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MOBILITY, NETWORKS AND INNOVATION:
THE ROLE OF REGIONS' ABSORPTIVE CAPACITY

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Abstract
The purpose of this paper is to assess the extent to which regions' absorptive capacity determines knowledge flows' impact on regional innovation intensity. In particular, it looks at the role of the cross-regional co-patenting and mobility of inventors in fostering innovation, and how regions with large absorptive capacity make the most of these two phenomena. The paper uses a panel of 274 regions over 8 years to estimate a regional knowledge production function with fixed-effects. Network and mobility variables, and interactions with regions' absorptive capacity, are included among the r.h.s. variables to test the hypotheses. We find evidence of the role of both mobility and networks. However, inflows of inventors are critical for wealthier regions, while have more nuanced effects for less developed areas. It also shows that regions' absorptive capacity critically adds an innovation premium to the benefits to tap into external knowledge pools. Indeed, the present study corroborates earlier work on the role of mobility and networks for spatial knowledge diffusion and subsequent innovation. However, it clearly illustrates that a certain level of technological development is critical to take advantage of these phenomena, and therefore "one-size-fits-all" innovation policies need to be reconsidered.

Keywords: absorptive capacity, inventor mobility, spatial networks, patents, regional innovation
Article Classification: Research paper

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1. Introduction

Launched by the Lisbon Agenda back in 2000, the European Research Area (ERA) initiative is also meant to be at the heart of the European Union's (EU) 2020 growth strategy. Through the ERA, the EU aims at building an integrated pan-European research and innovation system, which enables and facilitates "free circulation of researchers, knowledge and technology" across national borders (European Commission, 2008, p.4). Thus, at the roots of the ERA, the European Commission has encouraged, among others, the promotion of "greater mobility of researchers" within the continent, "improving the attraction of Europe for researchers from the rest of the world", "networking of existing centres of excellence in Europe", and "closer relations between the various organisations of scientific and technological cooperation in Europe" (European Commission, 2000, p.8).

Two key elements stand out from the ERA documentation: the inter-regional and international mobility of scientists and engineers, and the formation of networks of scientific and technological collaboration. The emphasis on these two elements is hardly surprising. A fundamental observation of knowledge diffusion is that it tends to be highly localized in space (Hippel, 1994; Jaffe et al., 1993; Nelson & Winter, 1982). Undeniably, the implications of this for the most peripheral European regions are important – i.e., the sticker the knowledge, the lower the peripheral territories will access it (Rodriguez-Pose & Crescenzi, 2008). Skilled mobility and networks become critical to overcome the spatial stickiness of knowledge. Theoretical and empirical evidence in support of a relation between high-skilled workers mobility and knowledge diffusion is extensive (Almeida & Kogut, 1999; Arrow, 1962; Boschma et al., 2009; Magnani, 2006; Oettl & Agrawal, 2008; Rosenkopf & Almeida, 2003; Singh & Agrawal, 2011; Stephan, 1996). When skilled workers move, they take their embodied knowledge with them, and firms learn about other firms' research after employing these high-skilled employees. Further, when they move from place to place, their knowledge and skills move as well, and geographical knowledge diffusion occurs (Breschi et al., 2010; Coe & Bunnell, 2003). Networks are also critical means to diffuse knowledge and promote the cross-pollination of ideas (Katz & Martin, 1997). As stated by Bathelt et al. (2004) and Owen-Smith & Powell (2004), firms in regions build 'pipelines' in the form of alliances to benefit from knowledge hotspots around the world. Again, empirical evidence in support of networks as vehicles for the dissemination of ideas is large (Breschi &

Lissoni, 2009; Cowan & Jonard, 2004; Gomes-Casseres et al., 2006; Simonen & McCann, 2008; Singh, 2005).

Understanding the way in which spatial mobility of high-skilled employees and geographical networks interact with knowledge diffusion and subsequent regional innovation production is critical to effectively build a coherent ERA and promote regional economic growth and cohesion. In this respect, empirical evidence has also established a strong link between networks and mobility, on the one side, and regional innovation, on the other, both within (Fleming et al., 2007; Lobo & Strumsky, 2008; Miguélez & Moreno, 2011) and across regions (Miguélez & Moreno, 2013a, 2013b; Ponds et al., 2010). This latter evidence has also motivated a number of papers looking at the determinants of these two phenomena (Chessa et al., 2013; Hoekman et al., 2009; Hoekman, Frenken, & Tijssen, 2010; M. A. Maggioni, Nosvelli, & Uberti, 2007; M. Maggioni & Uberti, 2009; Miguélez & Moreno, 2013c; Morescalchi et al., 2013). Broadly speaking, they find that distance and geographical peripherality, and particularly, regions' overall economic performance and country borders, explain a substantial part of the variation of both geographical networks and spatial mobility of skilled personnel and determine the effective construction of the ERA.

The present paper contributes to this literature. In particular, we estimate a regional knowledge production function (KPF) in a panel data framework, for the case of 274 European regions of 27 countries, from 2000 to 2007. We include among our explanatory variables measures of high-skilled workers geographical mobility – i.e., inventors – and cross-regional networks – co-inventions.

A second contribution of the present paper deals with the differentiated effects of networks and mobility on regional innovation across groups of regions. This is an important issue, given that one critical ERA aim is to "reduce brain drain, notably from weaker regions, as well as the wide regional variation in research and innovation performance" (European Commission, 2012). In our view, however, this is at odds with the "one-size-fits-all" policy inferred from the *Lisbon 2000* and *Europe 2020* agendas (Camagni & Capello, 2013). If innovation returns to geographical networks and mobility are significantly different, policies aimed to encourage such phenomena – e.g., EU's Framework Programmes or Marie Curie Actions – need to be redefined and adapted to each region's specificities – which is precisely at the heart of the smart specialization initiative (Foray et al., 2009). We investigate this issue by making use of two ad-hoc regional typologies in Europe, one based on space (EU accession date) and one based on economic development (based on EU's Cohesion Policy classification of regions according to different economic policy objectives).

Finally, the main hypothesis of this paper states that regions' absorptive capacity determines networks and mobility returns to innovation. Innovation is an evolutionary and cumulative process. In consequence, only with the necessary capability to identify, assimilate and develop useful external knowledge can the host regions effectively benefit from incoming technology flows through research networks and labour mobility. As discussed by Cohen & Levinthal (1990), the differential impact of external incoming knowledge flows depends mainly on firms' absorptive capacity. In the present inquiry, we argue that absorptive capacity is needed to understand and transform inflows of extra-regional knowledge – those that mobility and networks convey – into regional innovation.

Overall, we conclude that both labour mobility of high-skilled workers as well as the participation in research networks are critical means to transmit knowledge as they positively affect the patenting activity of European regions. It seems, though, that this impact is far from being homogeneous across the EU territory, with more developed regions obtaining higher returns from such potentially incoming knowledge flows. When disentangling what makes them more efficient in assimilating and using these knowledge flows, our results point that the absorptive capacity of regions has a main role.

The rest of the paper is organized as follows: in section 2 we present the empirical model and our main hypotheses; section 3 shows the data; whilst section 4 includes the descriptive and econometric results. Finally, section 5 presents the conclusions and implications of our research.

2. Theory and methods

2.1. High-skilled workers mobility, spatial networks and innovation

We test our hypotheses in a regional KPF framework (Anselin et al., 1997; Bottazzi & Peri, 2003; Feldman & Audretsch, 1999; Moreno et al., 2005). In particular, we estimate the following specification:

$$\begin{aligned} \ln PATp.c._{it} &= \beta_0 + \beta_1 \cdot \ln RDp.c._{it-1} + \beta_2 \cdot HK_{it-1} + \beta_3 \cdot \ln PopDens_{it-1} + \\ &+ \beta_4 \cdot PopDens^2_{it-1} + \beta_5 \cdot MOBILITY_{it-1} + \beta_6 \cdot NETWORKS_{it-1} + \delta_i + \varepsilon_{it} \end{aligned} \tag{1}$$

where $PATp.c.$ is the knowledge output of a given region – patents per capita, which depends upon regional R&D expenditures per capita ($RDp.c.$) as well as regional endowments of human capital (HK). Equation (1) includes population density ($PopDens$) to control for agglomeration economies and ensuing localized knowledge spillovers, which may translate into larger productivity and innovation levels (Carlino et al., 2007; Ciccone & Hall, 1996) – while its squared term ($PopDens^2$) accounts for potential nonlinearities due to agglomeration diseconomies existent in excessively large metropolis. In addition, δ_i stands for regional time-invariant fixed-effects (FE), which enable 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, research and higher education institutions, social capital and, in general, all the historical path-dependent features that may importantly affect spatial differences in knowledge production rates. Note that equation (1) includes the subscript t-1 in all the explanatory variables, which indicates that we lag one period all these variables to lessen endogeneity problems due to system feedbacks.

As we sketched in the introductory section, we hypothesize that regions' innovation capability benefits from accessing extra-regional pools of ideas by means of skilled workers' mobility ($MOBILITY$) and bilateral technological linkages ($NETWORKS$). As a proxy for $MOBILITY$, we use the inward migration rate (IMR) – the number of incoming inventors to region i over the number of local inventors in i, as a measure of incoming inflows of high-skilled individuals, in a given time period t.

Alternative mobility variables are computed – running different models for each of the variables in order to avoid collinearity problems. In particular, we include the net migration rate (NMR) – inflows minus outflows to the current number of inventors. Recent studies 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). For instance, Agrawal et al. (2006), Corredoira & Rosenkopf (2010) and Oettl & Agrawal (2008) report disproportionate knowledge flows from inventors leaving a region, a firm or a country back to their former colleagues. Miguelez (2013) shows that European inventors in the biotech industry are more likely to build ties across the space – in the form of co-patents – with their former co-located colleagues than if they had never lived there. Following these ideas, we also test the role of the outward migration rate (OMR) – the outflows of inventors to the local number of inventors. We also include the gross migration rate (GMR) – inflows plus outflows of inventors to the local number of inventors. All else equal, we expect positive and significant coefficients for the IMR, the NMR, and the GMR. Concerning the OMR, the direction of the estimated coefficient might be positive – if the 'brain circulation' hypothesis holds – or negative – if, as largely discussed in the literature, the innovation potential of sending regions is undermined by the lack of innovators (Agrawal et al., 2011).

To investigate the relationship between inventors' *NETWORKS* and regions' inventiveness, we compute, for each region, the average number of co-inventions (co-patents) per inventor with inventors from outside the inventor's focal region. This measure proxies for the extent to which the local pool of inventors is involved in co-patenting with colleagues from other areas. A positive effect on innovation is also expected. Section 3 includes further details regarding the construction of all the variables used in the present analysis.

2.2. Regional heterogeneity in returns

A key issue of the present paper is the analysis of differentiated spatial patterns on the returns to geographical mobility of skilled workers and their cross-regional co-inventorship networks. The underlying idea is that these two mechanisms of geographical knowledge diffusion may not have a homogeneous impact in all regions. In other words, we hypothesize that, quite likely, they yield different results in terms of innovation generation and subsequent economic growth, which in turn ultimately depends on the regions' socio-economic characteristics. If innovation returns to geographical networks and mobility are significantly different, policies aimed to encourage such phenomena – e.g., EU's Framework Programmes or Marie Curie Actions – need to be redefined and adapted to each region's specificities – which is precisely at the heart of the smart specialization strategy.

In order to test this hypothesis, we make use of two ad-hoc regional typologies in Europe, one based on spatial features, and the other one based on economic development conditions. The first one corresponds to the time of accession to the European Union: *EU15*, *EU Enlargement* – which corresponds to the 2004 and 2007 enlargements of the EU (except Malta and Cyprus), and the *EFTA* countries – except Iceland and Liechtenstein[1]. This 3-group typology intends to account for pure spatial heterogeneity in the returns of mobility and networks – e.g., Western-Eastern Europe, core-periphery dichotomy. More importantly, this typology takes on board the different levels of integration into the EU and, as a consequence, the time elapsed during which these regions have enjoyed the benefits arising from the functioning of the Internal Market – specifically related to the diffusion and adoption of new technologies (Manca et al., 2011; Suriñach et al., 2009).

The second regional classification refers to the one made by the Regional Policy of the EU, also referred as Cohesion Policy, which aims at removing economic, social and territorial disparities across the EU. EU's Cohesion Policy covers all European regions, although they fall into different tiers, depending mostly on their level of economic development. Regions under the *Convergence objective* constitute Europe's poorest regions whose per capita GDP is less than 75% of the EU average. This includes nearly all the regions of the new member states, most of Southern Italy, East Germany, Greece and Portugal, South and West of Spain, and Western regions of the United Kingdom (UK). The *Regional competitiveness and employment objective* covers all European regions that are not covered by the Convergence objective. This includes all Denmark, Luxembourg, Netherlands and Sweden, most regions in Austria, Belgium, Finland, France, Germany, North of Italy and the UK, some regions in Ireland and North-East Spain, and one region in the Czech Republic, Hungary, Portugal and Slovakia. Yet, a third tier is considered. With the 2004 and 2007 EU enlargements, the EU average GDP has fallen. As a result, some regions in the EU's "old" member states (EU-15), which used to be eligible for funding under the *Convergence objective*, are now above the 75% threshold. These regions now receive transitional "phasing out" support until 2013. Similarly, regions that used to be covered under the convergence criteria but are now above the 75% EU-15 average per capita GDP are receiving "phasing in" support. We consider the regions receiving *phasing-in* and *phasing-out* support together and separately from the rest. Finally, the regions of Norway and Switzerland (*EFTA*) are grouped together and considered separately from the other tiers.

Our empirical strategy proceeds as follows: we create a dummy variable for each tier under the two typologies. Afterwards, we interact our focal variables (MOBILITY and NETWORKS) with all dummies, separately for the two typologies. Equation (2) exemplifies the method we follow, for the case of the accession typology – for mobility, and equation (3) for the case of the EU's Regional Policy classification:

$$\begin{aligned}\ln PATp.c._{it} &= \beta_0 + \beta_1 \cdot \ln RDp.c._{it-1} + \beta_2 \cdot HK_{it-1} + \beta_3 \cdot \ln PopDens_{it-1} + \beta_4 \cdot PopDens^2_{it-1} + \\ &+ \gamma_1 \cdot MOBILITY_{it-1} \cdot EU15_i + \gamma_2 \cdot MOBILITY_{it-1} \cdot EUEnlargement_i + \\ &+ \gamma_3 \cdot MOBILITY_{it-1} \cdot EFTA_i + \beta_6 \cdot NETWORKS_{it-1} + \delta_i + \varepsilon_{it}\end{aligned} \tag{2}$$

$$\begin{aligned}\ln PATp.c._{it} &= \beta_0 + \beta_1 \cdot \ln RDp.c._{it-1} + \beta_2 \cdot HK_{it-1} + \beta_3 \cdot \ln PopDens_{it-1} + \beta_4 \cdot PopDens^2_{it-1} + \\ &+ \phi_1 \cdot MOBILITY_{it-1} \cdot COMPETITIVE_i + \phi_2 \cdot MOBILITY_{it-1} \cdot PHASING\_IN\_OUT_i + \\ &+ \phi_3 \cdot MOBILITY_{it-1} \cdot CONVERGENCE_i + \phi_4 \cdot MOBILITY_{it-1} \cdot EFTA_i + \\ &+ \beta_6 \cdot NETWORKS_{it-1} + \delta_i + \varepsilon_{it}\end{aligned} \tag{3}$$

Then, we look at the size, significance and direction of parameters, respectively, γ_1 through γ_3 and ϕ_1 through ϕ_4. Moreover, we run pairwise Wald tests to verify whether the estimated differences across coefficients are statistically significant. The same applies for the case of cross-regional co-inventorship networks.

2.3. Absorptive capacity and knowledge flows

One central hypothesis of this paper states that absorptive capacity is needed to understand and transform the inflows of extra-regional knowledge into regional innovation. According to Cohen & Levinthal (1990, p. 128), absorptive capacity refers to the "ability of a firm to recognize the value of new, external information, assimilate it, and apply it to commercial ends". Those firms with higher levels of absorptive capacity can manage external knowledge flows more efficiently, and therefore, stimulate innovative outcomes (Escribano et al., 2009). Thus, even firms exposed to the same amount of external knowledge – within a cluster, for instance – might not enjoy the same benefits, because of their different endowments of absorptive capacity (Giuliani & Bell, 2005).

Although most related empirical evidence is at the firm level, the notion of absorptive capacity has also been effectively applied to more aggregate contexts, such as at the level of regions (Cantwell & Iammarino, 2003; Doloreux & Parto, 2005; Mukherji & Silberman, 2013; Roper & Love, 2006; Von Tunzelmann, 2009). Thus, it is argued that the absorptive capacities of the local firms and organizations determine the overall absorptive capacity of the host region, as these firms constitute the basic elements in a regional innovation system. However, regional absorptive capacity is more than just the sum of the individual firms' absorptive capacities located in a given region, but also the interactions and inter-relations between them (Abreu, 2011). A fundamental observation of this scant literature establishes that external-to-the-region knowledge is absorbed relatively easier in areas that already have a relatively large stock of knowledge.

A major complication in empirical research is how to operationalize the concept of absorptive capacity. The related literature has extensively used the R&D intensity of firms, regions and countries as proxy for their absorptive capacity. Cohen & Levinthal (1989) already suggested the double role of R&D, that is, not only as a generator of new knowledge, but also as a means to enhance the firm's ability to assimilate and exploit existing information. Thus, R&D activities of organizations are regarded as having two faces. One is the widely acknowledged knowledge creation function – i.e., as a direct input into the innovation process; another one is their role in the formation of absorptive capacity (Aghion et al., 1998; Aghion & Howitt, 1992; Griffith et al., 2003). In a similar vein, when firms in regions engage in R&D activities, the region itself increases its ability to assimilate and understand the discoveries of others, thereby raising the speed at which technology transfer into those regions occurs. Thus, the presence of internal R&D investments improves the capacity of a region to absorb foreign knowledge.

On the double role of R&D, Griffith et al. (2003) show strong evidence of its 'second face': country-industry pairs lagging behind the productivity frontier catch-up particularly fast if they invest heavily in R&D. Similarly, Cameron et al. (1999) look at the role of internal R&D as a source of both domestic innovation and capacity to assimilate technological spillovers for a panel of UK industries. At the firm level, Cassiman & Veugelers (2006) show that the reliance on more basic R&D, which proxies a firm's absorptive capacity, positively affects the complementarity between internal and external innovation activities. Finally, among the scarce evidence at the regional level, Fu (2008) investigates the impact of foreign direct investment (FDI) on the development of regional innovation capabilities using a panel data set from China, concluding that the strength of local absorptive capacity in the host regions are crucial for FDI to serve as a driver of knowledge-based development.

In light of these arguments, this paper argues that the impact of high-skilled workers spatial mobility and cross-regional networks on local innovation outcomes is critically determined by the level of absorptive capacity of regions. Following previous studies, we account for the double role of R&D – innovation input and absorptive capacity – by including interaction terms between regional R&D and proxies for incoming knowledge flows (Cassiman & Veugelers, 2006; Fu, 2008; Jaffe, 1986; Veugelers, 1997). Thus, we test the hypothesis by including interactions between local R&D expenditures and networks and mobility among the r.h.s. variables of our model – see equation (4).[2] The direction, size and significance of parametres θ_1 and θ_2 will indicate the extent to which regions' absorptive capacity is important to make the most of external-to-the-region knowledge flows conveyed by skilled labour mobility and co-inventorship networks.

$$\begin{aligned}\ln PATp.c._{it} &= \beta_0 + \beta_1 \cdot \ln RDp.c._{it-1} + \beta_2 \cdot HK_{it-1} + \beta_3 \cdot \ln PopDens_{it-1} + \beta_4 \cdot PopDens^2_{it-1} + \\ &+ \beta_5 \cdot MOBILITY_{it-1} + \beta_6 \cdot NETWORKS_{it-1} + \theta_1 \cdot MOBILITY_{it-1} \cdot \ln RDp.c._{it-1} + \\ &+ \theta_2 \cdot NETWORKS_{it-1} \cdot \ln RDp.c._{it-1} + \delta_i + \varepsilon_{it}\end{aligned} \tag{4}$$

3. Data

This paper uses a sample of 274 NUTS2 European regions of 27 countries – EU-27 (except Cyprus and Malta) plus Norway and Switzerland, to estimate a regional KPF. Thanks to data availability, we estimate a panel FE model of 8 periods (2000 to 2007). Again, using longitudinal data and including FE in our regressions allow us to improve previous estimates of the KPF key parametres – to the extent that these FE account for a number of time-invariant unobservable characteristics of the regions that might bias the results if not included.

Regional innovation is measured using patent applications at the European Patent Offfice (EPO) per million inhabitants.[3] We acknowledge that not all inventions are patented, nor do they all have the same economic impact, as they are not all commercially exploitable (Griliches, 1990). Despite its caveats, the related literature widely uses this variable to proxy innovation outcomes. Indeed, patent data have proved useful for proxying inventiveness as they present minimal standards of novelty, originality and potential profits – and they constitute good proxies for economically profitable ideas (Bottazzi & Peri, 2003). We retrieve patent data at the regional level from the OECD REGPAT database – January 2010 edition (Maraut et al., 2008).

As for the explanatory variables, R&D expenditures per capita were collected from Eurostat and some National Statistical Offices, with some elaboration for regions in specific countries (Belgium, Switzerland, Greece, Netherlands). The share of population with tertiary education (Population aged 15 and over by ISCED level of education attained) proxies human capital endowments of regions and the data come again from Eurostat.[4] Both variables, as well as the remaining regressors, are time-lagged one period in order to lessen endogeneity problems. We also collect population and regional area data from Eurostat to compute the population density variables.

We use unit-record data retrieved from EPO patents – OECD REGPAT database, January 2010 edition – to construct the mobility and network variables. 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, we need 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 use different heuristics for singling out individual inventors using patent documents. In brief, we first clean, harmonize and code all the inventors' names and surnames. Afterwards, we test whether each pair of names belong to the same individual, using a wide range of characteristics (Miguélez & Gómez-Miguélez, 2011). Once each inventor has been assigned an individual identification, mobility and network data can be calculated for each region. Note that we compute these variables for 1-year lagged 5-year moving windows. Thus, mobility and network measures of the period *t* include data from t-5 to t-1.

We compute in- and out-flows of inventors in regions through observed changes in the reported region of residence in patent documents by the inventors themselves. We assign each movement in time 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.

For each 5-year time window, we calculate the number of inventors as the sum of inventors listed in at least one patent application during this time window, by region. We use these data as denominator to compute the ratios IMR, NMR, OMR, and GMR.

Inventors are also used to build the network variables. In particular, we calculate the average number of co-inventions per inventor with inventors from outside the inventor's focal region, again within each 5-year time window.[5]

4. Results

4.1. Preliminary evidence

Table 1 takes a 5-year time window (2001-2005) and summarizes the patterns of mobility and networking of inventors. From this Table we draw the following insights. On average, the distance covered by inventors' movements during this period is 395 km, while it is 355 km for the case of co-patents with other areas. This is in considerable contrast to the average actual distance between all European pairs of regions – 1,787.5 km. This is hardly surprising given that innovation activity in Europe is highly localized among few, nearby areas. Strikingly, 67% of movements and 77% of co-patents involve NUTS2 regions that belong to the same country. Clearly, the spatial and international scope of both phenomena remains considerably limited. The figures are in line with previous results (Chessa et al., 2013; Hoekman et al., 2009; Miguélez & Moreno, 2013c) and likely explain the well-known findings reported by Jaffe et al. (1993) on the localization of knowledge flows (Breschi & Lissoni, 2009).

[Table 1 about here]

The distribution of both inflows of inventors and networks across the European geography is highly skewed too. Only 20 regions – out of 274 – concentrate 49.8% of inventors' inflows. Meanwhile, 50% of co-patents (one of the ends of the bilateral collaboration) accumulate also in only 20 regions during this period – although they are not exactly the same regions. The Gini index computed for both variables confirms this concentration, since it features above 0.7 for both cases – the index ranges from 0 (perfect equality) to 1 (perfect inequality).

Even though the skewness of both variables seems to be comparable, differences arise in terms of their scope: 13.5% of regions do not receive inventors during this 5-year time window, whilst 30.66% only host 5 or less of them. In the meantime, only 1.46% of regions do not co-patent with inventors from other regions and barely 3% co-patent 5 or fewer times. Indeed, these differences suggest that, by and large, networks reach a large number of regions. Similar conclusions arise when splitting the sample across groups of regions – *EU15*, *EU enlargement*, *competitiveness*, *phasing in/out*, and *convergence*: The proportion of regions with zero inflows of inventors is systematically larger – among the number of regions classified in each group – than the share with no co-patents with other areas. From Table 1 it is also apparent that less developed areas – *convergence* – are the most affected by the absence of incoming skilled workers – 39.74%. *Phasing in/out* regions follow – 16.67%. Conversely, the percentage of zero networks is relatively low for all groups of regions – although slightly lower for the wealthier areas (*Regional competitiveness*). Again, this points to the fact that cross-regional co-inventorship networks are widely spread across the majority European regions, irrespective of their level of economic development.

Table 2 displays some statistics of the variables we use in the regressions – for the whole sample as well as broken down across typologies. Broadly speaking, *EU15* and *Competitiveness* regions presents higher levels of patents, R&D expenditures, human capital and population density – these two latter ones are not presented broken down to save space. They also stand out on the average number of co-patents per inventor, except for the case of *phasing in/out* regions, which show the largest average value. Conversely, for the case of the IMR, *Convergence*, *Phasing in/out*, and *EU enlargement* regions present the largest values – although together with extremely high deviations from the mean.[6] Interestingly enough, these regions also present large values of outflows of inventors. As a result, some of them present relatively low NMR as compared to other groups – especially the EFTA regions, which stand out for the case of the NMR.

[Table 2 about here]

4.2. Mobility, collaborations and innovation production

Table 3 shows the results of the FE estimation of the KPF once we include geographical mobility of inventors as well as the research networks in which they participate among the regressors. We compute Hausman tests (Hausman, 1978) for all the models and they always reject the null hypothesis that individual effects are uncorrelated with the independent variables, so the FE model is preferred to the expense of the random-effects (RE). In all columns of Table 3, the elasticity of patents with respect to R&D expenditures presents significant and positive values (around 0.24), which is in line with the value obtained in the literature (Acs et al., 1994; Bottazzi & Peri, 2003; Jaffe, 1989). The human capital parameter is also significant and with the expected positive sign. Additionally, population density is also significantly positive, pointing to the presence of agglomeration and urbanization economies, and its quadratic form is significant, but negative – which indicates that overly dense areas suffer congestion effects (negative externalities).

[Table 3 about here]

Results also illustrate the importance of attracting skilled labour for regional patenting – positive and significant estimates of the IMR coefficient. Interestingly, the OMR (column 2), which takes on board the outward mobility of skilled workers, is negative. The result gives support to the brain drain hypothesis (Agrawal et al., 2011) against the brain circulation/brain gain one (Saxenian, 2006). However, its point estimate is not statistically significant. Columns 3 and 4 introduce, respectively, the NMR and the

GMR, and the main results and conclusions hold – only the GMR, although significant, presents relatively lower point estimates. In its turn, the proxy for cross-regional collaborations positively affects patenting activity of regions. Overall, we confirm our first hypothesis on the positive effect of spatial mobility of skilled labour and geographical networks on regional patent intensity. Thus, the evidence provided herein suggests that both mechanisms can be used to access a wider range of skills, information, knowledge, inputs and competences external to the region, resulting in higher patenting activity.

4.3. Regional heterogeneity and absorptive capacity

We introduce interactions between our focal variables and the two typologies in Tables 4 and 5. We aim to test whether regional variation in the returns to innovation of networks and inventors' mobility exists, across a number of pre-defined dimensions – summarized in our two typologies. The IMR is significant and of equal size for *EU15* and *EU enlargement* regions – and not significant for *EFTA* regions (column 1 of Table 4). Column 2 mimics the same estimation procedures, but for the case of the NMR. The results are comparable – the estimated coefficient for the *EU15* regions is slightly larger, but the difference is not statistically significant according to the Walt test performed. For the case of cross-regional collaborations (column 3), again the coefficients are positive and significant for *EU15* and *EU enlargement* regions and of similar magnitude – and not for *EFTA* regions.

[Table 4 about here]

From Table 5 we learn the following findings. The regions under the *Regional competitiveness* objective are the most benefited by the inflow of inventors. The IMR is also significant for *convergence* regions – those below the 75% of the average GDP per capita of the EU. However, point estimates are statistically larger for the former than for the latter regions – according to the Wald test. The NMR presents similar results, with the exception that *EFTA* region do benefit from the net incoming flows of high-skilled individuals. Differences in favour of the *EFTA* and *Competitiveness* regions are again statistically significant. Strikingly, *Convergence* regions are the only ones benefiting from collaboration networks with external inventors.

[Table 5 about here]

In sum, our analysis makes clear that inflows of high-skilled workers are effectively used as means to reach extra-regional knowledge in the majority of regions, although the wealthier areas present higher returns to innovation outcomes. Contrariwise, the less economically developed regions are the ones benefitting the most from the geographical diffusion of knowledge through networks of technological cooperation.

We now turn to the analysis to the role of regions' absorptive capacity in managing external knowledge flows derived from mobility and networks. As argued by the economic literature, knowledge is absorbed relatively easier in regions that already have a relatively large pool of knowledge. We also motivate this particular analysis by the evidence we just provided on the different impact of mobility and networks on innovation outcomes across groups of regions. Following previous literature and our own evidence, we hypothesize that those regions with large absorptive capacity – measured here as regional R&D expenditures, obtain an innovation premium from incoming skilled individuals and networks. The results provided in Table 6 are broadly supportive of this hypothesis. Interaction terms between R&D and the IMR are positive, but not significant. Conversely, the estimated interaction with the NMR is positive and significant. The evidence provides support to the proposition on the role of absorptive capacity in the assimilation of the knowledge flows from labour mobility. Thus, regions with higher absorptive capacity are more able to translate external knowledge coming from the inflow of skilled workers into new specific commercial applications more efficiently than in the absence of this feature. The result is expected given the empirical evidence we have provided in previous tables. Admittedly, this only applies to the NMR, and not the IMR. Thus, regions' absorptive capacity is especially efficient when receiving areas are able to retain their incoming skilled talent and provide opportunities for local interactions and ideas' diffusion.

[Table 6 about here]

Interestingly enough, interactions between R&D and cooperation are also positive and significant, which advocates for the enhancing effects of absorptive capacity on networks' innovative role. Despite the fact that not all regions benefit from technological collaborations with external inventors – as we showed in Table 5, still, regions' stock of knowledge critically determines their effectiveness on producing further innovations.

In sum, we have provided consistent evidence on the dual role of R&D and we have confirmed our third hypothesis: R&D of regions does not only contributes directly to innovation but also helps building up region's absorptive capacity, which contributes to making innovative activities more productive.

5. Conclusions and implications

Technology and innovation rank high among the factors behind the lack of convergence across the EU regions. Part of the economic growth literature highlights the growth-enhancing role of innovation and considers that most of the regional divergence in growth patterns can be ascribed to the localized and intrinsically path-dependent nature of the innovation process (Abreu et al., 2008). This is probably why public administrations have, over the last years, engaged in policies aimed at increasing the importance of technology in their territories, and specially supporting research investments, mainly public but also private. This fact has been particularly true for regions with less economic development levels (Bilbao-Osorio & Rodríguez-Pose, 2004).

From a more aggregated policy perspective, the EU have made efforts to create an integrated pan-European research and innovation system capable to dismantle the barriers that anchored economic activity to specific locations, and spread knowledge, and economic development, to the whole European geography. Mobility and networks are central elements of the construction of the ERA. The present inquiry has found strong support for the positive relationship between geographical labour market mobility and regional innovation intensity. The influence of networks is also fairly important. However, the present paper has shown that the benefits of these two phenomena – at least to what refers to innovation – are likely to differ across regions. In particular, we show that regions with large levels of absorptive capacity are especially apposite to make the most of flows of knowledge and information brought in by mobile labour and cooperation networks. Mindful that other regional features, not explored here, could also play a role – i.e., human capital, social capital or institutions.

All in all, the results in this paper align with the thinking that innovation policies which neglect the absorption capacity of firms and regions are problematic – or at least incomplete. They also pinpoint that policies used in an undifferentiated manner for all kinds of regions may be misleading.

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Table 1. Descriptive evidence on mobility and networks

Mobility 2001-2005		Networks 2001-2005	
Average distance covered	395.14km	Average distance covered	355.48km
Movements from within national borders	67.87%	Networks from within national borders	77.48%
% inflows in top 20 regions	49.76%	% networks in top 20 regions	49.99%
Gini index inflows' distribution	0.73	Gini index networks' distribution	0.73
Regions with 0 inflows	37 (13.50%)	Regions with 0 networks	4 (1.46%)
Regions with 5 or less inflows	84 (30.66%)	Regions with 5 or less networks	9 (3.28%)
Regions with 0 inflows EU15	11 (5.34%)	Regions with 0 networks EU15	4 (1.94%)
Regions with 0 inflows Enlargement	26 (48.15%)	Regions with 0 networks Enlargement	0 (0.00%)
Regions with 0 inflows Competitive	2 (1.26%)	Regions with 0 networks Competitive	0 (0.00%)
Regions with 0 inflows Phasing in/out	4 (16.67%)	Regions with 0 networks Phasing in/out	2 (8.33%)
Regions with 0 inflows Convergence	31 (39.74%)	Regions with 0 networks Convergence	2 (2.56%)

Table 2. Summary statistics. Total and by region group

	# obser.	Mean	Std.Dev.	Min	Max
		Total sample			
Patents p.c.	2,192	106.87	127.62	0.02	1014.57
RDp.c.$_{t-1}$	2,192	0.38	0.41	0.00	2.88
Hum.Cap.$_{t-1}$	2,192	10.53	4.27	0.73	26.44
Pop. Dens. $_{t-1}$	2,192	336.92	824.58	3.08	9275.65
I.M.R. $_{t-1}$	2,192	4.29	5.70	0.00	66.67
N.M.R. $_{t-1}$	2,192	0.19	5.19	-50.00	66.67
O.M.R. $_{t-1}$	2,192	4.08	5.45	0.00	59.06
Co-pat. per inv. $_{t-1}$	2,192	1.20	0.74	0.00	6.69
		EU15			
Patents p.c.	1,648	123.28	124.39	0.09	1014.57
RDp.c.$_{t-1}$	1,648	0.43	0.40	0.01	2.88
I.M.R. $_{t-1}$	1,648	4.25	4.33	0.00	66.67
N.M.R. $_{t-1}$	1,648	0.29	3.23	-28.57	66.67
O.M.R. $_{t-1}$	1,648	3.97	3.54	0.00	50.00
Co-pat. per inv. $_{t-1}$	1,648	1.25	0.79	0.00	6.69
		EU enlargement countries			
Patents p.c.	432	6.34	10.29	0.02	64.94
RDp.c.$_{t-1}$	432	0.05	0.07	0.00	0.57
I.M.R. $_{t-1}$	432	4.57	9.60	0.00	50.00
N.M.R. $_{t-1}$	432	-0.24	10.02	-50.00	50.00
O.M.R. $_{t-1}$	432	4.73	10.10	0.00	59.06
Co-pat. per inv. $_{t-1}$	432	1.04	0.54	0.00	3.37
		EFTA countries (Norway & Switzerland)			
Patents p.c.	112	230.17	175.74	8.48	630.82
RDp.c.$_{t-1}$	112	0.87	0.44	0.05	1.83
I.M.R. $_{t-1}$	112	3.76	3.97	0.00	37.50
N.M.R. $_{t-1}$	112	0.34	1.14	-4.35	5.88
O.M.R. $_{t-1}$	112	3.42	4.19	0.00	41.18
Co-pat. per inv. $_{t-1}$	112	1.01	0.37	0.44	2.52
		Regions under the competitiveness and employment objective			
Patents p.c.	1,272	147.28	128.36	1.09	1014.57
RDp.c.$_{t-1}$	1,272	0.51	0.41	0.02	2.88
I.M.R. $_{t-1}$	1,272	3.84	2.60	0.00	28.95
N.M.R. $_{t-1}$	1,272	0.18	1.41	-7.69	18.18
O.M.R. $_{t-1}$	1,272	3.66	2.39	0.00	25.00
Co-pat. per inv. $_{t-1}$	1,272	1.23	0.73	0.25	6.69
		Regions under the phasing out the convergence objective & phasing in competitiveness			
Patents p.c.	184	38.82	37.60	0.09	172.63
RDp.c.$_{t-1}$	184	0.17	0.10	0.01	0.40
I.M.R. $_{t-1}$	184	5.20	6.45	0.00	50.00
N.M.R. $_{t-1}$	184	-0.23	3.33	-20.00	15.56
O.M.R. $_{t-1}$	184	5.42	6.97	0.00	50.00
Co-pat. per inv. $_{t-1}$	184	1.33	0.96	0.00	4.00
		Regions under the convergence objective			
Patents p.c.	624	12.63	24.63	0.02	166.98
RDp.c.$_{t-1}$	624	0.07	0.10	0.00	0.83
I.M.R. $_{t-1}$	624	5.12	9.45	0.00	66.67
N.M.R. $_{t-1}$	624	0.32	9.63	-50.00	66.67
O.M.R. $_{t-1}$	624	4.76	8.89	0.00	59.06
Co-pat. per inv. $_{t-1}$	624	1.13	0.72	0.00	3.82

Table 3. FE estimations, regional KPF 2000-2007. Mobility and networks

	(1) FE	(2) FE	(3) FE	(4) FE
$\ln(\text{RDp.c.})_{t-1}$	0.233***	0.237***	0.242***	0.233***
	(0.0456)	(0.0459)	(0.0456)	(0.0458)
Share tertiary educ. $_{t-1}$	0.0273***	0.0275***	0.0253***	0.0283***
	(0.00887)	(0.00894)	(0.00888)	(0.00890)
ln(Pop. density) $_{t-1}$	5.664**	4.789*	5.711**	5.077**
	(2.452)	(2.459)	(2.453)	(2.455)
ln(Pop. density)^2 $_{t-1}$	-0.629***	-0.578**	-0.648***	-0.587**
	(0.243)	(0.245)	(0.244)	(0.244)
(Inward Migration Rate) $_{t-1}$	0.0114***			
	(0.00250)			
(Outward Migration Rate) $_{t-1}$		-0.000331		
		(0.00288)		
(Net Migration Rate) $_{t-1}$			0.0112***	
			(0.00244)	
(Gross Migration Rate) $_{t-1}$				0.00539***
				(0.00186)
ln(Co-patents per inventor) $_{t-1}$	0.229***	0.250***	0.241***	0.235***
	(0.0523)	(0.0525)	(0.0521)	(0.0525)
Constant	-8.039	-4.965	-7.689	-6.226
	(6.204)	(6.202)	(6.195)	(6.203)
Observations	2,192	2,192	2,192	2,192
Hausman	323.29	319.36	320.42	321.87
p-value	0.000	0.000	0.000	0.000
# Regions	274	274	274	274
Region FE	Yes	Yes	Yes	Yes
Log Lik	-879.87	-891.73	-879.65	-886.90
F-test	21.77	18.12	21.84	19.60
p-value	0.00	0.00	0.00	0.00

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Explanatory variables expressed as percentages are not log-transformed for ease their interpretation.

Table 4. FE estimations, regional KPF 2000-2007. Differences across EU accession date

	(1) FE	(2) FE	(3) FE
ln(RDp.c.)$_{t-1}$	0.234***	0.255***	0.233***
	(0.0457)	(0.0462)	(0.0463)
Share tertiary educ. $_{t-1}$	0.0273***	0.0253***	0.0279***
	(0.00889)	(0.00889)	(0.00894)
ln(Pop. density) $_{t-1}$	5.608**	5.864**	5.762**
	(2.459)	(2.454)	(2.458)
ln(Pop. density)^2 $_{t-1}$	-0.623**	-0.667***	-0.630***
	(0.244)	(0.244)	(0.243)
(Inward Migration Rate) $_{t-1}$			0.0114***
			(0.00251)
ln(Co-patents per inventor) $_{t-1}$	0.228***	0.234***	
	(0.0525)	(0.0525)	
(I.M.R.) $_{t-1}$*EU15	0.0119***		
	(0.00366)		
(I.M.R.) $_{t-1}$*EU enlargement	0.0114***		
	(0.00360)		
(I.M.R.) $_{t-1}$*EFTA	0.00707		
	(0.0107)		
(N.M.R.) $_{t-1}$* EU15		0.0150***	
		(0.00444)	
(N.M.R.) $_{t-1}$* EU enlargement		0.00924***	
		(0.00292)	
(N.M.R.) $_{t-1}$* EFTA		0.0869**	
		(0.0432)	
ln(Co-patents p.i.) $_{t-1}$* EU15			0.223***
			(0.0766)
ln(Co-patents p.i.) $_{t-1}$*EU enlarge.			0.241***
			(0.0714)
ln(Co-patents p.i.) $_{t-1}$* EFTA			-0.206
			(0.446)
Constant	-7.910	-7.948	-8.508
	(6.218)	(6.195)	(6.248)
Observations	2,192	2,192	2,192
Hausman	317.68	303.43	313.28
p-value	0.000	0.000	0.000
# Regions	274	274	274
Region FE	Yes	Yes	Yes
Log Lik	-879.77	-877.21	-879.31
F-test	16.33	16.93	16.44
p-value	0.00	0.00	0.00

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Explanatory variables expressed as percentages are not log-transformed for ease their interpretation.

Table 5. FE estimations, regional KPF 2000-2007. Differences across regional development level

	(1) FE	(2) FE	(3) FE
$\ln(RDp.c.)_{t-1}$	0.243***	0.253***	0.237***
	(0.0455)	(0.0461)	(0.0456)
Share tertiary educ. $_{t-1}$	0.0249***	0.0262***	0.0328***
	(0.00885)	(0.00887)	(0.00936)
ln(Pop. density) $_{t-1}$	4.656*	6.727***	5.704**
	(2.449)	(2.462)	(2.453)
$\ln(\text{Pop. density})^2{}_{t-1}$	-0.511**	-0.747***	-0.591**
	(0.244)	(0.244)	(0.244)
(Inward Migration Rate) $_{t-1}$			0.0113***
			(0.00250)
ln(Co-patents per inventor) $_{t-1}$	0.233***	0.240***	
	(0.0521)	(0.0519)	
(I.M.R.) $_{t-1}$*Competitiveness objective	0.0381***		
	(0.00745)		
(I.M.R.) $_{t-1}$*Phasing in or out	-0.0111		
	(0.00688)		
(I.M.R.) $_{t-1}$*Convergence objective	0.0116***		
	(0.00295)		
(I.M.R.) $_{t-1}$*EFTA	0.00677		
	(0.0106)		
(N.M.R.) $_{t-1}$*Competitiveness object.		0.0460***	
		(0.0108)	
(N.M.R.) $_{t-1}$*Phasing in or out		-0.00369	
		(0.0135)	
(N.M.R.) $_{t-1}$*Convergence objective		0.00960***	
		(0.00253)	
(N.M.R.) $_{t-1}$* EFTA		0.0874**	
		(0.0431)	
ln(Co-patents p.i.) $_{t-1}$* Competitiveness			-0.0843
			(0.190)
ln(Co-patents p.i.) $_{t-1}$*Phasing in or out			0.268
			(0.210)
ln(Co-patents p.i.) $_{t-1}$*Convergence			0.252***
			(0.0554)
ln(Co-patents p.i.) $_{t-1}$*EFTA			-0.309
			(0.450)
Constant	-6.125	-10.16	-9.247
	(6.185)	(6.220)	(6.233)
Observations	2,192	2,192	2,192
Hausman	335.39	306.09	335.02
p-value	0.000	0.000	0.000
# Regions	274	274	274
Region FE	Yes	Yes	Yes
Log Lik	-866.17	-870.99	-877.58
F-test	17.33	16.33	14.96
p-value	0.00	0.00	0.00

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Explanatory variables expressed as percentages are not log-transformed for ease their interpretation.

Table 6. FE estimations, regional KPF 2000-2007. The role of absorptive capacity

	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE
$\ln(RDp.c.)_{t-1}$	0.227***	0.240***	0.241***	0.236***	0.248***
	(0.0459)	(0.0455)	(0.0457)	(0.0460)	(0.0456)
Share tertiary educ. $_{t-1}$	0.0281***	0.0265***	0.0236***	0.0244***	0.0232**
	(0.00890)	(0.00888)	(0.00902)	(0.00906)	(0.00904)
ln(Pop. density) $_{t-1}$	5.413**	5.458**	5.797**	5.568**	5.562**
	(2.463)	(2.452)	(2.451)	(2.461)	(2.451)
ln(Pop. density)^2 $_{t-1}$	-0.609**	-0.631***	-0.663***	-0.644***	-0.660***
	(0.244)	(0.243)	(0.244)	(0.244)	(0.244)
(Inward Migration Rate) $_{t-1}$	0.0177***		0.0113***	0.0170***	
	(0.00622)		(0.00250)	(0.00622)	
$\ln(RDp.c.)_{t-1}$*(I.M.R.) $_{t-1}$	0.00173			0.00156	
	(0.00157)			(0.00157)	
(Net Migration Rate) $_{t-1}$		0.0295***			0.0290***
		(0.00794)			(0.00794)
$\ln(RDp.c.)_{t-1}$*(N.M.R.) $_{t-1}$		0.00427**			0.00420**
		(0.00176)			(0.00176)
ln(Co-patents per inventor) $_{t-1}$	0.228***	0.229***	0.452***	0.446***	0.427***
	(0.0523)	(0.0523)	(0.114)	(0.114)	(0.114)
$\ln(RDp.c.)_{t-1}$*ln(Co-patents) $_{t-1}$			0.0595**	0.0581**	0.0529*
			(0.0270)	(0.0270)	(0.0270)
Constant	-7.357	-6.905	-7.792	-7.183	-6.647
	(6.234)	(6.195)	(6.198)	(6.229)	(6.191)
Observations	2,192	2,192	2,192	2,192	2,192
Hausman	316.55	317.37	315.50	308.77	304.07
p-value	0.000	0.000	0.000	0.000	0.000
# Regions	274	274	274	274	274
Region FE	Yes	Yes	Yes	Yes	Yes
Log Lik	-879.17	-876.26	-877.08	-876.51	-874.05
F-test	18.83	19.61	19.39	17.09	17.66
p-value	0.00	0.00	0.00	0.00	0.00

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Explanatory variables expressed as percentages are not log-transformed for ease their interpretation.

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1 The EFTA countries are European countries that do not belong to the European Union. Norway and Switzerland were among the founding Member States of EFTA in 1960. Iceland joined EFTA in 1970, followed by Liechtenstein in 1991.

2 In unreported results we experiment with a measure of R&D stocks, instead of R&D expenditures – calculated using the perpetual inventory method. The results remain virtually unchanged.

3 Patent data are allocated in time according to the priority date of the application– that is, the first year in which the applicant filed the patent anywhere.

4 We are grateful to CRENoS (University of Cagliari and University of Sassari) for providing us with data on R&D and human capital.

5 We added a small value, 0.1, to this variable in order to allow for the logarithmic transformation.

6 This result may well be due to the low values of the denominator, local number of inventors, in such regions.

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