WP3/15 SEARCH WORKING PAPER

Are geographical movements of inventors and the formation of research networks a phenomenon bounded in the space?

Ernest Miguélez and Rosina Moreno

May 2013

SEARCH
SHARING KNOWLEDGE ASSETS: INTERREGIONALLY COHESIVE NEIGHBORHOODS

EUROPEAN COMMISSION
European Research Area
SEVENTH FRAMEWORK PROGRAMME
Funded under Socio-economic Sciences & Humanities

The research leading to these results has received funding from the European Community's Seventh Framework Programme (FP7/2010-2.2-1) under grant agreement n° 266834

ARE GEOGRAPHICAL MOVEMENTS OF INVENTORS AND THE FORMATION OF RESEARCH NETWORKS A PHENOMENON BOUNDED IN THE SPACE?

Ernest Miguélez and Rosina Moreno

Abstract

The aim of this paper is to analyse the existence of regional variations in the returns to labour mobility and networking. In such a case, we could conclude that development policies based on stimulating these mechanisms of knowledge diffusion could differ in their effectiveness according to local conditions.

1. Introduction

The goal of this paper is to analyse the contribution made by research networks and the labour and geographical mobility of inventors to the process of knowledge creation, and specifically, to provide empirical evidence on the existence of regional variations in their returns. To this end, we extend the typical regional Knowledge Production Function (KPF hereafter) to the inclusion of such features of the local labour market, which are likely to explain the spatial heterogeneity in patent production across 287 European regions, in a multivariate econometric model.

This paper builds upon the long tradition of the regional KPF within the geography of innovation literature (Audretsch and Feldman, 2004), and try to take on board the multiple criticisms this approach has received, both from a methodological viewpoint, as well as from an interpretative perspective. Specifically, our motivation is based upon two strands of criticisms. On the one side, we take on board those claims against the linear perspective of regional innovation production, which states that all kind of R&D efforts will systematically lead to a larger number of inventions. We argue that this argument overlooks the importance of a set of factors that actually account for how innovation is generated at the regional level (Rodriguez-Pose and Crescenzi, 2008). Hence, we aim to estimate disproportionate levels of patent production that are attributable to the aforementioned features –mobility and networks, above and beyond regional R&D endowments and other control variables. On the other side, we take into account those criticisms to the localization of knowledge diffusion and claim that, indeed, it is not enough by 'being there' to access private pools of knowledge within regions. Rather, knowledge diffuses within the region by means of structured and defined channels, such as networks and labour mobility of human capital, whose spatial distribution explains a non negligible part of patent production heterogeneity across regions.

The second part of the paper focuses its attention on the external dimension of regional knowledge production. As it has been argued in the literature, we claim that cross-regional research networks and movements of skilled workers across regions act as main channels through which knowledge is transferred throughout the space (Fratesi and Senn, 2009). As stated by Bathelt et al. (2004) and Owen-Smith and Powell (2004), firms in regions build 'pipelines' in the form of alliances to benefit from knowledge hotspots around the world. In a similar vein, as Breschi et al. (2010) put it, 'knowledge always travels along with people who master it. If those people move away from where they originally learnt, researched, and delivered their inventions, knowledge will diffuse in space. Otherwise, access to it will remain constrained in bounded locations'. In consequence 'crucial extra-regional exchanges of knowledge take place beyond firm networks, in particular through the migratory patterns of different types of mobile individuals embodying tacit knowledge' (Coe and Bunnell, 2003). With these ideas in mind, we examine in detail the role of external-to-the-region research alliances in the likelihood to patent at the regional level, as well as the influence exerted by the geographical mobility patterns of knowledge workers.

When analysing both objectives signalled above, we want to analyse whether there exists substantial regional variations in the returns to inventors' mobility and research networks, indicating that development policies based on stimulating these knowledge diffusion mechanisms differ in effectiveness. As labour mobility and research networks are assumed to be a fundamental factor in the creation of knowledge, an unequal distribution of such mechanisms in the territory could be a cause of regional differences in knowledge levels and economic development in general. Knowledge can therefore be considered to be a causal factor in regional disparities. As a consequence, it can be thought that policies aimed at encouraging the mobility of high skilled workers or enhancing the participation in research networks (as promoted by the European Commission through Marie Curie programs or the Framework Programs) in less productive regions can constitute a key factor in the creation of knowledge and development, or at least a necessary condition for it. However, the effectiveness of this policy depends in large part on each region's capacity to give returns to labour mobility and the participation in research networks. One would expect these returns to be homogeneous in all regions if they were also homogeneous in other aspects, such as industrial mix, propensity to generate and adopt innovations and technological specialisation, among others. When this is not the case, returns to labour mobility and research networks may differ between regions. Any appraisal of the value of this policy as a tool for use in regional development would therefore be particularly useful if information about the regional distribution of such returns were available.

The rest of the paper is organized as follows: in section 2 we present a testable empirical model; section 3 presents the data; whilst section 4 includes the results. Finally, section 5 presents the conclusions and identifies certain limitations in the approach.

2. Research design

We first suggest an empirical model where local mobility and networks are included as main explanatory variables under scrutiny. In the second part, extra-regional linkages are included as regressors.

Our point of departure is the simplest specification of this model:

$$Y = f(RD, HK, Z), \qquad (1)$$

where Y is the knowledge output of a given region, which depends on regional R&D expenditures (RD) as well as the stock of human capital (HK). To capture a variety of returns that might affect knowledge outcomes, Z are a number of time-variant controls that account for specific features of the region i at time t. Among them, the level of inventors' labour mobility within a given region, as well as the scale and density of its collaborative research networks are included. Population of the regions (POP) is also included in order to control for size and market potential. As it is customary in the related literature, it is assumed that the KPF follows a multiplicative functional form:

$$Y_{it} = e^{\theta} \cdot RD_{it}^{\beta} \cdot HK_{it}^{\gamma} \cdot POP_{it}^{\rho} \cdot Z_{it}^{\alpha} \cdot e^{\delta_i}, \qquad (2)$$

where e^{θ} is a constant term capturing the impact of all common factors affecting knowledge. In additional, e^{δ_i} stands for 287 regional time-invariant fixed-effects, that allow us to capture unobserved time-invariant heterogeneity that might importantly bias our estimates if they are not considered. In particular, we refer to institutional features that may affect knowledge, technology-oriented regional policies, inherited skills of the local community, prestige of research and higher education institutions, inherited knowledge culture, social capital and, in general, all the historical path-dependent features that may importantly affect spatial differences in knowledge rates.

2.1. Labour mobility, research networks and knowledge

In the present paper, social network analysis (SNA) tools are employed to investigate empirically the quantitative relationship between inventors' collaborations and levels of inventiveness.[1] We are interested in measuring some particular aspects of inventors' networks. First of all, the scale of these networks, i.e., whether a greater number of social ties are beneficial for inventive intensity. A positive effect on creativity is expected. Second, the extent of the local network is also of interest, i.e., whether a large number of local inventors involved in co-inventions is beneficial for regional knowledge. Finally, we are concerned with the strength of the inventors' community ties, measured as the network density. The naïve, expected effect of density on innovation is positive. However, we should bear in mind Granovetter's (1985) warning that overly strong interpersonal ties might well hamper innovation because of the fact that, at some point, the information flowing across those ties becomes redundant and less valuable. In consequence, the scale and extent of research networks, as well as their intensity within the region, are included as additional regressors. Besides, the degree of labour mobility within the region is also included. Thus,

$$Z_{it} = g(MOB_{it}, DEGREE_{it}, CONN_{it}, DENS_{it}, X_i), \tag{3}$$

where MOB is the measure of mobility, $DEGREE$ stands for the average degree centrality of skilled workers, that is, the average 'popularity' of inventors in regions, $CONN$ stands for the overall connectivity of the local network, i.e., the inclusiveness of the local network, and $DENS$ is a measure of the density of the regional network. Finally, X controls for the existence of specialization and concentration economies. Assuming that (3) also follows a multiplicative functional form and inserting it into the logarithmic transformation of (2) yields to:

$$\begin{aligned}\ln Y_{it} &= \theta + \beta \cdot \ln RD_{it-1} + \gamma \cdot \ln HK_{it-1} + \rho \cdot POP_{it-1} + \omega_1 \cdot MOB_{it-1} + \\ &\omega_2 \cdot \ln DEGREE_{it-1} + \omega_3 \cdot CONN_{t-1} + \omega_4 \cdot \ln DENS_{it-1} + \omega_n \cdot \ln X_{it-1} + \delta_i + \varepsilon_{it}\end{aligned} \tag{4}$$

[1] SNA has been widely applied to collaboration in research and innovation studies, although a review of detailed methodological contributions falls outside the scope of this chapter. In fact, in recent years many contributions have been made to economics and economic geography using SNA tools, most notably Balconi et al. (2004), Breschi and Catalini (2009), and Ter Wal and Boschma (2009). For a more complete theoretical discussion of the methods and applications of SNA, see Wasserman and Faust (1994).

Note that the subscript t-1 is now introduced in all the explanatory variables in order to make clear that they have been time lagged one period in order to lessen endogeneity problems. Section 9.4 includes further details regarding the construction of all the variables used in the present analysis and a brief summary is provided in Annex A.9.1.

2.2. Spatial heterogeneity of labour mobility and networks impacts on knowledge

The aim of this subsection is to analyse the existence of regional variations in the returns to labour mobility and networking. In such a case, we could conclude that development policies based on stimulating these mechanisms of knowledge diffusion could differ in their effectiveness according to local conditions. In order to do it, we have initially introduced a cross-effect of the corresponding focal variable, both labour mobility and the different proxies for research networks, with a dummy for each region. This way we are able to compute a specific elasticity for each regional economy in Europe. However, with the idea of providing more general patterns of heterogeneity in the returns to labour mobility and networks, we give a step forward and obtain different elasticities according to a set of typologies of the European regions. Specifically, we consider the following typologies:

- Type and moment of accession of the corresponding country to the EU: EU15, EU New Entrants 12, EFTA 4
- The development level of the regions: Convergence regions, Transition regions, Competitive regions
- The territorial innovation patterns across European regions: European Science-based area, Applied science area, Smart Technological specialisation area, Smart and Creative diversification area, Creative imitation area

2.3. Cross-regional collaborations and inter-regional mobility

As stated in the previous section, a second aim of this paper is the analysis of extra-local linkages, in the form of skilled labour mobility and spatial networks, on the knowledge performance of European regions. Regions are not isolated entities not interacting with the rest of the world; rather, an increasing number of studies have identified that firms in regions source more and more their knowledge in non-local knowledge interactions.

First, as it has been stated elsewhere, local knowledge diffusion is favoured by the labour mobility of skilled workers (Breschi and Lissoni, 2009; Almeida and Kogut, 1997, 1999).

However, to the extent that knowledge travels along with people who master it (Breschi et al., 2010), what happens when highly-skilled individuals move in the space? Geographical mobility of knowledge workers has been regarded to be a source of knowledge diffusion across areas and, on top, is responsible for the recombination of previously unconnected pieces of knowledge that may lead to increased knowledge rates. In order to analyse the role of skilled geographical mobility on the knowledge performance of regions, we correlate two different measures proxying inflows of skilled migration with regional patent production. Again, within the KPF framework, where typical knowledge inputs, as well as structural controls, are included as regressors, the rate of incoming skilled individuals, as well as the net rate, are included among the r.h.s. variables, running two different models in order to avoid collinearity problems. Positive and significant coefficients are expected for both variables.

Recently, several authors pinpoint at outward migration of skilled individuals as an alternative source of knowledge flows and interactions back to the home location of the left skilled employee, reverting the 'brain drain' phenomenon into 'brain gain' or 'brain circulation' (Saxenian, 2006). Thus, for instance, Agrawal et al. (2006) and Oettl and Agrawal (2008) report disproportionate knowledge flows from inventors leaving a region or a country back to their former colleagues. Kerr (2008) and Agrawal et al. (2008, 2011) do likewise and estimate disproportionate knowledge flows from ethnic inventors in the US to their origin countries, stressing the role of diasporas in accessing frontier knowledge. Following these ideas, we also test the role of the gross migration rate (inflows plus outflows) of skilled individuals, as well as the outward migration rate, as patent production predictors in regions.

Next, we also hypothesize that the more inventors collaborate with fellow inventors outside the region, the greater are the returns on knowledge. As it is for the case of geographical mobile inventors, spatial networks formation is also likely to be conducive to knowledge diffusion, knowledge recombination and innovation. At the level of European regions, Ponds et al. (2010) and Maggioni et al. (2007) show the importance of cross-regional networks to the process of knowledge diffusion. Following these ideas, we conjecture that higher amounts of patents co-authored with fellow inventors outside the region are expected to explain spatial differences in innovation.

As an extension of this hypothesis, we take on board insights from the literature on 'related variety' (Boschma and Iammarino, 2009) and break down our variable into cross-regional linkages with different areas of the world, that is, Europe, US, East-Asia, and rest of the OECD countries. The underlying logic states that when the external knowledge is the same to existing competences in the region, it can be absorbed locally, but the new knowledge will not add much to the existing local knowledge base (op. cit.). Logically, a follow-up analysis would require breaking down knowledge linkages by sectors. This type of analysis goes however beyond the scope of the present study.

3. Data

In order to meet the goals identified in previous sections, the KPF is estimated for 287 NUTS2 European regions of 31 countries (EU-27 plus Iceland, Liechtenstein, Norway and Switzerland). Thanks to data availability, we are in position to estimate a panel fixed-effects model of 6 periods (2001 to 2006). Again, the use of longitudinal data and the inclusion of fixed effects in our regressions allow us to improve previous estimates in a KPF framework, to the extent that these fixed effects account for a number of time-invariant unobservable characteristics of the regions that might bias our results if not included.

Next, knowledge is measured by patent applications (PAT), a variable widely used in the literature to proxy knowledge outcomes. As well known, this proxy presents serious caveats since not all inventions are patented, nor do they all have the same economic impact, as they are not all commercially exploitable (Griliches, 1991). In spite of these shortcomings, patent data have proved useful for proxying inventiveness as they present minimal standards of novelty, originality and potential profits, and as such are a good proxy for economically profitable ideas (Bottazzi and Peri, 2003). Patent data come from the KIT database, collected from the OECD REGPAT database. Since these data are prone to exhibit lumpiness from year to year, we have averaged out patent figures. Thus, a three-year moving average is computed for every observation, thereby mitigating the effects of annual fluctuations in this variable, especially in those less populated areas.

As for the explanatory variables, R&D expenditures data also come from the KIT project and again figures are averaged out from the same reason. Specifically, all the data were collected from EUROSTAT and some National Statistical Offices, with some elaboration for regions in specific countries (Belgium, Switzerland, Greece, Netherlands). Human capital is measured as the absolute population with tertiary education (Population aged 15 and over by ISCED level of education attained) and is extracted again from the KIT records, collected from EUROSTAT. Annual figures are considered in this case. Both variables, as well as the remaining regressors, are time-lagged one period in order to lessen endogeneity problems. Thus, for instance, the average R&D expenditures in time t are computed using data from t-3 to t-1, whereas data from t-1 is used to compute human capital figures in the t period. Population data is computed used a single (lagged) year as well, and retrieved from Eurostat databases.

The data for constructing the mobility and network variables are based on individual inventor information retrieved from EPO patents, taken from the REGPAT database (January 2010 edition). However, in spite of the vast amount of information contained in patent documents, a single ID for each inventor and anyone else is missing. In order to draw the mobility and networking history of inventors, it is necessary to identify them individually by name and surname, as well as via the other useful details contained in the patent document. The method chosen for identifying the inventors is therefore of the utmost importance in studies of this nature. In line with a growing number of researchers in the field, we apply several algorithms squeezing patent data information for singling out individual inventors (Miguélez and Gómez-Miguélez, 2011).

Once each inventor has been assigned an individual identification, mobility and network data can be calculated for each region. Note that, in line with related studies (Schilling and Phelps, 2007; Breschi and Lenzi, 2011), a 1-year lagged 5-year moving window is adopted to compute all the mobility and network variables, as well as for the case of the control variables. Thus, mobility or network measures of the period t include data from t-5 to t-1.

A “mobile” inventor is broadly defined as an individual who moves across different organisations offering his/her services (Breschi and Lissoni, 2009). Therefore, mobility can refer either to labour mobility understood in its strictest sense (an employee leaving a firm to take up a position in a new one), or to that demonstrated by consultants, freelance workers, university inventors, and the like. We assume that both constitute sources of knowledge flows to the extent that in the two instances knowledge is transferred from former employers or customers to new ones. Mobility is then proxied as the share of mobile inventors to the absolute number of inventors per region, as is usually done in the labour literature.

The design of the network variables is built upon the theory of SNA. Thus, the inventors form the nodes in the network, and these are grouped via edges or ties (in this instance, co-patents) into different components.

Two different, though complementary, variables measure the scale of network connectivity among inventors in regions. Average degree centrality is calculated by averaging out the degree centrality of the nodes (inventors) by region. The degree centrality of a node is the number of linkages it has to other nodes. That is to say, it measures how well connected, how popular, is each of the nodes. Thus, it measures the extent to which inventors in regions are prone, on average, to be connected with other inventors through networks of research collaboration. On its side, connectivity goes a little bit further and tries to take on board the scope of the local network by computing the share of inventors with at least one tie in the form of co-patent. That is, the number of connected nodes of the whole network minus the number of isolated nodes, as a proportion of the total number of nodes (inclusiveness, in SNA terms). Formally,

$$\mathrm{CONN}_{it} = \frac{\mathrm{Q}_{it} - \mathrm{NQ}_{it}}{\mathrm{Q}_{it}}, \tag{7}$$

where Q_{it} stands for the total number of inventors in region i and time t, and NQ_{it} stands for the number of isolated inventors.

The strength of these ties is proxied by the network density, which is the number of ties between inventors within the region divided by the possible number of ties within that region. Formally,

$$\mathrm{DENS}_{it} = \frac{\mathrm{T}_{it}}{\mathrm{Q}_{it}(\mathrm{Q}_{it} - 1)/2}, \tag{8}$$

where T_{it} stands for the number of edges (ties) within a given region, and Q_{it} is again the total number of inventors within that region. As stressed earlier, the expected effect (be it positive or negative) of knowledge density is not so clear a priori.

As regards the variables proxying meaningful linkages across regions, the 1-year lagged 5-year moving window criteria is also adopted. The Net Migration Rate (NMR) is computed as the inflows minus outflows of inventors to the current number of inventors, for each time window. The Inward Migration Rate (IMR) corresponds only to the inflows of inventors to the current number of inventors, whereas the Outward Migration Rate (OMR) computes the outflows of inventors to the current number of inventors, again within each time window. Finally, Gross Migration Rate (GMR) measures inflows plus outflows of inventors to the current number of inventors. Note, importantly, that spatial mobility is computed through observed changes in the reported region of residence by the inventor in patent documents. Note also that we compute each movement in between the origin and the destination patent, but only if there is a maximum lapse of 5 years between them. Otherwise, the exact move date is too uncertain.

Cross-regional networks of research collaboration are computed as the sum of local patents, fractional count, co-authored with inventors from outside, to the total number of inventors of the region, within each 5-year time window. Extra-regional inventors include both European and non-European ones. In this way, as we will show later on, we are in position to estimate also the influence of extra-regional linkages broken down according to the geographical scope of these ties. Thus, cross-regional networks are computed both as a whole and broken down into: (i) linkages with other European regions (of 31 countries); (ii) linkages with the US; (iii) linkages with singular East-Asian countries (Japan, China and India); and (iv) linkages with remaining OECD countries (Australia, Brazil, Canada, Chile, Croatia, Israel, South Korea, Mexico, New Zealand, Russia, Turkey, and South Africa).

As explained in the methodological section, several variables were also included in our regressions to control for other regional time-variant features that may affect spatial differences in patent production. Thus, a specialization index and a concentration index of industries constructed using patents from 30 IPC[2] technological sectors –OST subdivision- are also included, in order to control for the influence of specialization and concentration economies on innovation (Feldman and Audretsch, 1999). To calculate the technological specialization index, we employ the following formula

$$\mathrm{SpIn}_{it} = \frac{1}{2}\sum_{j}\left|\frac{\mathrm{PAT}_{ijt}}{\mathrm{PAT}_{it}} - \frac{\mathrm{PAT}_{Cjt}}{\mathrm{PAT}_{Ct}}\right|, \tag{9}$$

where PAT is the number of patents in each region i for each sector j, expressed as a difference for the whole sample of regions (C). The concentration index is built as follows:

$$\mathrm{ConIn}_{it} = \sum_{jt}\left(\mathrm{PAT}_{ijt} / \mathrm{PAT}_{jt}\right)^2 . \tag{10}$$

Three additional controls capture differences in technological content across regions: the shares of biotechnology (BIOTECH), organic chemistry (CHEM), and pharmaceuticals

[2] International Patent Classification.

(PHARMA) in their patenting activity, according to the IPC classification - since these three sectors tend to be more research intensive.[3,4]

4. Results of the econometric specifications

4.1. Results on the role of research networks and labour mobility on knowledge: Evidence on the direct impact

Table 1 presents the results of the fixed effect estimation of the KPF once labour mobility of inventors as well as the scale and density of the research networks in which they participate are included as additional variables. In principle, the coefficients can be interpreted as elasticities, since the variables in the regression are either expressed in natural logarithmic form or as in percentage terms: the proportional increase in patenting activity in response to a 1% increase in a given explanatory variable. Note also that Hausman tests (Hausman, 1978) have been also computed for all the models and the null hypothesis that individual effects are uncorrelated with the independent variables is always rejected, so the fixed-effects model is preferred to the expense of the random-effects.

Some results are worth highlighting. In general, the KPF holds in the European regional case for the period under consideration. The elasticity of patents with respect to R&D expenditures when the FE estimation is carried out presents a significant value of 0.19, which is in line with the value obtained in the literature although in the lower limit. In fact, the elasticity goes from 0.2 to 0.9 in the USA (Jaffe, 1989; Acs et al, 1994; Anselin et al., 1997), and from 0.24 to 0.8 in the European case (Bottazzi and Peri, 2003; Moreno et al, 2005). It should be noted that with respect to these previous contributions we exploit a more disaggregated and updated database for the European regions, covering more countries and in a panel data set. In fact, our parameter resembles more the ones obtained in the study by Moreno et al (2005), with an elasticity of 0.25, where a vector of control variables are included, as in our case. Additionally, the human capital parameter is, in general, strongly significant and with the expected positive sign, with similar values to those reported elsewhere in the literature when a similar indicator is used (as in Bottazi and Peri, 2003, with values between 0.4 and 0.5).

[Insert Table 1 about here]

---

[3] Although overall employment in these sectors would be a better proxy, these data are not available.
[4] We added a small value, 0.01, to all the explanatory variables presenting zero values in at least one observation to allow for a logarithmic transformation.

The foci variables of this study are also significant. Labour mobility, for example, is significant at 1%, presenting a parameter of 0.01, whilst the relationship between the scale of the networks and knowledge is always positive and strongly significant –no matter whether it is proxied through the average degree centrality or the connectivity measure. Thus, we can conclude that collaborative research networks of inventors boost regional knowledge capability and that the mobility of inventors within the local labour market of a region enhances knowledge intensity. In addition, network density shows a significant negative impact on knowledge intensity, which bestows credibility to Granovetter's (1985) arguments about weak ties and knowledge. In other words, it seems that in the European case, strong personal ties hamper knowledge once the information flowing becomes redundant. Finally, we must say that the results are robust to the inclusion of a large number of time-variant controls. In this sense, although among the control variables only the share of patents in biotechnology has a significant and negative parameter, we have decided to leave all of them in the regression. However, once they are discarded the main results on the foci variables remain.

In short, the empirical analyses undertaken here support the hypotheses concerning the importance of labour mobility and networks in the local labour market for the creation of regional knowledge. However, several extensions to this initial approach can now be made.

4.2. Results on the returns to mobility and networking by typologies of regions

The results for the whole of the European regions mask substantial regional variations in the returns to innovation with respect to mobility and networking. In order to analyse this variability of the elasticity, we have introduced cross-effects of the corresponding focal variable with a dummy for each region. This way we are able to compute a specific elasticity for each regional economy in Europe. Figures 1 to 4 show the extent of these variations.

According to Figure 1, which plots the elasticity of knowledge with respect to labour mobility, it is clear that the highest values are obtained for most of the regions in West Germany, Austria, Denmark and Switzerland, as well as some regions in the Netherlands, North France, North-East Italy, Finland and Sweden, in all the cases with figures higher than 0.09 (first quartile). On the contrary, the non-significant or lowest values of the labour mobility elasticity (values lower than 0.01, fourth quartile) are depicted in almost the whole of the Eastern countries as well as the Mediterranean ones (Spain, Portugal, Greece and the South of Italy). It is worth highlighting some exceptions to this general pattern, since in the group of regions with the highest returns we find Cyprus, two Bulgarian regions, one from the Slovak Republic and another from Spain. On the contrary, some regions hosting capital cities, such as Île de France, London or Berlin are among the lowest ranges of the return. A plausible explanation of this a priori contra-intuitive result is the potential existence of non-disclosure agreements between knowledge employers and employees in regions with large levels of internal competition, that prevent the later ones to reveal their secrets to other local competing firms (Lissoni, 2001; Marx et al., 2007).

In the case of the elasticity of knowledge with respect to the scale of the research networks in the different European regions, the maps look slightly different depending on the measure used. In the case of the average degree centrality (Figure 3), the distribution resembles very much that of the elasticity of labour mobility just described. However, for the index of connectivity (Figure 2), although the general pattern of high values in the core countries and lower values in the Eastern and Southern countries is maintained, it must be highlighted that some of the regions in Eastern and Southern countries are not in the range of the lowest elasticities, but in the intermediate ranges (with values between 0.02 and 0.07). Finally, looking at the network density impact on knowledge (Figure 4), we can conclude that most of the regions where network density hampers knowledge more deeply are in the countries of Germany, Austria, Denmark, Switzerland and North of Italy. In such regions, strong ties hamper knowledge because the knowledge flowing becomes, at some point, redundant. On the contrary, the regions in the East as well as in the South of Europe (Portugal, West Spain, Greece and South Italy) suffer much more slightly from this redundancy in the information transmitted.

[Insert Figures 1 to 4 about here]

We turn now to the variation in the return to labour mobility and networking according to different typologies. When taking into account the kind of accession to the European Union (column 1 in Tables 2-5), it seems clear that the regions belonging to the EU15 countries are the only ones with significant returns to labour mobility and with the highest positive returns to the scope and scale of the research networks. Additionally, they are also the ones that suffer more strongly from the redundancy in the information in dense networks, as shown by the highest negative and significant return of network density.

With respect to the level of development (column 2 in Tables 2-5), the regions belonging to the competitive group show the highest positive return of knowledge to mobility, followed by the EFTA, the transition and lastly the convergence regions, being all of them significant. The same pattern is observed in the case of the two measures of the scale of the research networks, namely the degree centrality and connectivity indices: the highest in the competitive regions and the lowest in the convergence regions. Further, the same although with negative sign occurs for the return to network density, since competitive regions are hindered more importantly from the existence of dense networks.

Additionally, labour mobility is more efficiently used (i.e. shows a greater elasticity) in those regions that are more knowledge and innovation intensive, such as those in the European science-based area and in the Applied science area (column 3 in Tables 2-5). On the one hand, the first group is composed of regions that are the most knowledge and innovation intensive, and endowed with those preconditions frequently associated to greater endogenous capacity of knowledge creation (highly educated population and presence of scientific human capital). The second group includes regions that maintain a rather strong knowledge and innovation intensity, but differently from the former ones, they are more technologically diversified. In both cases, the results would suggest that the regions in these two areas are able to translate internal and external knowledge into new specific commercial applications more efficiently than in the rest, and that part of the external knowledge could come from workers coming from other enterprises. On the contrary, regions characterised by low levels of R&D spending as well as a rather narrow innovation profile (Creative imitation area) do not benefit from the mobility of skilled workers, being their elasticity of knowledge to labour mobility non-significant in this case.

Similarly, the average effect of the research networks on knowledge creation hides a great variety of behaviour across regions, both considering the average degree centrality and the connectivity degree indices. In fact, having an important share of inventors participating in research networks is more efficiently used (i.e. shows a greater elasticity) in regions that outperform the others in terms of their propensity to networking, such as those in the European science-based area and in the Applied science area. It must be signalled, though, that the elasticity in the case of the regions of the Smart technological application area, of the Smart and creative diversification area and the Creative imitation area is also positive and significant, although of lower magnitude. This can be explained by their rather narrow knowledge and innovation profile. Finally, the same although with negative sign occurs for the return to network density, with regions in the European Science-based area and Applied Science area being hampered more deeply from the existence of dense networks.

[Insert Tables 2 to 5 about here]

4.3. Results on the existence of cross-regional linkages

In order to obtain empirical evidence concerning the relevance of cross-regional knowledge for the generation of knowledge we present the estimation that includes cross-regional collaborations in patenting as well as inter-regional mobility (Table 6). The results corroborate the importance of the inflow of skilled-workers for a regional economy, since only the variable considering inward migration rates of such workers present positive and significant parameters. That is, the greater the number of inventors moving into a region, the greater the patenting activity of such region. This geographical mobility of knowledge workers can be considered, thus, a source of knowledge diffusion, allowing for a recombination of previously unconnected pieces of knowledge. However, the other three variables proxying for geographical mobility of knowledge workers (Net migration rate, Outward migration rate and Gross migration rate) offer a non significant parameter. This would point to the fact that once the workers have moved to other regions, the contacts they maintain with their former colleagues do not seem to play a significant role in the patenting activity of a region. Outward migration of skilled individuals can not be considered, therefore, as an alternative source of knowledge flows and interactions back to the home location of the left skilled employee.

In relation with the outside collaborations in the development of patents and their impact on the patenting activity of a region, we obtain a positive and significant impact. However, in column (5) of Table 6, when the co-patenting variable is broken down according to the geographical scope of the linkages (with other European regions, with the US, with singular East-Asian countries and with remaining OECD countries), only co-patents with the US and the remaining OECD countries turn out to be significant. The underlying logic of this exercise would state that when the external knowledge is the same to existing competences in the region, it can be absorbed locally, but the new knowledge will not add much to the existing local one (Boschma and Iammarino 2009). This way, one possible interpretation would be that the collaborations maintained between inventors in Europe and other OECD countries or the US provide with less redundant pieces of knowledge, which would allow enhancing creativity.

Again, the average results for the whole of the European regions mask substantial regional variations in the elasticities of knowledge with respect to cross-regional mobility and networking. With the inclusion of a cross-effect of the corresponding focal variable with a dummy for each region, we are able to compute a specific elasticity for each regional economy in Europe. Figures 5 and 6 show the extent of these variations.

Figure 5 plots the elasticity of knowledge with respect to geographical mobility. We observe that, as usual in the returns to knowledge, the highest values are obtained in some of the regions in Germany, Austria, Denmark, Belgium, the Netherlands and Switzerland, as well as some Finnish and French regions. However, different from other figures, we must highlight the following: firstly, only a little number of regions in those countries get elasticities in the upper quartile; secondly, in any of the cases the regions hosting the capital cities are in this upper range of elasticities; and thirdly, among the regions with the highest elasticities we find many Italian regions (in the north-half part of the country), 3 Spanish regions (Catalonia, the Basque Country and Navarra), 1 Hungarian region (Eszak Alfold), the region of Border Midland in Ireland or Iceland.

A different pattern is detected for the elasticity of knowledge with respect to cross-regional co-patenting (Figure 6). We note that, as usual, many German regions are in the first quartile, together with two Swiss, one Austrian, one Belgian, one Finnish, 2 Dutch, 3 Norwegian, and five British regions, as well as Iceland and Liechtenstein. However, differently from other elasticities of knowledge: first, only some few regions in those countries obtain high elasticities; second, some regions in Spain (Galicia and Canary Islands), in Italy (Abruzzo, and none in the North), in Hungary (Eszak Alfold), in Ireland (Border Midland), in Slovenia (Vzhodna) as well as the whole Iceland, also report very high elasticities of knowledge to the co-patenting activity with inventors in other regions.

In sum, from these two maps we can conclude, therefore, that the regions benefiting from knowledge coming from other regions –both in the form of mobile skilled workers and research networks- are not so concentrated in the core of Europe. Put differently, some peripheral regions might get larger advantages –in terms of returns on knowledge - in building knowledge linkages with distant knowledge hotspots, compared to the core regions, which most likely source their knowledge from their local pools of ideas or the ones from their immediate vicinity.

[Insert Figures 5 and 6 about here]

As in the within-the-region case, we turn now to the variation in the return to geographical mobility and networking according to different typologies. According to the level of development (column 2 in Tables 7 and 8), the regions belonging to the competitive group show the highest positive return of knowledge to cross-regional mobility and co-patenting, followed by the EFTA and the transition regions, being all of them significant, whereas the convergence regions do not seem to benefit from this geographical diffusion of knowledge. Additionally, the return obtained from this spatial mobility and networks is greater in those regions that are more knowledge and innovation intensive, such as those in the European science-based area and in the Applied science area (column 3 in Tables 7 and 8). This is not strange since the regions in these two groups are the most knowledge and innovation intensive, and endowed with those preconditions frequently associated to greater endogenous capacity of knowledge creation (highly educated population and presence of scientific human capital). On the contrary, regions in the Creative imitation area and Smart and creative diversification area, characterised by knowledge and innovation variables that show smaller values than the EU average, do not benefit from this cross-regional diffusion of knowledge.

[Insert Tables 7 and 8 about here]

5. Conclusions, implications and limitations

The research conducted here sought to assess the importance of specific knowledge flow and knowledge creation mechanisms, namely networks of co-invention and labour mobility, on regional knowledge, as opposed to the impact from R&D efforts or other mechanisms of knowledge creation and diffusion. Within a KPF framework, several hypotheses have been suggested and, although we are unable to confirm them all, a number of interesting conclusions can be identified.

Strong support for the positive relationship between regional labour market mobility and regional knowledge intensity is found. The influence of networks is also fairly important, but the strength of these ties (measured as the network density) was found to have a negative influence on knowledge. In line with studies elsewhere, we rely on the explanations proffered by Grannovetter (1985) concerning the importance of weak ties for knowledge.

As labour mobility and research networks have been obtained to be a fundamental factor in the creation of knowledge, the unequal distribution of such features in the territory could explain regional differences in innovation performance and economic development. In this sense, policies aimed at encouraging the mobility of high skilled workers or enhancing the participation in research networks (as promoted by the European Commission through Marie Curie programs or the Framework Program Projects), specially in less innovative regions, may play a critical role in the creation of knowledge, and subsequent economic growth. Clearly, though, the effectiveness of such policies, as shown by the results of this paper, crucially depends on each region's capacity to give returns to such labour mobility and the participation in research networks. To this respect, we have provided evidence that those regions that are more knowledge and innovation intensive obtain higher returns since they are able to translate internal and external knowledge into new specific commercial applications more efficiently than the less innovative regions. Therefore, the idea that R&D spending and knowledge production in general spill-over to neighbouring regions is not so evident in the absence of a certain level of receptivity to exploit external knowledge. Recall, however, that certain threshold effects seem to arise as evidenced by the negative influence of the networks' strength and the null impact of mobility in certain high performance regions.

Finally, from a policy perspective, the present paper fleshes out empirically pivotal pillars of the Smart Specialisation strategy put recently to the fore by the European Commission. Thus, the concepts of local *embeddedness* of the local networks and labour market, as well as the degree of *connectedness* to external sources of knowledge, constitute core ideas of the Strategy. To some extent, both concepts are crucially related to the regional and cross-regional meaningful features which have been scrutinized in this paper.

References

Acs ZJ, Audretsch DB, Feldman MP (1994) R&D spillovers and recipient firm size. Review of Economics and Statistics 76: 363-367

Agrawal A, Cockburn I, McHale J (2006) Gone but not forgotten: labour flows, knowledge spillovers, and enduring social capital. Journal of Economic Geography 6: 571-591

Agrawal A, Kapur D, McHale J (2008) How do spatial and social proximity influence knowledge flows? Evidence from patent data. Journal of Urban Economics 64: 258-269

Agrawal A, Kapur D. McHale J, Oettl A (2011) Brain drain or brain bank? The impact of skilled emigration on poor-country innovation. Journal of Urban Economics 69: 43-55

Almeida P, Kogut B (1997) The exploration of technological diversity and the geographic localization of innovation. Small Business Economics 9: 21–31

Almeida P, Kogut B (1999) Localisation of knowledge and the mobility of engineers in regional networks. Management Science 45: 905-917

Anselin L., Varga A. and Acs Z. (1997) Local Geographic Spillovers between University Research and High Technology Innovations, Journal of Urban Economics 42, 422-48;

Audretsch DB, Feldman MP (1996) R&D Spillovers and the geography of innovation and production. The American Economic Review 86: 630-640

Audretsch DB, Feldman M (2004) Knowledge Spillovers and the Geography of Innovation. In: Henderson V, Thisse J (eds) Handbook of Urban and regional Economics, Volume 4

Autant-Bernard C., Mairesse J. and Massard N. (2009) Spatial knowledge diffusion through collaborative networks. Introduction, *Papers in Regional Science* 86, 3, 341-50;

Balconi M., Breschi S. and Lissoni F. (2004) Networks of inventors and the role of academia: an exploration of Italian patent data, Research Policy 33, 127–45;

Bathelt H, Malberg A, Maskell P (2004) Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation. Progress in Human Geography 28: 31-56

Bergman E. M. (2009) Embedding network analysis in spatial studies of innovation, *The Annals of Regional Science* 43, 3, 559-65;

Bettencourt L., Lobo J., Helbing D., Kühnert C., and West G. (2007a) Growth, innovation, scaling, and the pace of life in cities, Proceeding of the National Academy of Sciences 104, 7301-06;

Bettencourt L., Lobo J., and Strumsky D. (2007b) Invention in the city: Increasing returns topatenting as a scaling function of metropolitan, Research Policy 36, 107-20;

Boschma R (2005) Proximity and Innovation: A Critical Assessment. Regional Studies 39: 61-74

Boschma R, Eriksson R, Lindgren U (2009) How does labour mobility affect the performance of plants? The importance of relatedness and geographical proximity. Journal of Economic Geography 9: 169-190

Boschma R, Frenken K (2010) The spatial evolution of innovation networks. A proximity perspective. In: Boschma R, Martin R (eds) The Handbook of Evolutionary Economic Geography, Cheltenham: Edward Elgar, pp 120-135

Boschma RA, Iammarino S (2009) Related Variety, Trade Linkages and Regional Growth. Economic Geography 85: 289-311

Bottazzi L. and Peri G. (2003) Innovation and spillovers in regions: Evidence from European patent data, European Economic Review 47, 687 – 710;

Breschi S. and Catalini C. (2009) Tracing the linkages between science and technology: An exploratory analysis of the research networks among scientists and inventors, Research Policy 39, 14-26;

Breschi S, Lenzi C (2011) Net and the city. Co-invention networks and the inventive productivity of US cities, mimeo

Breschi S, Lissoni F (2001) Localised knowledge spillovers vs. innovative millieux: Knowledge “tacitness” reconsidered. Papers in Regional Science 80: 255-273

Breschi S. and Lissoni F. (2004) Knowledge networks from patent data: methodological issues and research targets, in Moed H., Glänzel W. and Schmoch U. (Eds) Handbook of Quantitative Science and Technology Research: The Use of Publication and Patent Statistics in Studies of S&T Systems, pp. 613–643. Springer Verlag, Berlin.

Breschi S. and Lissoni F. (2006) Cross-firm inventors and social networks: localised knowledge spillovers revisted, Annales d'Economie et de Statistique, 79-80;

Breschi S. and Lissoni F. (2009) Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows, Journal of Economic Geography 9, 4, 439-68;

Breschi S, Lenzi C, Lissoni F, Vezzulli A (2010) The geography of knowledge spillovers: the role of inventors' mobility across firms and in space. In: Boschma R, Martin R (eds) The Handbook of Evolutionary Economic Geography, Cheltenham: Edward Elgar, pp. 353-369

Camagni R (1991) Innovation networks: spatial perspectives. Belhaven-Pinter: London

Coe NM, Bunnell T (2003) 'Spatializing' knowledge communities: towards a conceptualisation of transnational innovation networks. Global Networks 3: 437-456

Corredoira R. A. and Rosenkopf L. (2006) Learning from those who left: the reverse transfer of knowledge through mobility ties, Management Department Working Paper

Cowan R. and Jonard N. (2004) Network structure and the diffusion of knowledge, Journal of Economic Dynamics and Control 28, 1557-75;

Crespi G., Geuna A. and Nesta L. (2007) The mobility of university inventors in Europe, Journal of Technology Transfer 32, 3, 195-215;

Feldman MP, Audretsch D (1999) Innovation in cities: Science-based diversity, specialization and localized competition. European Economic Review 43: 409-429

Foray D, David PA, Hall B (2009) Smartt Specialisation – The Concept. Knowledge Economists Policy Brief No. 9

Fleming L., King C., and Juda A. (2007) Small worlds and innovation, Organization Science 14, 5, 375-93;

Fratesi U, Senn L (2009) Regional Growth, Connections and Economic Modelling: An Introduction. In Fratesi U, Senn L (eds) Growth and Innovation of Competitive Regions: The Role of Internal and External Connections, pp. 3-28. Springer-Verlag, Berlin.

Gertler MS, Levite YM (2005) Local nodes in global networks: the geography of knowledge flows in biotechnology innovation. Industry and Innovation 12: 487-507

Gittelman M (2007) Does geography matter for science-based firms? Epistemic communities and the geography of research and patenting in biotechnology. Organization Science 18: 724-741

Glaeser E, Glaeser, E., H. Kallal, J. Scheinkman, and A. Shleifer (1992) Growth in Cities. Journal of PoliticalEconomy,100.6, 1126-52.

Gomes-Casseres B., Hagedoorn J., and Jaffe A. B. (2006) Do alliances promote knowledge flows?, Journal of Financial Economics 80, 5-33;

Grabher G. (1993) The weakness of strong ties: the lock-in of regional development in the Ruhr area. In: Grabher G (ed) The Embedded Firm, London: Routledge, pp. 255–277

Granovetter M. S. (1985) The strength of weak ties, American Journal of Sociology 78, 1360-80;

Griliches Z. (1979) Issues in assessing the contribution of research and development to productivity growth, The Bell Journal of Economics 10, 1, 92-116;

Griliches Z. (1991) Patent Statistics as Economic Indicators: A Survey, NBER Working Papers No. 3301, National Bureau of Economic Research;

Hausman JA (1978) Specification test in econometrics. Econometrica 46: 1251-1271

Hausman J.A., Hall B.H. and Griliches Z. (1984) Econometric models for count data with an application to the patent-R&D relationship, Econometrica 51, 4, 909-38;

Hoekman J., Frenken K. and van Oort F. (2009) The geography of collaborative knowledge production in Europe, The Annals of Regional Science 43, 3, 721-38;

Hoisl K. (2007) Does mobility increase the productivity of inventors?, Journal of Technology Transfer 34, 212-25;

Hoisl K. (2009) Tracing mobile inventors: The causality between inventor mobility and inventor productivity, Research Policy 36, 5, 615-36;

Jaffe A. B. (1986) Technological opportunity and spillovers of R&D: evidence from firms patents, profits and market value, American Economic Review 76, 5, 984-1001;

Jaffe A. B. (1989) Real effects of academic research, American Economic Review 79, 5, 957-70;

Jaffe AB, Trajtenberg M, Henderson R (1993) Geographic localisation of knowledge spillovers as evidenced by patent citations. Quarterly Journal of Economics 108: 577-598

Kerr WR (2008) Ethnic Scientific Communities and International Technology Diffusion. The Review of Economics and Statistics 90: 518-537

Kim J., Lee S. J. and Marschke G. (2006) International Knowledge Flows: Evidence from an Inventor-Firm Matched Data Set, NBER Working Paper No. 12692

Kroll H. (2009) Spillovers and proximity in perspective: A network approach to improving the operationalisation of proximity, Working Papers Firms and Regions No. R2/2009, Fraunhofer ISI;

Lambooy JG, Boschma RA (2001) Evolutionary economics and regional policy. Annals of Regional Science 35: 113-133

Laudel G (2003) Studying the Brain Drain: Can Bibliometric Methods Help? Scientometrics 57: 215-237

Lenzi C. (2009) Patterns and determinants of skilled workers' mobility: evidence from a survey of Italian inventors, Economics of Innovation and New Technology 18, 2, 161-79;

Lissoni F (2001) Knowledge codification and the geography of innovation: the case of Brescia mechanical cluster. Research Policy 30: 1479-1500

Lobo J. and Strumsky D. (2008) Metropolitan patenting, inventor agglomeration and social networks: A tale of two effects, Journal of Urban Economics 63, 871-84;

Maggioni MA, Nosvelli M, Uberti TE (2007) Space versus networks in the geography of innovation: A European analysis. Papers in Regional Science 86: 471-493

Maggioni MA, Uberti TE (2008) Knowledge networks across Europe: which distance matters? The Annals of Regional Science 43: 691-720

Maskell P, Bathelt H, Malmberg A (2006) Building global knowledge pipelines: The role of temporary clusters. European Planning Studies 14: 997-1013

Martin, P. and Ottaviano, G. (1999) Growing locations: Industry location in a model of endogenous growth. European Economic Review 43(2): 281-302.

Marx M, Strumsky S, Fleming L (2007) Noncompetes and Inventor Mobility: Specialists, Stars, and the Michigan Experiment, Harvard Business School WP 07-042

McCann P, Ortega-Argilés R (2011) Smart specialisation, regional growth and applications to EU cohesion policy. Document de treball de l'IEB 2011/14, Institut d'Economia de Barcelona

Miguélez E, Gómez-Miguélez IG (2011) Singling out individual inventors from patent data. IREA Working Paper 2011/05

Moreno R., Paci R. and Usai S. (2005a) Spatial spillovers and innovation activity in European regions, Environment and Planning A 37, 10, 1793-812;

Oettl A, Agrawal A (2008) International labor mobility and knowledge flow externalities. Journal of International Business Studies 39(8): 1242-1260

Owen-Smith J, Powell WW (2004) Knowledge networks as channels and conduits: the effects of spillovers in the Boston biotechnology community. Organization Science 15(1): 5- 21

Ponds R., van Oort F. and Frenken K. (2007) The geographical and institutional proximity of research collaboration, Papers in Regional Science 86, 3, 423-43;

Ponds R, Van Oort FG, Frenken K (2010) Innovation, spillovers and university-industry collaboration: An extended knowledge production function approach. Journal of Economic Geography 10 (2): 231-255

Rodríguez-Pose A (1999) Innovation prone and innovation averse societies: Economic performance in Europe. Growth and Change 30: 75-105

Rodríguez-Pose A, Crescenzi R (2008) Reseacrh and Development, Spillovers, Innovation Systems, and the Genesis of Regional Growth in Europe. Regional Studies 42: 51-67

Romer P. M. (1986) Increasing Returns and Long-run Growth, Journal of Political Economy 94, 5, 1002-37;

Romer P. M. (1990) Endogenous Technological Change; Journal of Political Economy 98, 5, 71-102;

Rosenkopf L. and Almeida P. (2003) Overcoming Local Search Through Allainces and Mobility, Management Science 49, 6, 751-66;

Saxenian A. (1994) Regional Advantage. Culture and Competition in Silicon Valley and Route 128. Harvard University Press, Cambridge, MA.

Saxenian A (2006) The New Argonauts: Regional Advantage in a Global Economy, Harvard University Press.

Schilling MA, Phelps CC (2007) Interfirm Collaboration Networks: The Impact of Large-Scale Network Structure on Firm Innovation. Management Sci. 53(7): 1113-1126

Simonen J, McCann P (2008) Firm innovation: The influence of R&D cooperation and the geography of human capital inputs. Journal of Urban Economics 64(1): 146-154

Singh J. (2005) Collaborative Networks as Determinants of Knowledge Diffusion Patterns, Management Science 51, 5, 756-70;

Singh J, Agrawal AK (2011) Recruiting for Ideas: How Firms Exploit the Prior Inventions of New Hires. Management Science 57(1): 129–150

Shalem R. and Trajtenberg M. (2008) Software patents, inventors and mobility, Working Paper

Song J., Almeida P. and Wu G. (2003) Learning-by-hiring: When is mobility more to facilitate interfirm knowledge transfer?, Management Science 49, 4, 351-65;

Ter Wal A. L. J. and Boschma R. (2009) Applying social network analysis in economic geography: framing some key analytic issues, The Annals of Regional Science 43, 739-56;

Trippl M. and Maier G. (2007) Knowledge spillover agents and regional development, SRE-Discussion 2007/01

Watts DJ, Strogatz SH (1998) Collective dynamics of 'small-world' networks. Nature 393: 440-442

Wasserman S. and Faust K. (1994) Social Network Analysis: Methods and Applications. Cambridge University Press, Cambridge.

Zucker LG, Darby MR, Armstrong J (1998) Geographically Localized Knowledge: Spillovers or Markets? Economic Inquiry 36(1): 65-86

Annex 1: Variables, data construction, and data source

Variable	Proxy	Source
Patents	Patents, fractional count, 3-year moving average	REGPAT January 2010 edition
R&D	R&D expenditures (in euros), 3-year moving average	Eurostat
Human capital	Total population with tertiary education	Eurostat
Mobility	Share of multi-patent inventors with more than one applicant	REGPAT January 2010 edition
Average degree centrality	Average number of personal links in the form of co-patents per inventor	REGPAT January 2010 edition
Connectivity	Share of multi-patent inventors with at least 1 co-inventor	REGPAT January 2010 edition
Network density	$DENS_{it} = \frac{T_{it}}{Q_{it}(Q_{it}-1)/2}$	REGPAT January 2010 edition
Net Migration Rate	Inflows minus outflows of inventors to the local no. of inventors	REGPAT January 2010 edition
Inward Migration Rate	Inflows of inventors to the local no. of inventors	REGPAT January 2010 edition
Gross Migration Rate	Inflows plus outflows of inventors to the local no. of inventors	REGPAT January 2010 edition
Outward Migration Rate	Outflows of inventors to the local no. of inventors	REGPAT January 2010 edition
Cross-regional networks	No. of patents, fractional count, co-authored with outside inventors, to the local no. of inventors	REGPAT January 2010 edition
Cross-regional networks – Europe (ESPON countries)	No. of patents, fractional count, co-authored with inventors from the remaining ESPON regions, to the local no. of inventors	REGPAT January 2010 edition
Cross-regional networks – US	No. of patents, fractional count, co-authored with inventors from the US, to the local no. of inventors	REGPAT January 2010 edition
Cross-regional networks – China, Japan and India	No. of patents, fractional count, co-authored with inventors from China, Japan and India, to the local no. of inventors	REGPAT January 2010 edition
Cross-regional networks – remaining OECD countries	No. of patents, fractional count, co-authored with inventors from remaining OECD countries, to the local no. of inventors	REGPAT January 2010 edition
Specialisation Index	$SpIn_{it} = \frac{1}{2}\sum_j \left\lvert \frac{PAT_{ijt}}{PAT_{it}} - \frac{PAT_{Cjt}}{PAT_{Ct}} \right\rvert$	REGPAT January 2010 edition
Concentration index	$ConIn_{it} = \sum_{jt} \left(PAT_{ijt} / PAT_{jt}\right)^2$	REGPAT January 2010 edition
% Organic chemistry	Share of patents in IPC chemistry	REGPAT January 2010 edition
% Pharmaceuticals	Share of patents in IPC pharmaceuticals	REGPAT January 2010 edition
% Biotechnology	Share of patents in IPC biotechnology	REGPAT January 2010 edition

Annex 2: List of abbreviations

EFTA - European Free Trade Association

EPO – European Patent Office

EU – European Union

GMR – Gross Migration Rate

KIT – Knowledge, Innovation and Territory

KPF – Knowledge Production Function

IMR – Inward Migration Rate

IPC – International Patent Classification

MSA – Metropolitan Statistical Areas

NMR – Net Migration Rate

NUTS – “Nomenclature d’unites territoriales statistiques”

OECD – Organisation for Economic Cooperation and Development

OMR – Outward Migration Rate

OST - Observatoire des Sciences et des Techniques

R&D – Research and Development

SNA – Social Network Analysis

US – United States

Table 1. Baseline estimations. Regional networks and regional mobility.

Dep. Var.: $\ln(\text{Patents})_t$ ‡	
	FE
$\ln(\text{RD})_{t-1}$	0.19***
	(0.07)
$\ln(\text{HK})_{t-1}$	0.50***
	(0.10)
$\ln(\text{POP})_{t-1}$	-0.19
	(0.81)
$(\text{Mobility})_{t-1}$	0.01***
	(0.00)
$\ln(\text{Average Degree})_{t-1}$ ‡	0.04*
	(0.02)
$(\text{Connectivity Degree})_{t-1}$	0.02***
	(0.00)
$\ln(\text{Network Density})_{t-1}$ ‡	-0.18***
	(0.04)
$\ln(\text{SpecIn})_{t-1}$ ‡	0.02
	(0.11)
$\ln(\text{ConIn})_{t-1}$ ‡	-0.03
	(0.03)
$(\text{Chemistry})_{t-1}$	-0.00
	(0.00)
$(\text{Biotechnology})_{t-1}$	-0.01***
	(0.00)
$(\text{Pharmaceuticals})_{t-1}$	0.00
	(0.00)
$\ln(\text{RD})_{t-1}$* $(\text{Mobility})_{t-1}$	
$\ln(\text{RD})_{t-1}$* $\ln(\text{Average Degree})_{t-1}$	
$\ln(\text{RD})_{t-1}$*$(\text{Connectivity Degree})_{t-1}$	
$\ln(\text{RD})_{t-1}$* $\ln(\text{Network Density})_{t-1}$	
Constant	1.56
	(11.21)
Observations	1,722
Number of Regions	287
R2 within	0.1408
R2 between	0.7706
R2 overall	0.7474

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors in parentheses. ‡ We added 0.01 to these variables before the logarithmic transformation.

Table 2. Regional within mobility by typologies.

Dep. Var.: ln(Patents)$_t$ ‡	(1) Pooled OLS	(2) Pooled OLS	(3) Pooled OLS
ln(RD)$_{t-1}$	0.59***	0.52***	0.56***
	(0.03)	(0.03)	(0.03)
ln(HK)$_{t-1}$	0.12**	0.04	-0.03
	(0.06)	(0.06)	(0.06)
ln(POP)$_{t-1}$	-0.02	0.15**	0.11**
	(0.06)	(0.06)	(0.06)
EU15*(Mobility)$_{t-1}$	0.03***		
	(0.00)		
New Entrants*(Mobility)$_{t-1}$	-0.00		
	(0.00)		
EFTA*(Mobility)$_{t-1}$	0.01	0.05***	
	(0.01)	(0.01)	
Convergence*(Mobility)$_{t-1}$		0.01**	
		(0.00)	
Transition*(Mobility)$_{t-1}$		0.03***	
		(0.01)	
Competitive*(Mobility)$_{t-1}$		0.07***	
		(0.01)	
Creative imitation*(Mobility)$_{t-1}$			0.00
			(0.00)
Smart and creative*(Mobility)$_{t-1}$			0.03***
			(0.00)
Smart Techno.*(Mobility)$_{t-1}$			0.05***
			(0.01)
Applied science* (Mobility)$_{t-1}$			0.08***
			(0.01)
Science-Based* (Mobility)$_{t-1}$			0.09***
			(0.01)
ln(Average Degree)$_{t-1}$ ‡	0.38***	0.34***	0.34***
	(0.03)	(0.02)	(0.02)
(Connectivity Degree)$_{t-1}$	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
ln(Network Density)$_{t-1}$ ‡	-0.51***	-0.46***	-0.51***
	(0.05)	(0.05)	(0.05)
Controls(1)	yes	yes	yes
Constant	0.04	-1.71**	-1.07
	(0.74)	(0.74)	(0.68)
Observations	1,722	1,722	1,722
Number of Regions	287	287	287
Adjusted R2	0.522	0.913	0.535

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1)**Control variables include**: ln(SpecIn)$_{t-1}$; ln(ConIn)$_{t-1}$ (Share_Chemistry)$_{t-1}$; (Share_Biotechnology)$_{t-1}$; (Share_Pharmaceuticals)$_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation.

Table 3. Average degree centrality by typologies.

Dep. Var.: $\ln(\text{Patents})_t$ ‡	(1) Pooled OLS	(2) Pooled OLS	(3) Pooled OLS
$\ln(RD)_{t-1}$	0.58***	0.48***	0.58***
	(0.03)	(0.03)	(0.03)
$\ln(HK)_{t-1}$	0.10*	0.07	0.03
	(0.06)	(0.06)	(0.06)
$\ln(POP)_{t-1}$	-0.06	0.11*	0.03
	(0.06)	(0.06)	(0.06)
$(\text{Mobility})_{t-1}$	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
EU15*ln(Average Degree) $_{t-1}$ ‡	0.48***		
	(0.03)		
New Entrants* ln(Average Degree) $_{t-1}$ ‡	0.12***		
	(0.04)		
EFTA* ln(Av.Degree) $_{t-1}$ ‡	0.18**	0.76***	
	(0.09)	(0.10)	
Convergence* ln(Av.Degree) $_{t-1}$ ‡		0.30***	
		(0.03)	
Transition* ln(Av.Degree) $_{t-1}$ ‡		0.41***	
		(0.03)	
Competitive* ln(Av.Degree) $_{t-1}$ ‡		1.07***	
		(0.05)	
Creative imitation* ln(Av.Degree) $_{t-1}$ ‡			0.34***
			(0.03)
Smart and creative* ln(Av.Degree) $_{t-1}$ ‡			0.32***
			(0.03)
Smart Techno.* ln(Av.Degree) $_{t-1}$ ‡			0.58***
			(0.05)
Applied science* ln(Av.Degree) $_{t-1}$ ‡			0.83***
			(0.05)
Science-Based*ln(Av.Degree) $_{t-1}$ ‡			0.92***
			(0.07)
(Connectivity Degree) $_{t-1}$	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
ln(Network Density) $_{t-1}$ ‡	-0.52***	-0.45***	-0.51***
	(0.05)	(0.05)	(0.05)
Controls$^{(1)}$	yes	yes	yes
Constant	0.63	-1.10	-0.19
	(0.71)	(0.70)	(0.68)
Observations	1,722	1,722	1,722
Number of Regions	287	287	287
Adjusted R2	0.875	0.884	0.879

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1)**Control variables include**: $\ln(\text{SpecIn})_{t-1}$; $\ln(\text{ConIn})_{t-1}$ $(\text{Share\_Chemistry})_{t-1}$; $(\text{Share\_Biotechnology})_{t-1}$; $(\text{Share\_Pharmaceuticals})_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation.

Table 4. General within connectivity by typologies.

Dep. Var.: $ln(Patents)_t^{‡}$	(1) Pooled OLS	(2) Pooled OLS	(3) Pooled OLS
$ln(RD)_{t-1}$	0.62***	0.55***	0.58***
	(0.03)	(0.03)	(0.03)
$ln(HK)_{t-1}$	0.12*	0.08	0.06
	(0.06)	(0.06)	(0.06)
$ln(POP)_{t-1}$	-0.09	0.01	-0.00
	(0.06)	(0.06)	(0.06)
$(Mobility)_{t-1}$	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
$ln(Average\ Degree)_{t-1}^{‡}$	0.36***	0.37***	0.36***
	(0.03)	(0.02)	(0.02)
$EU15*(Connectivity)_{t-1}$	0.02***		
	(0.00)		
$New\ Entrants*(Connectivity)_{t-1}$	0.01***		
	(0.00)		
$EFTA*(Connectivity)_{t-1}$	0.01**	0.02***	
	(0.00)	(0.00)	
$Convergence*(Connectivity)_{t-1}$		0.01***	
		(0.00)	
$Transition*(Connectivity)_{t-1}$		0.01***	
		(0.00)	
$Competitive*(Connectivity)_{t-1}$		0.03***	
		(0.00)	
$Creative\ imitation*\ (Connectivity)_{t-1}$			0.01***
			(0.00)
Smart and creative* $ln(Av.Degree)_{t-1}^{‡}$			0.02***
			(0.00)
$Smart\ Techno.*(Connectivity)_{t-1}$			0.02***
			(0.00)
$Applied\ science*\ (Connectivity)_{t-1}$			0.03***
			(0.00)
$Science\text{-}Based*(Connectivity)_{t-1}$			0.04***
			(0.00)
$ln(Network\ Density)_{t-1}^{‡}$	-0.51***	-0.46***	-0.51***
	(0.05)	(0.05)	(0.05)
Controls(1)	yes	yes	yes
Constant	1.13	0.31	0.34
	(0.72)	(0.71)	(0.68)
Observations	1,722	1,722	1,722
Number of Regions	287	287	287
Adjusted R2	0.870	0.876	0.875

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1)**Control variables include**: $ln(SpecIn)_{t-1}$; $ln(ConIn)_{t-1}$ $(Share\_Chemistry)_{t-1}$; $(Share\_Biotechnology)_{t-1}$; $(Share\_Pharmaceuticals)_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation.

Table 5. Regional network density by typologies.

Dep. Var.: $\ln(\text{Patents})_t$ ‡	(1) Pooled OLS	(2) Pooled OLS	(3) Pooled OLS
$\ln(\text{RD})_{t-1}$	0.57***	0.50***	0.53***
	(0.03)	(0.03)	(0.03)
$\ln(\text{HK})_{t-1}$	0.14**	0.04	-0.04
	(0.06)	(0.06)	(0.06)
$\ln(\text{POP})_{t-1}$	-0.02	0.20***	0.14***
	(0.06)	(0.06)	(0.05)
$(\text{Mobility})_{t-1}$	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
$\ln(\text{Average Degree})_{t-1}$ ‡	0.38***	0.32***	0.34***
	(0.03)	(0.02)	(0.02)
$(\text{Connectivity})_{t-1}$	0.02***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)
EU15*$\ln(\text{Net.Density})_{t-1}$ ‡	-0.58***		
	(0.05)		
New Entrants* $\ln(\text{Net.Density})_{t-1}$ ‡	-0.47***		
	(0.05)		
EFTA* $\ln(\text{Net.Density})_{t-1}$ ‡	-0.53***	-0.52***	
	(0.06)	(0.05)	
Convergence*$\ln(\text{Net.Density})_{t-1}$ ‡		-0.31***	
		(0.04)	
Transition* $\ln(\text{Net.Density})_{t-1}$ ‡		-0.40***	
		(0.04)	
Competitive* $\ln(\text{Net.Density})_{t-1}$ ‡		-0.59***	
		(0.04)	
Creative imitation* $\ln(\text{Net.Density})_{t-1}$ ‡			-0.40***
			(0.05)
Smart and creative* $\ln(\text{Net.Density})_{t-1}$ ‡			-0.56***
			(0.05)
Smart Techno.* $\ln(\text{Net.Density})_{t-1}$ ‡			-0.64***
			(0.05)
Applied science* $\ln(\text{Net.Density})_{t-1}$ ‡			-0.71***
			(0.05)
Science-Based* $\ln(\text{Net.Density})_{t-1}$ ‡			-0.76***
			(0.05)
Controls(1)	yes	yes	yes
Constant	0.09	-2.28***	-1.71***
	(0.75)	(0.72)	(0.66)
Observations	1,722	1,722	1,722
Number of Regions	287	287	287
Adjusted R2	0.871	0.886	0.888

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1)**Control variables include**: $\ln(\text{SpecIn})_{t-1}$; $\ln(\text{ConIn})_{t-1}$ $(\text{Share\_Chemistry})_{t-1}$; $(\text{Share\_Biotechnology})_{t-1}$; $(\text{Share\_Pharmaceuticals})_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation.

Table 6. External links and innovation: Mobility and cross-regional co-patents

Dep. Var.: ln(Patents)$_t$ [‡]	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE
ln(RD)$_{t-1}$	0.15**	0.15**	0.14**	0.15**	0.11
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
ln(HK) $_{t-1}$	0.63***	0.69***	0.71***	0.70***	0.65***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
ln(POP) $_{t-1}$	1.12	0.51	0.57	0.49	0.88
	(0.81)	(0.81)	(0.82)	(0.82)	(0.80)
(Net Migration Rate) $_{t-1}$	0.55				
	(0.35)				
(Inward Migration Rate) $_{t-1}$		0.40*			0.39*
		(0.21)			(0.21)
(Outward Migration Rate) $_{t-1}$			0.17		
			(0.11)		
(Gross Migration Rate) $_{t-1}$				0.21	
				(0.22)	
ln(Cross-regional patents) $_{t-1}$	0.05**	0.05**	0.05**	0.05**	
	(0.02)	(0.02)	(0.02)	(0.02)	
ln(Cross-regional pat. Europe) $_{t-1}$					0.03
					(0.02)
ln(Cross-regional patents US) $_{t-1}$					0.04**
					(0.02)
ln(Cross-regional patents Asia) $_{t-1}$					-0.02
					(0.03)
ln(Cross-regional patents remaining OECD countries) $_{t-1}$					0.12***
					(0.02)
ln(SpecIn) $_{t-1}$ [‡]	0.02	0.03	0.04	0.04	0.03
	(0.12)	(0.11)	(0.11)	(0.11)	(0.11)
ln(ConIn) $_{t-1}$ [‡]	-0.03	-0.02	-0.03	-0.03	-0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
(Chemistry) $_{t-1}$	-0.00	-0.00	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(Biotechnology) $_{t-1}$	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(Pharmaceuticals) $_{t-1}$	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	-16.03	-10.52	-10.59	-11.68	-12.20
	(11.13)	(11.25)	(11.35)	(11.41)	(11.20)
Observations	1,722	1,722	1,722	1,722	1,722
Number of Regions	287	287	287	287	287
R2 within	0.0996	0.1008	0.0984	0.0997	0.1193
R2 between	0.4439	0.5091	0.4909	0.5071	0.4299
R2 overall	0.4351	0.4984	0.4807	0.4965	0.4220

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. ‡ We added 0.01 to these variables before the logarithmic transformation. Since the Net Migration Rate ranges [-1,1], we avoid the logarithmic transformation of all the cross-regional mobility variables. In consequence, their sign and significance can be fairly informative, but any interpretation of their magnitude should be treated with caution.

Table 7. Regional extra-local in-mobility by typologies.

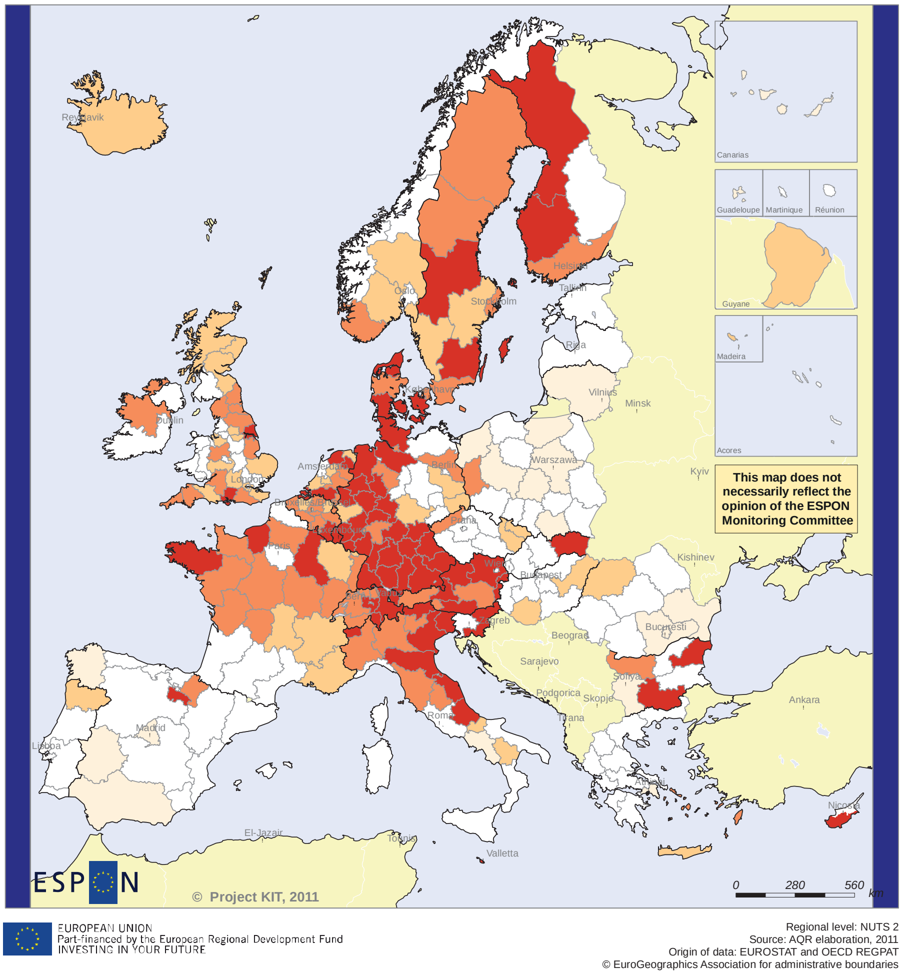
Dep. Var.: ln(Patents)$_t$ ‡	(1) Pooled OLS	(2) Pooled OLS	(3) Pooled OLS
ln(RD)$_{t-1}$	0.85***	0.75***	0.83***
	(0.02)	(0.02)	(0.02)
ln(HK)$_{t-1}$	0.23***	0.17***	0.16**
	(0.06)	(0.06)	(0.06)
ln(POP)$_{t-1}$	-0.25***	0.01	-0.12**
	(0.06)	(0.06)	(0.06)
EU15*(I.M.R.)$_{t-1}$	-0.93***		
	(0.32)		
New Entrants*(I.M.R.)$_{t-1}$	-0.21		
	(0.56)		
EFTA*(I.M.R.)$_{t-1}$	-7.64***	7.42***	
	(2.74)	(2.76)	
Convergence*(I.M.R.)$_{t-1}$		-1.19***	
		(0.27)	
Transition*(I.M.R.)$_{t-1}$		2.23**	
		(0.97)	
Competitive*(I.M.R.)$_{t-1}$		12.09***	
		(0.91)	
Creative imitation*(I.M.R.)$_{t-1}$			-1.78***
			(0.37)
Smart and creative*(I.M.R.)$_{t-1}$			-0.58
			(0.43)
Smart Techno.*(I.M.R.)$_{t-1}$			2.33***
			(0.82)
Applied science* (I.M.R.)$_{t-1}$			5.82***
			(0.89)
Science-Based* (I.M.R.)$_{t-1}$			7.27***
			(1.63)
ln(Cross-regional patents)$_{t-1}$ ‡	0.29***	0.26***	0.27***
	(0.02)	(0.02)	(0.02)
Controls[(1)]	yes	Yes	yes
Constant	5.29***	1.71**	3.57***
	(0.72)	(0.72)	(0.70)
Observations	1,722	1,722	1,722
Number of Regions	287	287	287
Adjusted R2	0.854	0.870	0.859

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1)**Control variables include**: ln(SpecIn)$_{t-1}$; ln(ConIn)$_{t-1}$ (Share_Chemistry)$_{t-1}$; (Share_Biotechnology)$_{t-1}$; (Share_Pharmaceuticals)$_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation. Since the Net Migration Rate ranges [-1,1], we avoid the logarithmic transformation of all the cross-regional mobility variables. In consequence, their sign and significance can be fairly informative, but any interpretation of their magnitude should be treated with caution.

Table 8. Regional extra-local co-patents by typologies.

Dep. Var.: $ln(Patents)_t$ ‡	(1) Pooled OLS	(2) Pooled OLS	(3) Pooled OLS
$ln(RD)_{t-1}$	0.84***	0.76***	0.83***
	(0.03)	(0.03)	(0.02)
$ln(HK)_{t-1}$	0.27***	0.17**	0.17***
	(0.07)	(0.06)	(0.07)
$ln(POP)_{t-1}$	-0.17***	0.06	-0.06
	(0.07)	(0.07)	(0.06)
(Inward Migration Rate) $_{t-1}$	-0.29	0.14	-0.32
	(0.30)	(0.29)	(0.29)
EU15*ln(Cross-regional pat.) $_{t-1}$	0.12***		
	(0.03)		
New Entrants*ln(Cross-regional pat.) $_{t-1}$	0.03		
	(0.03)		
EFTA* ln(Cross-regional pat.) $_{t-1}$	0.03	0.34***	
	(0.09)	(0.09)	
Convergence* ln(Cross-regional pat.) $_{t-1}$		-0.03	
		(0.02)	
Transition* ln(Cross-regional pat.) $_{t-1}$		0.16***	
		(0.05)	
Competitive* ln(Cross-regional pat.) $_{t-1}$		0.38***	
		(0.04)	
Creative imitation*ln(Cross-regional pat.) $_{t-1}$			-0.01
			(0.03)
Smart and creative* ln(Cross-regional pat.) $_{t-1}$			-0.00
			(0.03)
Smart Techno.* ln(Cross-regional pat.) $_{t-1}$			0.14***
			(0.04)
Applied science* ln(Cross-regional pat.) $_{t-1}$			0.31***
			(0.04)
Science-Based* ln(Cross-regional pat.) $_{t-1}$			0.26***
			(0.05)
Controls(1)	yes	Yes	yes
Constant	4.59***	1.65**	3.18***
	(0.77)	(0.79)	(0.74)
Observations	1,722	1,722	1,722
Number of Regions	287	287	287
Adjusted R2	0.841	0.851	0.848

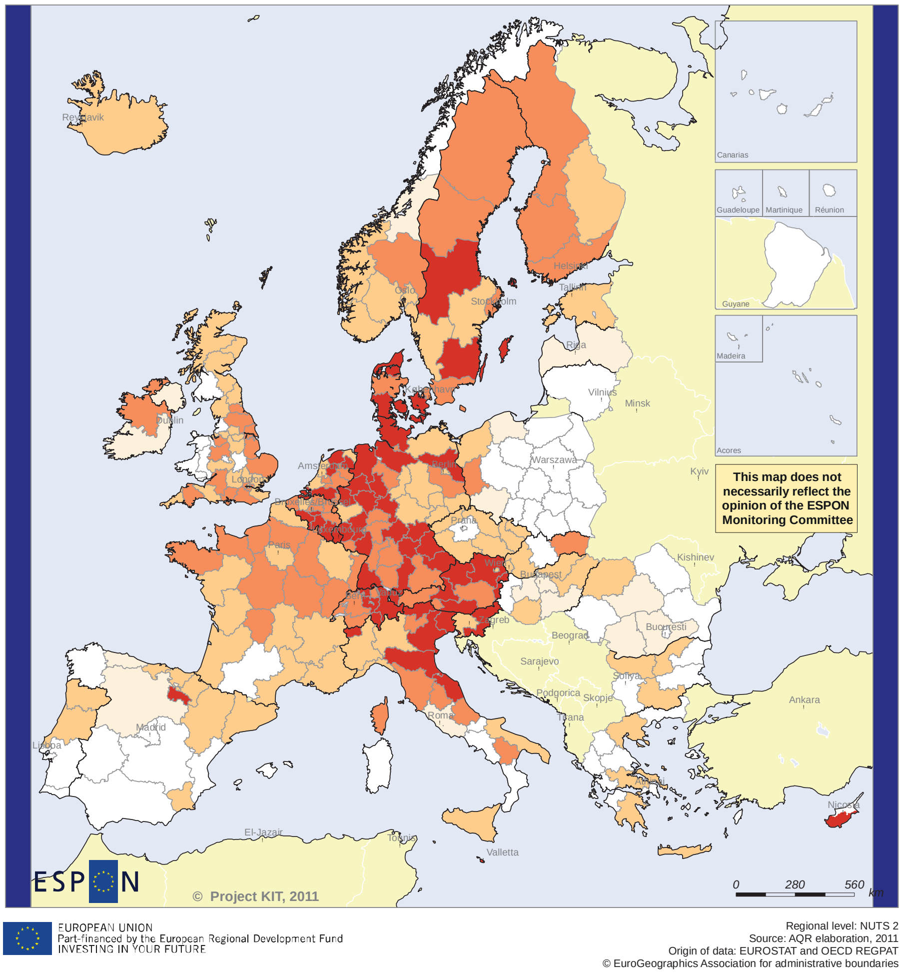
Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. (1)**Control variables include**: $ln(SpecIn)_{t-1}$; $ln(ConIn)_{t-1}$ $(Share\_Chemistry)_{t-1}$; $(Share\_Biotechnology)_{t-1}$; $(Share\_Pharmaceuticals)_{t-1}$. ‡ We added 0.01 to these variables before the logarithmic transformation. Since the Net Migration Rate ranges [-1,1], we avoid the logarithmic transformation of all the cross-regional mobility variables. In consequence, their sign and significance can be fairly informative, but any interpretation of their magnitude should be treated with caution.



Mobility impact on knowledge

- No impact
- Very low elasticity
- Low elasticity
- Medium elasticity
- High elasticity

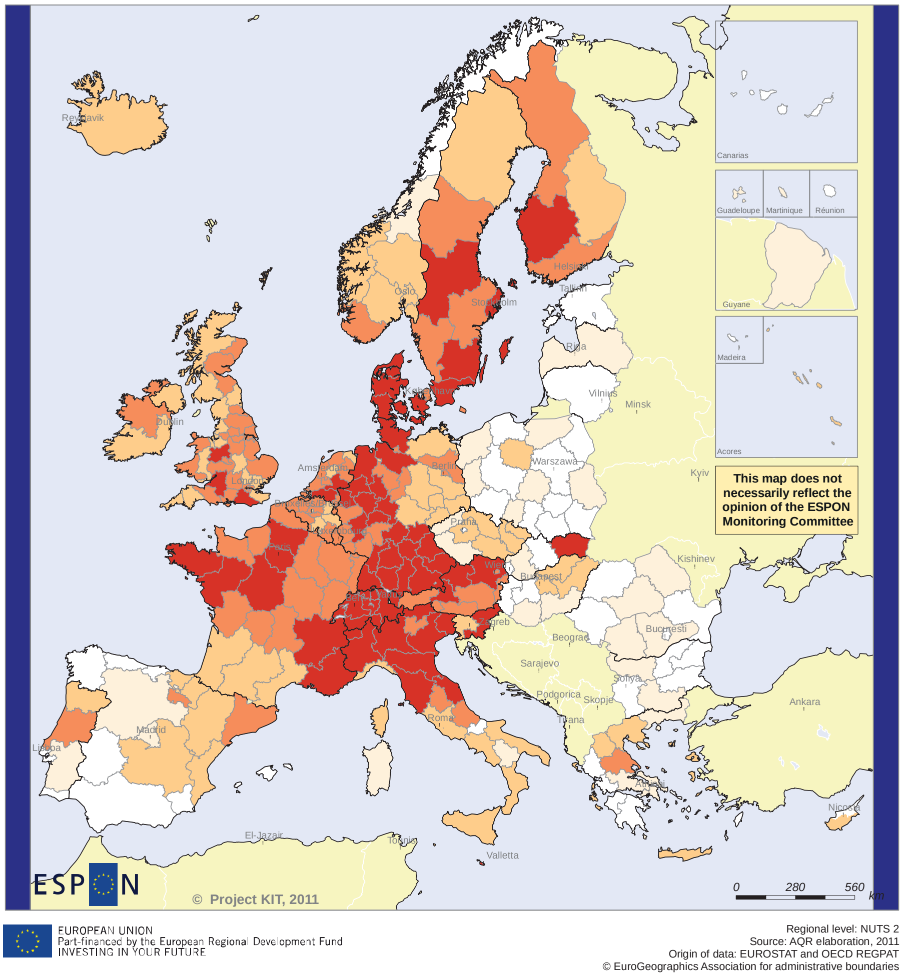
Figure 1. Elasticity of mobility on knowledge



Connectivity impact on knowledge

- No impact
- Very low elasticity
- Low elasticity
- Medium elasticity
- High elasticity

Figure 2. Elasticity of connectivity on knowledge



Average degree centrality impact on knowledge

- No Impact
- Very low elasticity
- Low elasticity
- Medium elasticity
- High elasticity

Figure 3. Elasticity of degree centrality on knowledge

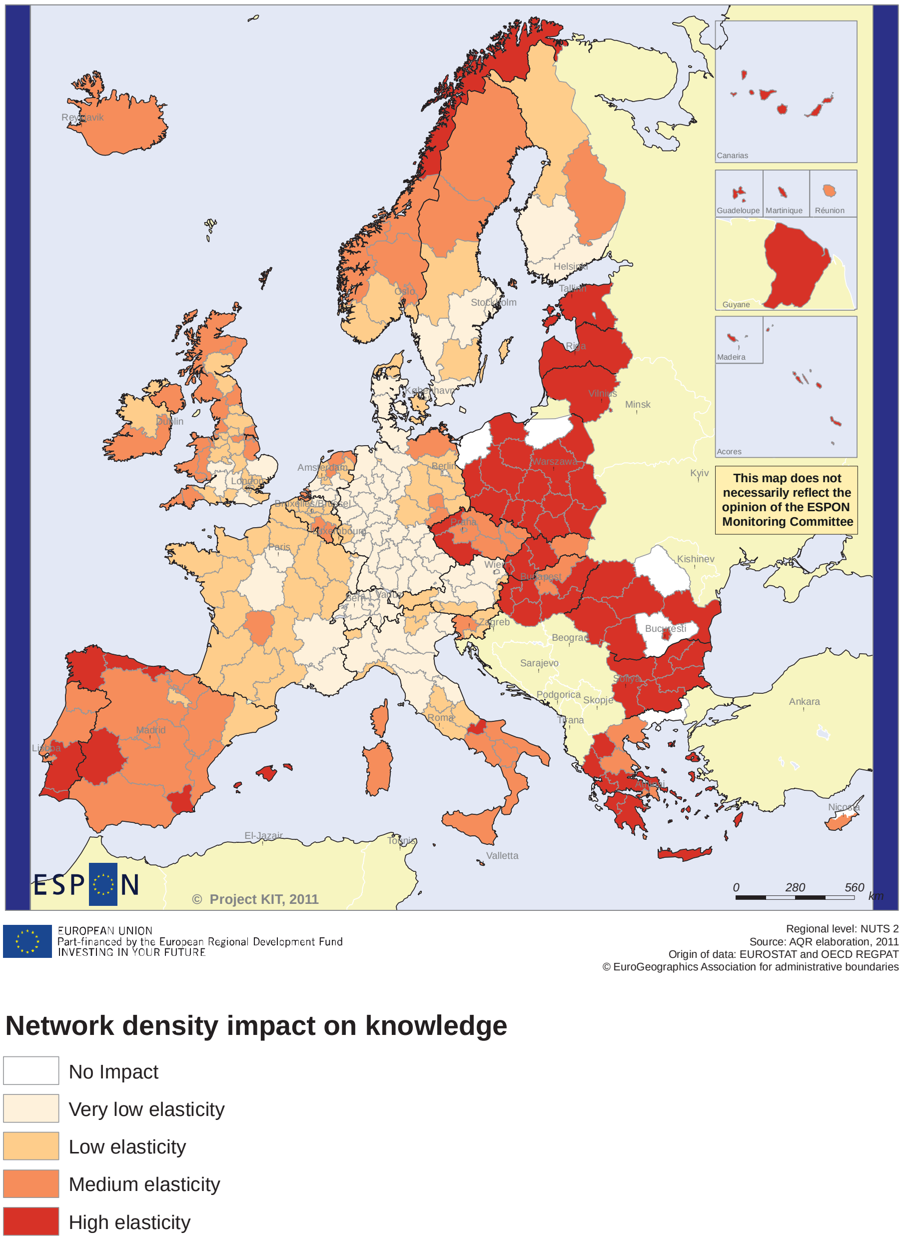


Figure 4. Elasticity of network density on knowledge

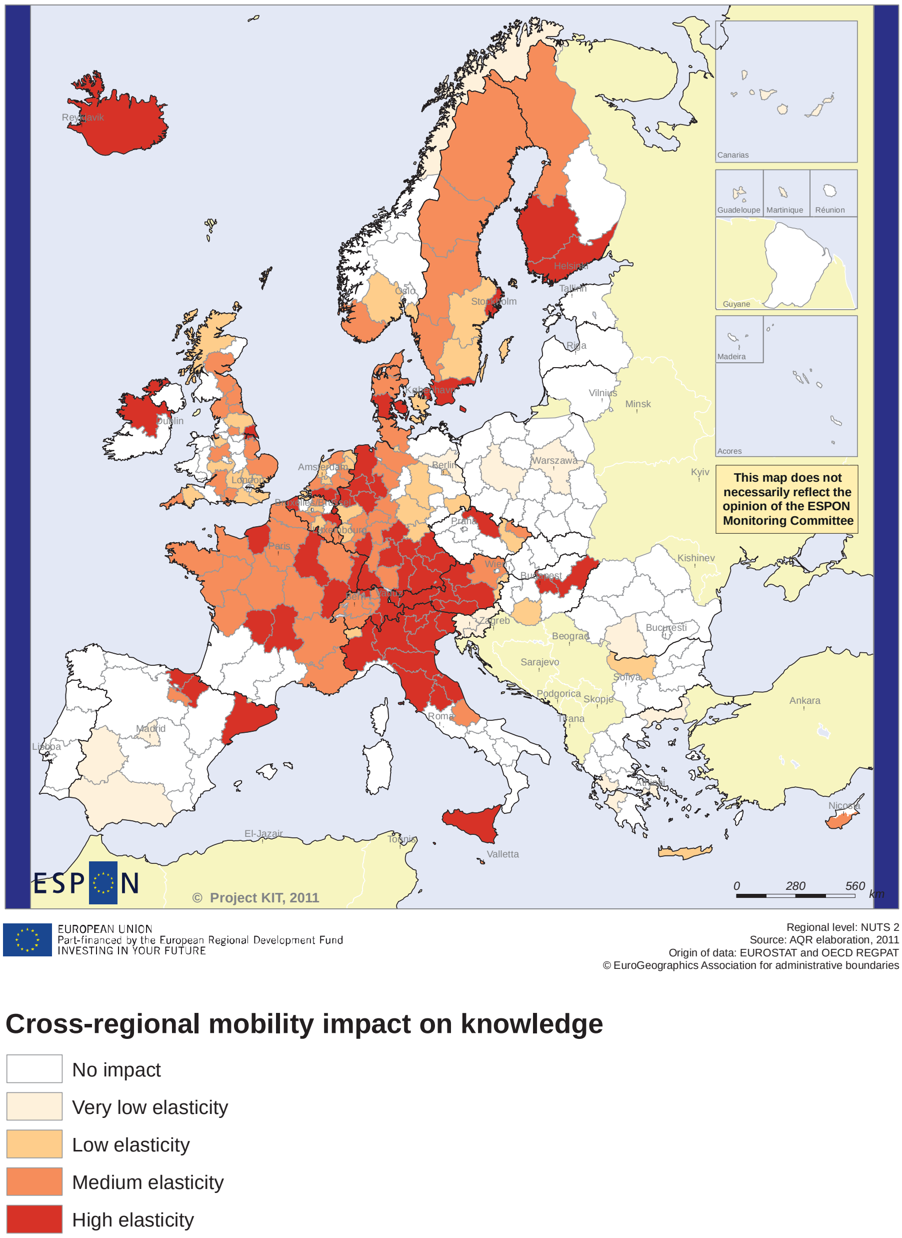
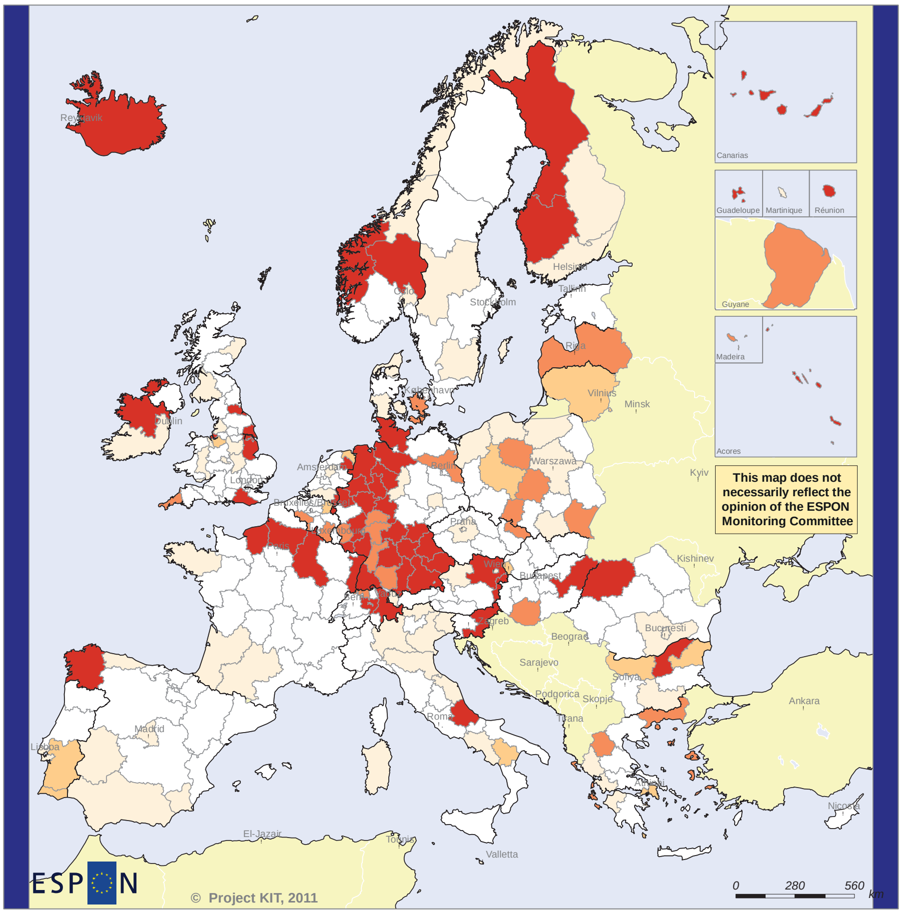


Figure 5. Elasticity of cross-regional mobility on knowledge



EUROPEAN UNION
Part-financed by the European Regional Development Fund
INVESTING IN YOUR FUTURE

Regional level: NUTS 2
Source: AQR elaboration, 2011
Origin of data: EUROSTAT and OECD REGPAT
© EuroGeographics Association for administrative boundaries

Cross-regional research network impact on knowledge

- No impact
- Very low elasticity
- Low elasticity
- Medium elasticity
- High elasticity

Figure 6. Elasticity of cross-regional research network on knowledge