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Knowledge creation in Europe along time: Indirect impact of high-skilled workers mobility and research networks

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KNOWLEDGE CREATION IN EUROPE ALONG TIME: INDIRECT IMPACT OF HIGH-SKILLED WORKERS MOBILITY AND RESEARCH NETWORKS

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Abstract

The aim of this paper is to investigate the relative contribution of different features of the local labour market for inventors on regional patenting, both direct and indirectly. By means of a knowledge production function and a sample of 276 European regions, in a first part of the paper we assess whether local labour mobility of inventors, as well as the scale and extent of their collaborative research networks, correlate with innovation outcomes. Additionally, in a second part of the paper, we extend the analysis to the role of inventors mobility and research networks allowing for higher returns of knowledge endowments on regional innovation.

Key words: inventors' mobility, networks of co-inventors, knowledge production function, European regions

JEL: J61, O31, O33, R1

1. Introduction

The goal of this paper is to analyse the contribution made by research networks and geographical mobility of inventors to the process of knowledge creation. In addition to this direct impact, in the second part of the paper, we extend the analysis to the role of inventors mobility and research networks allowing for higher returns of knowledge endowments on regional innovation, in other words, an indirect impact. To this end, we extend the typical regional KPF to the inclusion of such features of the local labour market, which are likely to explain the spatial heterogeneity in patent production across 276 European regions in a panel data framework.

Contrary to what is customary in this literature, we make use of a longitudinal dataset and estimate a fixed-effects model which allows us to control for a number of unobservable time-invariant confounders that might bias our results if not included. In addition, we extend previous empirical works by including a large sample of 287 NUTS2[1] regions of 31 European countries (EU-27 plus Norway, Iceland, Liechenstein and Switzerland) for the period 2001 to 2006. Besides, by drawing on patent data and standardized heuristics to identify individual inventors, a large dataset of individuals containing information regarding their personal address, their patenting history, or the co-authors of their patents –among other details, was constructed and used to build our main variables under scrutiny.

The rest of the paper is organized as follows: section 2 reviews the literature on knowledge diffusion, space, and innovation, as well as inventors' networks and mobility, and suggests our main hypotheses under examination. In section 3 we present a testable empirical model; section 4 presents the data; whilst section 5 includes the results. Finally, section 6 presents the conclusions and identifies certain limitations in the approach.

[1] NUTS stands for the French acronym "*nomenclature d'unités territoriales statistiques*", and refers to administrative divisions within Europe devised for statistical purposes.

2. Background and present contributions

2.1 The direct role of research networks and inventors' mobility

The literature on collaborative research networks in innovation economics has expanded greatly in recent years. Part of this literature has been devoted to explaining the determinants of these collaborative patterns (Hoekman et al. 2009; Maggioni and Uberti 2008), while a further important line has focused on networks as mechanisms for inter-regional R&D spillovers (Kroll 2009; Ponds et al. 2009), and, in particular, networks as the means by which knowledge diffuses between individuals and across firms (Breschi and Lissoni 2004, 2009; Gomes-Casseres et al. 2006; Singh 2005).

Arguably, the features of the inventors' network structure at any given location are likely to play a significant role in regional innovation outcomes. In this sense, a number of macro-level empirical analyses have recently been conducted in a KPF framework by Bettencourt et al. (2007), Fleming et al. (2007) and Lobo and Strumsky (2008) for the case of US metropolitan statistical areas. These studies have shown, however, that the agglomeration of inventors is much more critical in explaining regional innovation rates than structural properties of inventors' networks, such as the 'small world' configuration –which combines low average path length among individuals in a network and high levels of clustering, and which has been identified to be innovation-prone (Watts and Strogatz 1998; Cowan and Jonard 2004). Breschi and Lenzi (2011), by contrast, find 'small world' properties to be positively correlated with MSA's rates of innovation. The present paper's aim is rather different, though, since it does not attempt to appraise 'small world' properties' impact on regional innovation, but the general degree of connectivity through networks of research collaboration as well as the strength of these networks.

The rationale behind the study of networks in regional science and innovation studies rely on the idea that networks of inventors definitely influence innovation. The motivation supporting this statement is manifold (Katz and Martin 1997): first of all, the simple cross-pollination of previously unconnected ideas will lead to better knowledge outputs. Second, the need to benefit from others' tacit knowledge and technology increases the desire to collaborate. Third, the current complexity of new inventions, which requires more and more frontier knowledge, division of labour and scientific/technological specialization of manpower, and larger levels of funding, in order to achieve significant advances and valuable inventions. Finally, technological specialized machinery is usually expensive and collaborations might be an opportunity to share its costs among the partners involved. Moreover, collaborative research projects may achieve scale economies and may lessen research costs by reducing duplication of efforts and decreasing uncertainty among the participants in the network (Powell and Grodal 2005).[2] Given these arguments, we aim to test empirically whether, in the Spanish case, the more inventors involved in networks of collaboration, the larger the number of local patents and whether the more connected, on average, are the local inventors, the larger the number of patents produced

The literature addressing the relationship between skilled labour mobility and knowledge diffusion and subsequent innovation is vast (see pioneering studies by Arrow, 1962; Rosen, 1972; or Stephan, 1996). Related to the present paper, more recent studies have examined how the labour mobility of inventors acts as a key mechanism in the cross-fertilization of previously unconnected ideas, enhancing firms' and individuals' innovation rates (Almeida and Kogut 1999; Rosenkopf and Almeida 2003; Saxenian 1994). Skilled workers take their knowledge with them and share it in a new workplace with their new colleagues, at the same time as they provide their new employer with this knowledge. In return, they acquire new knowledge from their new colleagues, establish new links and social networks for future collaborations based on trust and, in general, promote new combinations of ideas (Laudel 2003). For example, in a pioneering study, Almeida and Kogut (1999) show that inter-firm mobility of patent holders in the semiconductor industry of the US influences the local transfer of knowledge across firms. Similar findings are reported in a study conducted by Breschi and Lissoni (2009) for US inventors in selected technological fields.

On the other hand, recent studies have shown that mobile inventors are more productive than their non-mobile counterparts, as measured either by patent applications or citations received to their work (Hoisl 2007, 2009; Lenzi 2009; Singh and Agrawal 2011). Among other things,

[2] We are aware about an important debate within the literature on whether the strength of social ties matters for innovation (Granovetter, 1973) and the detrimental role of too much social proximity (socially embedded relations between actors) for knowledge diffusion and innovation due to the problem of lock-in (Boschma, 2005; Uzzi, 1997). The present inquiry does not, however, enter this debate and, as such, we prefer to leave this discussion and potential empirical analysis for further research.

local labour mobility of high human capital improves the match employer-employee quality, which in turn implies efficiency gains, enhanced firms' and inventors' productivity and in consequence increased firms' and inventors' innovation rates (see, for instance, Jovanovic, 1979; Liu, 1986 and Topel and Ward, 1992). Hence, communities of inventors with larger degrees of labour mobility are expected to be more productive and innovation intensive.

Based on the above considerations, one main contribution of the present analysis is to quantify how the degree of job-to-job mobility of the local labour market of skilled individuals impacts on regional innovation outputs. Accordingly, we also aim to find empirical evidence on whether labour mobility of inventors in the local labour market is a positive, significant predictor of the number of local patents

2.2 The indirect impact of inventors' mobility and research networks

We turn now to investigate the specific role of our foci variables, not only as an knowledge creation mechanism, but also as knowledge diffusion mechanisms. It is commonplace in the related literature that close network links should prove more useful in transferring complex knowledge (Cowand and Jonard, 2004), especially that with a high component of 'tacitness' (Singh, 2005). Similarly, individuals connected within a collaborative framework are more willing to learn from each other than is the case of isolated inventors. Additionally, participating in networks reduces the degree of uncertainty and provides fast access to different kinds of knowledge. All this would signal to the fact that belonging to a research network may imply higher returns of knowledge endowments, such as R&D and human capital investments, on regional innovation.

On the other hand, mobility may favour knowledge diffusion as well. Knowledge, especially that of tacit nature, is mostly embedded in individuals. Moving themselves means moving the knowledge capital they accumulate. Their movement across firms must therefore contribute to knowledge exchange between firms (Boschma et al., 2009). Skilled workers take their knowledge with them and share it in a new workplace with their new colleagues, at the same time as they provide their new employer with this knowledge. In return, they acquire new knowledge from their new colleagues, establish new links and social networks for future collaborations based on trust and, in general, promote new combinations of knowledge

(Laudel, 2003; Trippl and Maier 2007). Therefore, the return obtained from the investments in R&D and human capital may increase with the level of mobile workers.

As a second objective in this paper, we want to provide evidence on this indirect impact of inventors' mobility as well as research networks.

3. Research design

In order to meet the goals identified in previous sections, the KPF framework at the regional level is used. Our point of departure is the simplest specification of this model:

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

where Y is the innovative 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 innovation outcomes, Z includes 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, extent and scope 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 innovation. In additional, e^{δ_i} stands for 276 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 innovation, technology-oriented regional policies, inherited skills of the local community, prestige of research and higher education institutions, inherited innovation culture, social capital and, in general, all the historical path-dependent features that may importantly affect spatial differences in innovation rates.

3.1 Labour mobility, research networks and innovation: direct impact

In the present paper, social network analysis (SNA) tools are employed to investigate empirically the quantitative relationship between inventors' collaborations and levels of inventiveness.[3] 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-innovations is beneficial for regional innovation. Finally, the degree of labour mobility within the region is also included. Thus,

$$Z_{it} = g(MOB_{it}, DEGREE_{it}, INCLUS_{it}, X_{i}), \tag{3}$$

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, and $INCLUS$ stands for inclusiveness of the local network, that is, the overall connectivity of the local network. In addition, 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:

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

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 to lessen endogeneity concerns due to system feedbacks. In (4), the coefficients ω measure changes in the response variables due to changes in our focal and control variables. Section 4 includes further details regarding the construction of all the variables used in the present analysis. In order to consider deviations from the theory, a well-behaved error term is also introduced, ε_{it}.

[3] 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 paper. 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).

3.2 Indirect impact of inventor's mobility and research networks

To address this issue, we allow now the coefficient of both R&D and human capital in equation (4) to be a function of a constant part, which can be identified as the direct impact on knowledge, and an additional element which is a function of one of the characteristics of the local labour market (we are reluctant to include the resulting interactions in the same equation in order to minimize collinearity problems). Thus,

$$\beta = \lambda_0 + \lambda_1 \cdot F_{it-1} \text{ and } \gamma = \tau_0 + \tau_1 \cdot F_{it-1} \tag{5}$$

where F stands for each of the variables included in the main model, that is, labour mobility, two measures of research networks, and network density. Therefore, (4) includes now interaction effects between R&D and each of the 4 foci variables in the main model, running 4 different estimations for each of the interactions included, as well as interactions between human capital and again our 4 variables under analysis:

$$\begin{aligned} \ln Y_{it} &= \theta + \lambda_0 \cdot \ln RD_{it-1} + \lambda_1 \cdot (F_{it-1} \cdot \ln RD_{it-1}) + \tau_0 \cdot \ln HK_{it-1} + \tau_1 \cdot (F_{it-1} \cdot \ln HK_{it-1}) \\ &+ \rho \cdot \ln POP_{it-1} + \omega_1 \cdot MOB_{it-1} + \omega_2 \cdot \ln DEGREE_{it-1} + \omega_3 \cdot CONN_{it-1} + \omega_4 \cdot \ln DENS_{it-1} + \\ &+ \omega_n \cdot \ln X_{it-1} + \delta_i + \varepsilon_{it} \end{aligned} \tag{6}$$

4. Data and variables construction

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,

$$\mathrm{CONN}_{it} = \frac{\mathrm{Q}_{it} - \mathrm{NQ}_{it}}{\mathrm{Q}_{it}}, \qquad (7)$$

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,

$$DENS_{it} = \frac{T_{it}}{Q_{it}(Q_{it}-1)/2}, \qquad (8)$$

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 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[4] 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

$$SpIn_{it} = \frac{1}{2}\sum_{j}\left|\frac{PAT_{ijt}}{PAT_{it}} - \frac{PAT_{Cjt}}{PAT_{Ct}}\right|, \qquad (9)$$

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:

$$ConIn_{it} = \sum_{jt}\left(PAT_{ijt} / PAT_{jt}\right)^{2}. \qquad (10)$$

[4] International Patent Classification.

Three additional controls capture differences in technological content across regions: the shares of biotechnology (BIOTECH), organic chemistry (CHEM), and pharmaceuticals (PHARMA) in their patenting activity, according to the IPC classification - since these three sectors tend to be more research intensive.[5,6]

5. Results

5.1 Results on the direct impact of research networks and labour mobility

Table 1 provides estimates for the regional KPF model. Column (1) of 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

[5] Although overall employment in these sectors would be a better proxy, these data are not available.
[6] 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.

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]

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, we turn next to their indirect impact.

5.2. Results on the indirect impact of labour mobility and research networks

As discussed in the research design section, there are theoretical arguments supporting the existence of indirect effects of networking and labour mobility due to knowledge diffusion. As a consequence, belonging to a research network would imply higher returns to the investments made in R&D and human capital, whereas their returns would also increase with the level of mobile workers.

The results provided in columns (2) to (5) of Table 1 gives insights with respect to these hypotheses through the introduction of cross-effects between these two variables (labour mobility and networks) and R&D.

Specifically, we do obtain that regions with higher number of individuals connected within a research network (measured through the average degree centrality measure) may obtain higher returns to R&D investments, probably due to the fact that its inventors are more prone to learn from each other, with faster access to new and complement knowledge. However, when the cross-effect is computed with the index of connectivity degree, no significant parameter is obtained. Additionally, it seems that the density of the network does not imply a reduction of the R&D return, so that we can conclude that even with highly dense networks, researchers belonging to networks may obtain higher returns from the investments made in innovation than in the case of isolated inventors.

However, the parameter for the cross-effect between R&D and labour mobility is not significant. We have, therefore, not obtained evidence that in regions with high levels of mobile workers, the investment made in R&D is more profitable that in those with lower levels of labour mobility.

We now turn to analysing the reinforcing effects of networks and mobility on human capital investments returns on patent production. Results provided in Table 2 offer similar conclusions than the ones above. What is more, all the interactions between human capital and our four focal variables are positive and significant, indicating the importance of these features to enhance human capital externalities in regions and their impact on local inventiveness levels.

[Insert Table 2 about here]

6. Conclusions, implications and limitations

In short, we find that both mobility and networks (within and between regions) explain a sizeable part of the spatial heterogeneity of innovation rates. From a policy perspective, these results illustrate that, not only R&D and human capital efforts are important to generate innovations, but also the *embeddedness* of agents in their local networks of alliances and mobility, as well as their degree of *connectedness* with the outside world. Further, it is precisely the concepts of *embeddedness* and *connectedness* which are in the core of the *smart specialisation* strategy recently launched by the European Commission (McCann and Ortega-Argilés 2011).

In practical terms, the results encountered in this paper provide additional evidence on the role that socioeconomic conditions plays to enhance regional innovation rates. Thus, policies aimed to increase the polarisation and concentration of innovation activities in the space in order to benefit from economies of scale may fail to achieve satisfactory results if the specific economic tissue of regions is not properly taken into consideration.

It should be borne in mind, however, that certain methodological limitations may affect our results, the most important one being inconsistent estimates due to endogeneity problems. Lagging variables of the right hand side of the models seeks to reduce endogeneity problems due to system feedbacks. However, the omission of other relevant variables might importantly bias our result. Admittedly, suitable instruments have still to be found for the explanatory variables, and so further research along these lines must first be undertaken.

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Table 1. Direct impact as well as interaction with RD. Regional networks and regional mobility.

Dep. Var.: ln(Patents)$_t$ ‡	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE
ln(RD)$_{t-1}$	0.19***	0.20***	0.16**	0.19**	0.40***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.13)
ln(HK) $_{t-1}$	0.50***	0.50***	0.46***	0.50***	0.50***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
ln(POP) $_{t-1}$	-0.19	-0.16	-0.45	-0.19	-0.02
	(0.81)	(0.82)	(0.81)	(0.81)	(0.82)
(Mobility) $_{t-1}$	0.01***	0.01*	0.01***	0.01***	0.01***
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
ln(Average Degree) $_{t-1}$ ‡	0.04*	0.04*	-0.13***	0.04*	0.04*
	(0.02)	(0.02)	(0.05)	(0.02)	(0.02)
(Connectivity Degree) $_{t-1}$	0.02***	0.02***	0.01***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
ln(Network Density) $_{t-1}$ ‡	-0.18***	-0.18***	-0.17***	-0.18***	-0.32***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.08)
ln(SpecIn) $_{t-1}$ ‡	0.02	0.02	0.00	0.02	0.03
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
ln(ConIn) $_{t-1}$ ‡	-0.03	-0.03	-0.04	-0.03	-0.03
	(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)
ln(RD)$_{t-1}$* (Mobility) $_{t-1}$		-0.00			
		(0.00)			
ln(RD)$_{t-1}$* ln(Average Degree) $_{t-1}$			0.06***		
			(0.02)		
ln(RD)$_{t-1}$*(Connectivity Degree) $_{t-1}$				0.00	
				(0.00)	
ln(RD)$_{t-1}$* ln(Network Density) $_{t-1}$					0.05*
					(0.03)
Constant	1.56	1.10	5.42	1.58	-1.34
	(11.21)	(11.26)	(11.20)	(11.23)	(11.31)
Observations	1,722	1,722	1,722	1,722	1,722
Number of Regions	287	287	287	287	287
R2 within	0.1408	0.1409	0.1500	0.1408	0.1429
R2 between	0.7706	0.7639	0.7686	0.7704	0.7019
R2 overall	0.7474	0.7415	0.7421	0.7472	0.6830

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. Interaction with HK.

Dep. Var.: ln(Patents)$_t$ ‡	(1) FE	(2) FE	(3) FE	(4) FE
ln(RD)$_{t-1}$	0.17**	0.14**	0.22***	0.17**
	(0.07)	(0.07)	(0.07)	(0.07)
ln(HK)$_{t-1}$	0.46***	0.45***	0.62***	1.28***
	(0.10)	(0.10)	(0.11)	(0.20)
ln(POP)$_{t-1}$	-0.08	-0.36	-0.19	-0.17
	(0.82)	(0.81)	(0.81)	(0.81)
(Mobility)$_{t-1}$	-0.01	0.00	0.01***	0.00
	(0.01)	(0.00)	(0.00)	(0.00)
ln(Average Degree)$_{t-1}$ ‡	0.03	-0.33***	0.03	0.05**
	(0.02)	(0.08)	(0.02)	(0.02)
(Connectivity Degree)$_{t-1}$	0.02***	0.01***	0.04***	0.01***
	(0.00)	(0.00)	(0.01)	(0.00)
ln(Network Density)$_{t-1}$ ‡	-0.19***	-0.19***	-0.18***	-0.94***
	(0.04)	(0.04)	(0.04)	(0.18)
ln(SpecIn)$_{t-1}$ ‡	0.03	0.00	0.04	-0.03
	(0.11)	(0.11)	(0.11)	(0.11)
ln(ConIn)$_{t-1}$ ‡	-0.03	-0.01	-0.03	-0.02
	(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)
(% Biotechnology)$_{t-1}$	-0.01***	-0.01***	-0.01***	-0.01***
	(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)
ln(HK)$_{t-1}$* (Mobility)$_{t-1}$	0.00*			
	(0.00)			
ln(HK)$_{t-1}$* ln(Average Degree)$_{t-1}$		0.10***		
		(0.02)		
ln(HK)$_{t-1}$*(Connectivity Degree)$_{t-1}$			0.01**	
			(0.00)	
ln(HK)$_{t-1}$* ln(Network Density)$_{t-1}$				0.18***
				(0.04)
Constant	0.11	4.47	0.93	-1.54
	(11.23)	(11.15)	(11.19)	(11.16)
Observations	1,722	1,722	1,722	1,722
Number of Regions	287	287	287	287
R2 within	0.1427	0.1528	0.1440	0.1523
R2 between	0.7353	0.7080	0.7919	0.7168
R2 overall	0.7148	0.6813	0.7691	0.6941

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.