Local Market potential, **<u>Population with –0.03exponential rate of decay</u>**

<table>
<tr><th>Standard errors in parenthesis Dep. Var: log (Patents)</th><th>I (100 Km cells) Basic</th><th>II Controlling for Human Capital [9]</th><th>III Controlling for infrastructures[10]</th><th>As in I (200 Km cells)</th><th>As in II (200 Km cells)</th><th>As in III (200 Km cells)</th></tr>
<tr><td>β_0</td><td>0.92***
(0.08)</td><td>0.97***
(0.08)</td><td>0.98***
(0.08)</td><td>0.83***
(0.07)</td><td>0.88***
(0.08)</td><td>0.86**
(0.07)</td></tr>
<tr><td>β_1</td><td>0.001
(0.01)</td><td>0.01
(0.01)</td><td>0.003
(0.01)</td><td rowspan="2">0.042**
(0.023)</td><td rowspan="2">0.050*
(0.029)</td><td rowspan="2">0.052*
(0.029)</td></tr>
<tr><td>β_2</td><td>0.04*
(0.022)</td><td>0.032
(0.020)</td><td>0.037
(0.020)</td></tr>
<tr><td>β_3</td><td>0.03
(0.02)</td><td>0.005
(0.05)</td><td>0.04
(0.04)</td><td rowspan="2">0.03
(0.05)</td><td rowspan="2">0.001
(0.11)</td><td rowspan="2">0.026
(0.05)</td></tr>
<tr><td>β_4</td><td>-0.03
(0.04)</td><td>-0.10
(0.09)</td><td>-0.05
(0.04)</td></tr>
<tr><td>β_{4+}</td><td>-0.01
(0.05)</td><td>0.01
(0.10)</td><td>0.001
(0.05)</td><td>-0.05
(0.05)</td><td>-0.09
(0.11)</td><td>-0.04
(0.05)</td></tr>
<tr><td>Average Country R&D</td><td>0.63***
(0.14)</td><td>0.52***
(0.16)</td><td>0.60**
(0.14)</td><td>0.71***
(0.14)</td><td>0.58***
(0.15)</td><td>0.69***
(0.14)</td></tr>
<tr><td>High Educated</td><td></td><td>6.9***
(2.6)</td><td></td><td></td><td>8.3***
(2.7)</td><td></td></tr>
<tr><td>Infrastr. Density</td><td></td><td></td><td>0.37**
(0.19)</td><td></td><td></td><td>0.33***
(0.19)</td></tr>
<tr><td>R^2</td><td>0.82</td><td>0.83</td><td>0.83</td><td>0.81</td><td>0.81</td><td>0.81</td></tr>
<tr><td>Observations</td><td>86</td><td>86</td><td>86</td><td>86</td><td>86</td><td>86</td></tr>
</table>

[9] Human capital is the share of workers in the region with college degree

[10] Infrastructure is the density in the region of roads and railways

Table 5: Indep. Var.: Log(R&D Employment), Geographical distance

Method of estimation, weighted IV estimation: Instruments= **Empl. in Services with –0.03exponential rate of decay**

Standard errors in parenthesis

Dep. Var: log (Patents)	I (100 Km cells) Basic	II Controlling for Human Capital [11]	III Controlling for infrastructures[12]	As in I (200 Km cells)	As in II (200 Km cells)	As in III (200 Km cells)
β_0	0.97*** (0.10)	0.95*** (0.12)	0.99*** (0.11)	0.98*** (0.09)	0.94*** (0.10)	1.00*** (0.10)
β_1	0.001 (0.039	0.02 (0.03)	0.005 (0.03)	0.15*** (0.06)	0.17*** (0.06)	0.16*** (0.06)
β_2	0.094*** (0.04)	0.12*** (0.04)	0.09*** (0.04)			
β_3	0.01 (0.04)	0.02 (0.09)	0.02 (0.07)	-0.04 (0.08)	-0.10 (0.11)	-0.05 (0.08)
β_4	0.01 (0.07)	-0.10 (0.11)	0.02 (0.07)			
β_{4+}	0.01 (0.07)	-0.11 (0.07)	0.01 (0.05)	0.01 (0.04)	-0.12 (0.08)	0.001 (0.04)
Average Country R&D	0.61*** (0.18)	0.26 (0.23)	0.61*** (0.19)	0.51*** (0.18)	0.28*** (0.29)	0.51*** (0.19)
High Educated		9.6*** (4.1)			9.1*** (3.6)	
Infrastr. Density			0.13 (0.24)			0.11 (0.24)
R^2	0.75	0.75	0.75	0.73	0.76	
Observations	86	86	86	86	86	86

[11] Human capital is the share of workers in the region with college degree

[12] Infrastructure is the density in the region of roads and railways

Table 6[13]: Indep. Var.: Log(R&D Employment), Geographical distance

Method of estimation, weighted IV estimation: Instruments= **I-O demand for intermediates with –0.03exponential rate of decay**

Standard errors in parenthesis

Dep. Var: log (Patents)	**I (100 Km cells) Basic**	**II Controlling for Human Capital [14]**	**III Controlling for infrastructures[15]**	**As in I (200 Km cells)**	**As in II (200 Km cells)**	**As in III (200 Km cells)**
β_0	1.08*** (0.10)	1.06*** (0.11)	1.10*** (0.10)	1.06*** (0.10)	1.06*** (0.10)	1.09*** (0.10)
β_1	0.003 (0.04)	0.003 (0.03)	0.002 (0.03)	0.12** (0.06)	0.12** (0.06)	0.13*** (0.06)
β_2	0.08** (0.4)	0.10*** (0.04)	0.08*** (0.04)			
β_3	0.06 (0.07)	0.07 (0.08)	0.07 (0.07)	0.001 (0.11)	-0.20 (0.20)	0.002 (0.11)
β_4	0.02 (0.07)	-0.10 (0.13)	0.001 (0.07)			
β_{4+}	-0.02 (0.04)	-0.09 (0.06)	-0.02 (0.04)	0.04 (0.12)	0.20 (0.20)	0.04 (0.12)
Average Country R&D	0.55*** (0.18)	0.35* (0.21)	0.57*** (0.19)	0.58*** (0.17)	0.55*** (0.18)	0.58*** (0.17)
High Educated		5.7 (4.4)			2.25 (3.20)	
Infrastr. Density			0.15 (0.25)			0.14 (0.25)
R^2	0.76	0.78	0.76	0.74	0.76	0.74
Observations	86	86	86	86	86	86

[13] Note for table 3,4,5,6 : in all cases except one its rejected the H_0 $\sum \beta_i$ =0 at the 10% significance level.

[14] Human capital is the share of workers in the region with college degree

[15] Infrastructure is the density in the region of roads and railways

Table 7a:

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***	0.83***	0.82***
	(0.11)	(0.10)	(0.10)
λ_a	-3.9***		
	(1.1)		
λ_b		0.017	
		(0.01)	
λ_c			87.1
			(100)
Country R&D	0.87	0.21	0.24
	(0.50)	(0.20)	(0.26)
R^2	0.55	0.50	0.53
Tot. observations	86	86	86

Table 7b:

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	99%	1%	10.0%	0%	0%	-5%
Non-Parametric, 200 Kms cells	99%	10%	10%	0%	-0%	-5%

Table 8: Indep. Var.: Log(R&D Employment), Geographical distance, IV: Historical market Potential

Method of Estimation: weighted IV estimation: Instruments= Historical Local Market potential[16], **with –0.03 exponential rate of decay**

Standard errors in parenthesis

Dep. Var: log (Patents)	I (100 Km cells)	II[17]	III[18]	IV[19]	V (200 Km cells)	VI (200 Km cells)	VII (200 Km cells)	VIII (200 Km cells)
β_0	0.88** (0.10)	0.95** (0.11)	0.93** (0.11)	1.05 (0.37)	0.90*** (0.10)	0.93** (0.10)	0.94** (0.10)	0.86** (0.29)
β_1	0.02 (0.03)	0.01 (0.03)	0.02 (0.03)	-0.01 (0.04)	0.10** (0.05)	0.10 (0.055)	0.12** (0.06)	0.10* (0.55)
β_2	0.081** (0.040)	0.075* (0.040)	0.080** (0.04)	0.06 (0.04)				
β_3	-0.01 (0.07)	-0.07 (0.10)	-0.01 (0.08)	-0.01 (0.07)	-0.04 (0.10)	-0.20 (0.23)	-0.06 (0.11)	0.05 (0.11)
β_4	-0.01 (0.07)	-0.10 (0.13)	-0.02 (0.08)	-0.06 (0.08)				
β_{4+}	0.04 (0.09)	0.10 (0.10)	0.05 (0.10)	0.12 (0.11)	0.01 (0.09)	0.15 (0.24)	0.03 (0.09)	-0.08 (0.12)
Country R&D	0.84*** (0.17)	0.59** (0.20)	0.85** (0.18)	0.80** (0.19)	0.78** (0.17)	0.58** (0.20)	0.76** (0.18)	0.72** (0.18)
High Educated		6.04** (3.20)				7.03** (3.4)	0.38** (0.25)	
Infrastr. Density			0.38 (0.25)					
R^2	0.71	0.74	0.73	0.52	0.71	0.74	0.72	0.52
Observations	86	86	86	86	86	86	86	86

[16] Local Mkt Potential is calcualted as the historical population of the region (i.e. population in 1930) plus the population of other regions multiplied by an exponentially declining factor (with coefficient of decay –0.03 or –0.01).
[17] Controlling for Human capital (= the share of workers in the region with college degree)
[18]Controlling for infrastructures (= the density in the region of roads and railways)
[19] Variables are in per capita terms

Table 9: Indep. Var.: Log(R&D Employment), Technological distance[20]

weighted OLS/ IV estimation: Instruments= Local Market potential, **Historical Population with –0.03exponential rate of decay**

Standard errors in parenthesis

Dep. Var: log (Patents)	**I OLS**	**II IV**	**III IV, Controlling for Human Capital [21]**	**As in I IV, Controlling for infrastructures[22]**
β_0 (own)	0.88*** (0.08)	0.89*** (0.09)	0.92*** (0.09)	0.90
β_1	0.28*** (0.06)	0.22*** (0.06)	0.20*** (0.06)	0.21
β_2	-0.17 (0.10)	-0.09 (0.08)	-0.05 (0.09)	-0.09
β_3	0.00 (0.04)	0.04 (0.03)	-0.06 (0.05)	0.04
Country R&D spending	0.41*** (0.16)	0.69*** (0.15)	0.45*** (0.17)	0.68*** (0.16)
High Educated			5.18** (2.60)	
Infrastr. Density				0.25 (0.22)
R^2	0.79	0.77	0.78	0.77
Observations	86	86	86	86

[20] The 3 cells of technological distance are measured taking the "Jaffe" index as measure of distance. The ranges, from the farthest to the closest are: [0-0.2], [0.2-0.4], [0.4-1.0].

[21] Human capital is the share of workers in the region with college degree

[22] Infrastructure is the density in the region of roads and railways

Table Appendix

Table 1A: Indep. Var.: Log(R&D Employment), Geographical distance

Method of estimation: weighted IV estimation: Instruments= Historical Local Market potential, **with –0.01exponential rate of decay**Standard errors in parenthesis

Dep. Var: log (Patents)	**I (100 Km cells)**	**II[23]**	**III[24]**	**IV[25]**	**V [26] (200 Km cells)**	**VI (200 Km cells)**	**VII (200 Km cells)**	**VIII (200 Km cells)**
β_0	0.95** (0.10)	0.99** (0.11)	0.98** (0.11)	1.5** (0.34)	0.95** (0.10)	0.96** (0.10)	0.98** (0.13)	1.1** (0.3)
β_1	0.01 (0.03)	0.01 (0.03)	0.01 (0.03)	0.02 (0.03)	0.12** (0.06)	0.11* (0.06)	0.13** (0.06)	0.13* (0.07)
β_2	0.08** (0.04)	0.08** (0.04)	0.08** (0.04)	0.06 (0.04)				
β_3	0.01 (0.07)	-0.01 (0.09)	0.01 (0.08)	0.01 (0.08)	-0.04 (0.10)	-0.06 (0.20)	-0.05 (0.10)	0.10 (0.20)
β_4	0.01 (0.07)	-0.13 (0.14)	0.01 (0.08)	-0.06 (0.08)				
β_{4+}	-0.01 (0.09)	0.03 (0.13)	0.01 (0.09)	0.05 (0.11)	-0.01 (0.09)	-0.05 (0.20)	0.001 (0.09)	-0.13 (0.14)
Country R&D employed	0.76** (0.17)	0.56** (0.20)	0.75** (0.18)	0.55** (0.20)	0.72** (0.17)	0.56** (0.20)	0.71** (0.18)	0.49** (0.18)
High Educated		5.59* (3.2)				7.10** (3.20)		
Infrastr. Density			0.31 (0.24)				0.31** (0.25)	
R^2	0.74	0.75	0.75	0.54	0.74	0.75	0.74	
Observations	86	86	86	86	86	86	86	86

[23] Controlling for Human capital (= the share of workers in the region with college degree)
[24]Controlling for infrastructures (= the density in the region of roads and railways)

[25] Variables are in per capita terms

Table 2A: Indep. Var.: Log(R&D real Spending), Geographical distance

Preferred specification, weighted IV estimation: Instruments= Historical Local Market potential, **Population in 1930 with –0.03exponential rate of decay**

Standard errors in parenthesis **Dep. Var: log (Patents)**	**I (100 Km cells) Basic**	**II Controlling for Human Capital** [27]	**III Controlling for infrastructures** [28]	**I, Basic (200 Km cells)**	**II (200 Km cells)**	**III (200 Km cells)**
β_0	0.88*** (0.08)	0.93*** (0.08)	0.94*** (0.08)	0.82*** (0.07)	0.87*** (0.08)	0.85** (0.07)
β_1	0.001 (0.01)	0.01 (0.01)	0.0006 (0.01)	0.041** (0.020)	0.050* (0.029)	0.050* (0.029)
β_2	0.04* (0.022)	0.03 (0.020)	0.037 (0.020)			
β_3	0.034 (0.04)	-0.005 (0.05)	0.033 (0.04)	0.03 (0.05)	0.001 (0.11)	0.023 (0.054)
β_4	-0.03 (0.04)	-0.10 (0.08)	-0.05 (0.04)			
β_{4+}	-0.01 (0.05)	0.01 (0.10)	0.002 (0.05)	-0.04 (0.05)	-0.09 (0.11)	-0.04 (0.05)
Average Country R&D	0.69*** (0.14)	0.57*** (0.16)	0.66** (0.14)	0.73*** (0.14)	0.60*** (0.15)	0.70*** (0.14)
High Educated		6.8*** (2.6)			8.6*** (2.7)	
Infrastr. Density			0.39** (0.19)			0.34*** (0.19)
R^2	0.82	0.83	0.83	0.81	0.81	0.81
Observations	86	86	86	86	86	86

[27] Human capital is the share of workers in the region with college degree
[28] Infrastructure is the density in the region of roads and railways