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### JEL codes:

C33, J61, O31, O33

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September 7, 2017

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# 1 Introduction

Since the development of endogenous growth theories, knowledge and innovation are largely accepted as key driving forces behind long-term economic growth (Romer, 1986). In this regard, economists have established that innovation depends on firms' own research capabilities, as well as their ability to use knowledge developed by other firms. At the regional level, the production function approach suggests that innovation depends on the level of human capital as well as the resources devoted to research. In addition, regions may benefit from additional inputs emanating from the research effort of neighbouring regions (Moreno et al., 2005). Building on these considerations, two streams of literature have analysed how knowledge is transmitted across firms and regions. The empirical geography of innovation literature has established that the transmission of knowledge proceeds mostly through personal ties. This is due to the tacit nature of knowledge, which is embodied in individuals, and is better transmitted through direct and frequent interactions (Howells, 2002). This effect is found to be particularly important in urban areas where the concentration of individuals provides numerous opportunities for interaction and reduces the cost of communication (Glaeser, 1999). Consequently, firms can gain access to external knowledge through the recruitment of key workers (Almeida and Kogut, 1999) or by actively engaging in collaborations networks (Singh, 2005). A second stream of research focused on firms' ability to absorb external knowledge (Cohen and Levinthal, 1989). Specifically, having access to knowledge, in particular through mobility and networks, is not sufficient so that only firms endowed with the capacity to decode and understand others' discoveries can use it productively (Caragliu and Nijkamp, 2012). Therefore, there exist a complementarity between internal and external inputs to innovation in the sense that firms actively engaging in research increase their likelihood to innovate, but also develop their ability to assimilate external knowledge (Cassiman and Veugelers, 2006). These two phenomena are interrelated and should be jointly analysed because they are key factors in explaining regional innovation.

This paper investigates the interactions among cities' research activity by studying accessi-

bility, absorptive capacity and innovation in an integrated framework. The main hypothesis is that mobility and networks provide access to knowledge, while the proportion of accessible knowledge effectively used for innovation depends on absorptive capacity (Miguelez and Moreno, 2013b). Specifically, this paper contributes to the empirical literature in four ways. First, the analysis is carried out at the level of urban areas, a meaningful unit of analysis with regards to arbitrarily defined regions commonly used in the literature. Second, it proposes a refinement of the typical weight matrices based on purely geographical criteria by using information on the mobility of inventors and their collaborative ties (Miguelez and Moreno, 2013a). In this paper, the notion of neighbourhood does not necessarily refer to spatially proximate cities, although this is often the case, but rather cities that are linked by mobility flows and networks ties. The iterative estimation method developed by Hazir et al. (2014) is used to draw inferences on the relative importance of these different forms of connectivity. Third, this paper estimates a production function for innovation using a spatial Durbin model (Autant-Bernard and LeSage, 2011) on a panel of 488 European urban areas over 1998–2009. The results provide an assessment of the relative importance of mobility and networks in accessing external knowledge. Fourth, there is evidence of absorptive capacity, as only a fraction of the accessible knowledge is used for innovation, depending on the level of human capital.

The main result is that innovation in cities is significantly influenced by the research activity of their neighbours. In other words, there is evidence of strong spatial dependence among cities' innovation processes. Specifically, three results are worth noting. First, the analysis confirms the importance of skilled mobility, and to a lesser extent networks, in accessing external knowledge. A related conclusion is that contiguity alone poorly reflects the nature of dependence, but serves as a proxy for more meaningful forms of proximity based on social ties. Second, maximum likelihood estimates confirm that R&D spending contributes to local innovation, but also significantly increases patenting in neighbouring cities. By contrast, the aggregate impact of human capital is not significant, because the positive effect on local innovation is offset by a negative spillover effect on neighbours, reflecting the existence of a competition effect between cities to attract skilled individuals. On theoretical grounds, these

opposing effects are well documented. While endogenous growth models established that human capital increases the rate of innovation, the new economic geography highlights a strong competition effect associated with the mobility of workers. Third, this paper provides an estimate of absorptive capacity, measured as the complementarity between local and external inputs, and shows that a certain level of human capital helps to take advantage of neighbours' discoveries.

These results have implications for the convergence debate. While greater accessibility encourages convergence, the notion of absorptive capacity implies a self-reinforcing effect leading to divergence (Aghion and Jaravel, 2015). Models that study growth and geography in an integrated framework recognize the importance of both workers' mobility and knowledge externalities in determining the location of innovation (Baldwin and Forslid, 2000). On the one hand, if a region becomes relatively more attractive, mobile workers will move to this region, causing it to grow at the expense of peripheral areas in a circular-causation mechanism. On the other hand, the strength of agglomeration depends negatively on the range of knowledge externalities. In this setting, the aggregate impact of skilled mobility is ambiguous because it favours the core-periphery equilibrium, while its role in the diffusion of knowledge give rise to dispersion. The theoretical literature is unclear about which effect prevails, partly because it does not account for the actual mechanisms through which knowledge diffuses in space. This work represents a step in this direction, as there is evidence of both complementarity and competition effects among neighbouring cities' innovation processes.

The remainder of this paper is structured as follows. Section 2 reviews the related literature. Section 3 describes the data and section 4 introduces the empirical model. Section 5 discusses the estimation results and section 6 concludes.

## **2 Background**

A number of empirical studies have established the existence of knowledge flows across firms and regions (Jaffe et al., 1993), so that the production of innovation depends on the amount of

R&D activity carried out locally, as well as the possibility to take advantage of neighbours' research effort (Moreno et al., 2005). Building on these considerations, two streams of literature have investigated the mechanisms through which knowledge is transmitted in space.

The empirical literature on the geography of innovation has established that the transmission of knowledge proceeds mostly through personal ties. This is due to the tacit nature of knowledge, which is embodied in individuals' minds and habits, and is better transmitted through direct and frequent interactions (Howells, 2002). Consequently, firms can gain access to knowledge through the recruitment of key workers. The rationale is that when these individuals move away from the place where they originally worked, they bring their embodied knowledge to their new workplace and promote innovation. From an empirical perspective, Almeida and Kogut (1999) tracked knowledge diffusion patterns using patent citations in the semi-conductor industry. They found evidence of knowledge flows only in the US states where the intra-regional mobility of inventors across companies is high. Miguelez and Moreno (2013a) reported similar evidence at the regional level. Using a spatial knowledge production function on a panel of European regions, they showed that regions linked by labour mobility and collaboration networks influence their respective innovation outcomes. In fact, a related mechanism for the transmission of knowledge is the presence of scientific networks, because they reduce uncertainty and coordination problems. As a result, firms that are embedded in collaboration networks are more likely to be exposed to original ideas. Singh (2005) estimated the probability of knowledge flow between pairs of inventors. By applying a choice-based sampling method to USPTO patent citations, he found that co-invention networks explain the subsequent patterns of patent citations, both at the regional and at the firm level. Finally, mobility and networks are two related phenomenon. Skilled workers on the move influence the structure of networks by creating new, bridging or closing existing networks. Conversely, a worker embedded in a professional network is better informed about vacancies and the receiving organisation, so that social relationships influence mobility decisions. For instance, Agrawal et al. (2006) looked at the mobility patterns of US inventors across MSA and showed that mobile inventors are more likely to be cited by their former colleagues, suggesting that

social ties persist even after formerly co-located inventors are separated.

The second stream of research focuses on firms' ability to absorb external knowledge. In a series of articles, Cohen and Levinthal (1989, 1990) argued that R&D does not only generate knowledge, but also facilitates the imitation of knowledge developed elsewhere. The intuition is that firms actively engaged in research in a particular technological field can assimilate more readily the discoveries of others. In this sense, there is a complementarity between internal and external inputs to innovation (Cassiman and Veugelers, 2006). The concept of absorptive capacity, originally developed in the context of firm theory, has been recently extended to larger spatial units such as regions. Absorptive capacity at the regional level can be defined as the ability of firms and individuals within the region to assimilate and use productively accessible knowledge developed elsewhere. Regions with a greater absorptive capacity are open to new ideas, and better able to use them for innovation. The connection with economic theory is provided by Griffith et al. (2003, 2004) who accounted explicitly for absorptive capacity in a structural model of endogenous growth. The empirical results suggest that the social returns to R&D and human capital are greater than previously thought at the industry level. This is consistent with Mukherji and Silberman (2013), who provided an estimate of absorptive capacity at the level of urban areas. Specifically, they interpret origin and destination fixed effects of a gravity model of patent citations as a measure of absorptive capacity, and use these estimates in a panel production function for innovation. Their results suggest that innovation in cities depend on their ability to use external knowledge produced in neighbouring areas. At the regional level, Caragliu and Nijkamp (2012) showed that a weak absorptive capacity increases knowledge flows towards neighbouring areas, hampering the regions' capability to decode and efficiently exploit new knowledge, both produced locally and originating from outside.

Such interdependencies among neighbouring regions' innovation processes can be explicitly modelled using a spatial specification. In her review of the literature, Autant-Bernard (2012) argued that spatial models are relevant to study of regional innovation because they account for two sources of dependence that characterize the geography of innovation. First, spa-



tial autocorrelation arise when innovation in a region is affected by the research effort of its neighbours. Second, spatial heterogeneity stems from the spatial concentration of innovative activity. These sources of dependence generate endogeneity and cause conventional models to produce biased and inconsistent estimates. From an empirical perspective, Miguelez and Moreno (2013a) looked at the role of mobility and networks on diffusion of knowledge for a panel of regions. Specifically, they estimated a series of gravity models of knowledge diffusion and used fitted values on mobility and networks to estimate a production function with neighbouring effects. Their main contribution is to model explicitly the sources of interaction in regional innovation, rather than using a connectivity structure based exclusively on geography. Recently, Hazir et al. (2014) proposed an interesting methodology to build weight matrices using multiple criteria. They computed a series of matrices based on collaborations and distance by means of gridding, and estimated the model iteratively to select the matrix associated with the best model fit. The resulting matrix is used to draw inference on the relative importance of different forms of connectivity. From a theoretical perspective, Autant-Bernard and LeSage (2011) showed that spatial dependence in innovation could be modelled parsimoniously using a spatial Durbin model. They demonstrated that to the extent that innovation inputs are not perfectly observed, and that both observable and unobservable inputs exhibit spatial dependence, the model should include spatial lags for the dependent as well as the independent variables.

### **3 Data**

The analysis is carried out at the level of urban areas. Innovation is measured by the number of patents in a city, weighted by forward citations in order to control for patent quality. Local inputs to innovation take the form of research investment and human capital. The amount of external inputs that a city can access from its neighbours depends on bilateral mobility flows, network collaborations as well as geographical proximity. Finally, control variables include population and technological diversity.

Table 1: List of variables

Variable	Proxy	Source
Innovation	Citations weighted patents	Crios-Patstat
<i>Inputs</i>		
Research investment	Spending in research and development	Eurostat
Human capital	Human resources in science and technology	Eurostat
<i>Connectivity</i>		
Mobility	Changes in inventor’s addresses	Crios-Patstat
Networks	Bilateral collaboration counts	Crios-Patstat
Geo. proximity	Inverse driving distance	OpenStreetMap
<i>Controls</i>		
Size	Population	Univ. of Geneva
Tech. diversity	Technological diversity index	Crios-Patstat

Patent data contains extensive information about the patents, the inventors and the assignees. Specifically, information relative to the patent include the date of application, detailed technological categories as well as citations made to previous patents. Besides, information about inventors comprise names and personal addresses, among others. This paper uses the Crios-Patstat database (Coffano and Tarasconi, 2014), which records patent applications at the European Patent Office up to 2013. The data is used extensively to compute innovation, mobility, networks and technological diversity at the level of urban areas. This requires geocoding inventors’ addresses to determine whether the patent was filled by an inventor residing in a city, which is done by cleaning and parsing addresses, before matching them against the OpenStreetMap database to retrieve geographical coordinates. Cities are defined using Functional Urban Areas (FUA), which provide a harmonized definition of metropolitan areas throughout the European Union (OECD, 2013). FUA are defined using population density and commuting patterns, so that each represents a self-contained labour market, an economically meaningful unit of analysis (appendix A1).

The number of patents is used as proxy for innovation. Although patents represent a well

understood measure of innovation, available on a large scale and consistent across space and over time, it has several limitations (Griliches, 1990). First, patents represent invention but not necessarily innovation, because some inventions are never exploited commercially. Second, not all inventions are patented, either because they don't meet the patentability criteria or because the firm favours other means of appropriability. Third, patents vary greatly in their economic value, and the distribution of this value is skewed toward the low end. In addressing this last issue, Trajtenberg (1990) argued that the number of citations received may be used as a proxy for patent value. Intuitively, highly cited patents should be more valuable than those that received only a few citations. However, counting citation-weighted patents involves two truncation problems, one regarding patent counts and the other, citation counts (Hall et al., 2005). First, there is a significant time lag between the patent application and the grant. As we approach the last year of the dataset, we observe only a fraction of the patents applied for that will eventually be granted (appendix A2). For this reason, a three-year safety lag is taken by exploiting patent data up to 2009. Second, the number of citations received by a patent is truncated because they are observed up to the last year of the dataset. Consequently, the citation intensity of patents applied for in different years is not directly comparable. This paper uses the fixed effects approach developed by Hall et al. (2001). For each patent, the citation intensity is expressed as a ratio to the mean citation intensity of its cohort, which includes patents with the same application date. Rescaling citations this way removes the effects due to truncation, the effects due to systematic changes over time in the propensity to cite, and the effects due to changes in the number of patents making citations. However, there is no way to do so without removing real differences between cohorts, which do not result from truncation.

Mobility is computed by tracking changes in inventors' personal addresses in patent documentation. For instance, consider an inventor who fills a patent at time  $t$  while residing in city  $i$ .

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For instance, it is not obvious that a five year old patent that received 11 citations is more valuable than a four-year old patent cited 10 times. Hall et al. (2001) discussed other sources of bias that may affect citation. For instance, there has been an increase in the number of patents over time, so that recent patents tend to be more cited than older ones. Besides, the average number of citations per patent has increased over time, and recent citations may be less valuable.

In  $t + 1$ , this same individual fills another patent while residing in city  $j$ . Therefore, we can say that between  $t$  and  $t + 1$ , this individual has moved from  $i$  to  $j$ . This measure of mobility is fairly straightforward but presents three drawbacks. First, the use of patent data restricts the analysis to inventors with at least two patents. Second, a move is recorded only if those inventors applied for a patent before and after the move, so this measure is lower bound. Third, patents record inventors' location at a point in time, therefore it is not possible to determine precisely when the move took place. It is assumed that mobility occurred exactly between the application dates of the patents at origin and destination, if there is no more than a four-year lag between the two. Mobility computed this way identifies inventors who filled at least two patents while residing in different urban areas. Another issue is that in practice, it is difficult to determine whether two inventors are the same person, since patent offices do not require unique identifiers for inventors. Therefore, disambiguation is necessary to determine whether two patents belong to the same inventor by comparing all pairs of inventor-patent instances. Inventors cannot be matched on the basis of their names for a least two reasons. The first is misspelling of the same inventor name on different occasions. The second occurs when two inventors with the same name are not actually the same person. The Massacrator routine developed by Pezzoni et al. (2014) is used to identify likely matches (appendix A3).

Turning to the network variable, a patent has often more than one designated inventor, if two inventors collaborate on the same patent, then a social tie exists. A network of inventors can be viewed as a social network whose nodes are individual inventors and links are co-inventorship relations. The network variable counts for each year, the number of collaborations between inventors residing in city  $i$  and those residing in  $j$  (appendix A4). Technological diversity is computed by grouping the patents technological classes into 30 broader sectors defined by Schmoch (2008), and comparing their relative distribution across cities. An issue is that patent with multiple classes often belong to more than one sector, which makes the aggregation difficult. Sectors are weighted according to their relative frequency of apparition in the patents (appendix A5). For each city, the technological diversity index is computed as  $1 - \sum_{t=1}^n s_t^2$  where

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I thank Michele Pezzoni for running several custom calibrations of Massacrator.

$s_t$  is the relative share of the technological sector  $t$  in the city. An index a value close to unity indicates that the city is technologically diverse.

Table 2: Descriptive statistics

	N. obs	Mean	St. Dev.	Min.	Max.
Number of patents	5856	100.91	264.50	0.00	3477.00
<i>Inputs</i>					
Spending in R&D ( $\times 10^6$ )	5856	272.91	811.13	0.00	14011.98
Human resources in S&T	5856	2890.82	8333.77	0.00	142625.00
<i>Connectivity</i>					
Mobility	488 <sup>2</sup>	0.01	0.17	0.00	144.00
Networks	488 <sup>2</sup>	0.29	7.06	0.00	2499.00
Distance	488 <sup>2</sup>	752.89	408.43	10.00	2223.70
<i>Controls</i>					
Population ( $\times 10^3$ )	5856	551.22	1047.53	19.00	11870.00
Tech. diversity index	5856	0.80	0.20	0.00	1.00

The analysis focuses on 488 cities over 12 years.

Finally, total R&D expenditures are used as a proxy for the research effort. The level of human capital is measured by the total number of R&D personnel and researchers in full time equivalent.

## 4 Model

The model is based on a knowledge production function (Griliches, 1979), which expresses innovation output ( $inn$ ) in a city  $i$  as a function of domestic inputs ( $int$ ) such as R&D spending and human capital, as well as a set of characteristics ( $chr$ ) specific to  $i$ . Since knowledge developed by neighbouring cities enter the production function, external inputs ( $ext$ ) are added to the model. This function is assumed to take a Cobb-Douglas form.

$$inn_i = chr_i^{\beta_1} \times int_i^{\beta_2} \times ext_i^{\beta_3} \quad (1)$$

Spatial econometrics provide a natural tool to investigate the interdependencies in neighbouring cities' research activity. Autant-Bernard and LeSage (2011) provide a formal motivation to estimate equation (1) using a spatial Durbin model (SDM). Specifically, to the extent that innovation inputs are not perfectly observed and that both observable and unobservable inputs exhibit spatial dependence, the model should include spatial lags for the dependent as well as the independent variables. These assumptions seem reasonable in our setting because R&D spending and human capital represent rather aggregate measures of innovation inputs and, as made clear in the previous section, cities' research activities are expected to exhibit spatial dependence. This gives the following empirical model, expressed in logarithms.

$$Y_t = \rho WY_t + \beta X_t + \theta W X_t + c + \varepsilon_t \quad (2)$$

$Y$  is a vector of innovation output ( $inn$ ).  $X$  is a matrix of local innovation inputs ( $int$ ) and city-specific characteristics ( $chr$ ) with  $\beta$  the associated vector of coefficients. Connectivity is introduced in the model through the weight matrix  $W$ . Two spatial lags vectors,  $WY$  and  $WX$ , account for spatial dependence, and represent external inputs to innovation ( $ext$ ). Each vector is a linear combination of neighbouring observations' dependent and independent variables, respectively. The scalar parameter  $\rho$  capture the global dependence among cities' innovation output, while the vector  $\theta$  may be interpreted as the average impacts of external inputs on local innovation. In addition,  $c$  is a vector of individual effects and  $\varepsilon_t$  is a vector of independent and identically distributed error terms with zero mean and constant variance  $\sigma_0^2$ .

One of the main weaknesses of the spatial economic literature is the arbitrary choice of the weight matrix. This is because  $W$  cannot be estimated and needs to be specified in advance according to some relevant criterion. This paper proposes a refinement of the typical matrices

based purely on geographical distance by using information on the mobility of inventors and their collaborative network patterns. In this setting, physical distance remains important because it increases the cost of mobility as well as the cost of forming and maintaining network ties (Breschi and Lissoni, 2009). At the same time, there is evidence of long-range knowledge flows (Owen-Smith and Powell, 2004), and distant cities may influence each others if they are linked by labour mobility and collaboration networks. Following Hazir et al. (2014), the weight matrix is expressed as a convex combination of three components. The strength of interactions between cities is assumed to be a function of bilateral (1) mobility flows, (2) network collaborations and (3) geographical proximity. Letting  $W_M$ ,  $W_N$  and  $W_D$  be the corresponding matrices, with  $\lambda_M$ ,  $\lambda_N$ , and  $\lambda_D$  their associated weights respecting  $\lambda_M + \lambda_N + \lambda_D = 1$ ,  $W$  is expressed as follows.

$$W = \lambda_M W_M + \lambda_N W_N + \lambda_D W_D$$

The resulting matrix has zeroes on the diagonal and non-null elements on the off-diagonals when observation  $i$  depends on observation  $j$ . In order to make the three matrices comparable in magnitude,  $W_{M,N,D}$  are normalized to a range between 0 and 1. Using different values of  $\lambda_{M,N,D}$  with increments of 0.1, sixty distinct weight matrices are generated, reflecting different forms of connectivity. Equation (2) is then estimated iteratively using each of the weight matrices. By comparing the different specifications, one can observe how the model fit varies in response to changes in the connectivity structure, and select the weight matrix associated with the model with the highest log-likelihood, as shown in table 3. The values of  $\lambda_{M,N,D}$  associated with this matrix can be used to draw inferences on the relative importance of different forms of connectivity.

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LeSage (2014) argued that a sparse and symmetric weight matrix performs better. The mobility and network matrices are made symmetric so that for instance, the mobility between  $i$  and  $j$  reflects the total number of moves between the two cities, regardless of the direction. Besides, the inverse distance matrix is made sparse by keeping only the 15 nearest neighbours. The results are robust to changes in the number of distance-based neighbours.

Table 3: Structures of dependence

Rank	$\lambda_M$	$\lambda_N$	$\lambda_D$	Log-lik.
1	0.4	0.5	0.1	-1388.6
2	0.5	0.4	0.1	-1392.1
3	0.7	0.2	0.1	-1400.7
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
52	0.0	1.0	0.0	-1499.8
53	1.0	0.0	0.0	-1500.6
60	0.0	0.0	1.0	-1516.6

As noted by LeSage and Pace (2009), specifying the weight matrix using non-spatial notions of proximity raises endogeneity concerns. In particular, mobility flows and network ties used in the definition of  $W$  should be correlated with the inputs to innovation. This is clearly a limitation of this empirical strategy, and to attenuate this issue, the weight matrix is lagged one period. Nonetheless, this connectivity structure has the advantage of being derived from the economic literature, rather than being a vague spatial pattern based on geography. Going back to the main hypothesis, it is assumed that mobility and networks provide access to knowledge, but the proportion of accessible knowledge effectively used for innovation depends on absorptive capacity. In our setting, absorptive capacity can be measured as the complementarity between internal and external inputs (Cassiman and Veugelers, 2006). Cities that engage actively in research and employ talented individuals should understand more readily the discoveries of others. Therefore, equation (2) is estimated with the addition of interaction terms between the domestic inputs and the spatial lag.

$$Y_t = \rho W Y_t + \beta X_t + \theta W X_t + \phi X_t W X_t + c + \varepsilon_t \quad (3)$$

$XWX$  is measure of absorptive capacity capturing the complementarity between internal and external inputs to innovation, and  $\phi$  is the associated vector of coefficients. Estimation results

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The correlation coefficient between the different matrices is 0.214 on average (appendix A4).



for the two models are presented in the next section. For clarity, the model in equation (2) is referred to as the accessibility model, while equation (3) is called the absorption model.

## 5 Results

The two models are estimated on a panel of 488 FUA located in 13 European countries (appendix A1) over 1998–2009. These cities account for over 92% of all patents applied for in European urban areas over this period. To avoid extreme heterogeneity, the data is pooled into three-years periods corresponding to 1998–2000, 2001–2003, 2004–2006 and 2006–2009. Besides, the weight matrix is not time-varying in our setting, so mobility and network data are pooled over the sample period. To attenuate endogeneity concerns, all independent variables are lagged one year. Table 4 reports the estimation output for the accessibility model. The linear model presented in the first two columns serves as a benchmark, while coefficient estimates for the spatial Durbin model are presented in columns (3) and (4). Each model is estimated twice, once as a regular model and once with the addition of individual fixed effects. The spatial Durbin models exhibit a better fit than their non-spatial counterpart and the log-likelihood statistic clearly favours the fixed effects specifications. Consequently, the discussion of the results is based on the estimation output presented in column (4).

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For all models, the Hausman test rejects the null hypothesis that individual effects are uncorrelated with the independent variables, so the fixed effects model is preferred over random-effects. In addition, the maximum likelihood estimator is generally inconsistent in the presence of fixed effects (Lee and Yu, 2010), especially when the length of the panel is short. The incidental parameter problem is solved using the Lee Yu transformation.

Table 4: Estimation output for the accessibility model

	Linear model (1)	Linear model (2)	Spatial Durbin (3)	Spatial Durbin (4)
<i>Internal inputs</i>				
R&D spending	0.178*** (0.018)	0.093*** (0.017)	0.078*** (0.021)	0.034** (0.013)
Human capital	0.071*** (0.017)	0.055** (0.021)	0.038** (0.015)	0.027* (0.017)
<i>External inputs</i>				
W × R&D spending	–	–	0.012** (0.004)	0.037** (0.014)
W × Human capital	–	–	–0.034** (0.013)	–0.029* (0.012)
<i>Controls</i>				
Population	0.675*** (0.044)	0.279*** (0.104)	0.638*** (0.043)	0.171* (0.074)
Tech. diversity	1.692*** (0.119)	1.073*** (0.109)	1.256*** (0.124)	1.003*** (0.127)
Rho ( $\rho$ )	–	–	0.604*** (0.028)	0.488*** (0.040)
Fixed effects	No	Yes	No	Yes
Log-likelihood	–	–316.3	–1187.8	168.2

\*90%, \*\*95% and \*\*\*99% confidence levels. Standard errors are robust.

### *Accessibility*

Our first hypothesis is that bilateral mobility and networks significantly affect neighbouring cities' research activity. The Rho estimate is positive and significant at the 1% level, which confirms the existence of strong and positive spatial dependence. Looking at the sources of dependence, table 3 shows that the best model fit is obtained when  $W$  is computed using weights of 50% on mobility, 40% on networks and 10% on distance. Interestingly, the case when  $W$  is expressed only by distance yields the worst fit, which confirm earlier findings that contiguity alone does not reflect the nature of dependence among innovation processes, but serves as a proxy for more meaningful forms of proximity based on social ties. In addition, it implies that the mobility flows and network ties linking distant cities matter for patenting. Distinguishing  $W_M$  from  $W_N$ , the matrix expressed by mobility alone outperforms the

network matrix in terms of model fit, so that mobility has a slightly stronger spillover effect. These findings motivate the use of a spatial specification that model explicitly the sources of interactions among neighbouring cities' research activity. Considering the variables of interest, both the R&D spending and the human capital variables have the expected sign and remain significant at the 5% and 10% level when adding the fixed effects. Because the Rho statistic is significant, their impact on the dependent variable must be interpreted in terms of direct, indirect, and total effects, reported in table 5.

Table 5: Average marginal effects for the accessibility model

	Direct effect	Indirect effect	Total effect
<i>Inputs</i>			
R&D spending	0.036** (0.014)	0.035** (0.013)	0.071** (0.028)
Human capital	0.027* (0.011)	-0.028** (0.011)	-0.001 (0.006)
<i>Controls</i>			
Population	0.168* (0.073)	1.085** (0.428)	1.254** (0.495)
Tech. diversity	0.988*** (0.130)	2.693*** (0.753)	3.681*** (0.799)

\*90%, \*\*95% and \*\*\*99% confidence levels. Standard errors are robust.

The direct effect measures the impact of a unit change in one input of the typical city  $i$  on the dependent variable of this same city  $i$ , averaged across all cities in the sample. In our framework, this means that a 1% change in R&D investment increases patenting in the city by 0.036%, which is an average elasticity response because of the log-transformation. Similarly, the elasticity of patenting associated with an increase in the level of human capital is 0.027%. The direct effect differs slightly from the estimates reported in table 4, because the spatial Durbin model produces a small feedback effect. By contrast, the indirect effect captures the

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The measure of mobility is sensitive to the disambiguation procedure. A robustness check using a more conservative definition of mobility (appendix A3) favours the  $W$  computed using weights of 40% on mobility, 50% on networks and 10% on distance, which is very similar. Estimation results are robust to this change in the connectivity structure.

A input variation in city  $i$  impacts city  $i$ 's output but also spills over the output of neighbouring cities, say  $j$ . This impact on  $j$ 's output produces in turn a spillover impact on output of cities neighbouring  $j$ , and  $i$  is one such city (LeSage and Pace, 2009).

average impact on the dependent variable city  $i$ , of a unit change in one input of cities  $j$  neighbouring  $i$ . The indirect effect typically represent a measure of spillovers, which arise in our setting from bilateral mobility and networks. A 1% change in neighbouring cities spending in R&D produces on average a spillover impact of 0.035% on local innovation. Interestingly, the indirect effect associated with an increase human capital is negative and significant. This is interpreted as a competition effect. Unlike R&D investments, which partly consists of research infrastructures; human capital is a mobile factor that relocates in space, and tend to cluster within a few urban areas. It seems plausible that an increase in human capital in a given city makes it more attractive to other skilled workers, and especially to those located in neighbouring cities who face a lower mobility cost. Consequently, the total impact of human capital is not significant, because it increases local patenting but has a negative spillover effect on neighbours. On theoretical grounds, these opposing effects are well documented. While the endogenous growth literature makes it clear that human capital increases the rate of innovation, new economic geography models highlight a strong competition effect associated with the mobility of workers. Turning to the control variables, the coefficient associated with population and technological diversity have the expected sign and remain significant in all the specifications.

#### *Absorptive capacity*

Our second hypothesis is that the amount of accessible knowledge effectively used for innovation depends on cities' absorptive capacity. In other words, cities that engage actively in research and employ talented individuals can use a larger share of their neighbours' knowledge, accessible through mobility and networks. The estimation results for the absorption model are detailed in table 6. Since R&D spending is associated with a positive spillover effect, the model includes two interaction terms between the spatial lag and the domestic inputs, interpreted as a measure of complementarity between internal and external inputs to innovation. The linear model presented in columns (1) and (2) serves as a benchmark, while coefficient estimates for the spatial Durbin model are presented last two columns. As before, the preferred specification is the spatial Durbin model with fixed effects in column (4), which

has the highest log-likelihood.

Table 6: Estimation output for the absorption model

	Linear model (1)	Linear model (2)	Spatial Durbin (3)	Spatial Durbin (4)
<i>Internal inputs</i>				
R&D spending	0.215*** (0.022)	0.098*** (0.021)	0.077** (0.030)	0.033* (0.014)
Human capital	0.090** (0.035)	0.029 (0.033)	0.056* (0.024)	0.023 (0.025)
<i>External inputs</i>				
W × R&D spending	–	–	0.014** (0.005)	0.038** (0.015)
W × Human capital	–	–	–0.074** (0.029)	–0.011 (0.014)
<i>Absorptive capacity</i>				
W RD × RD	0.119*** (0.041)	0.036 (0.038)	0.054* (0.023)	0.021 (0.035)
W RD × HC	0.073*** (0.027)	0.028** (0.011)	0.041** (0.016)	0.018* (0.007)
<i>Controls</i>				
Population	0.650*** (0.048)	0.413*** (0.131)	0.634*** (0.043)	0.173 (0.126)
Tech. diversity	2.028*** (0.145)	1.213*** (0.136)	1.242*** (0.124)	0.999*** (0.127)
Rho ( $\rho$ )	–	–	0.597*** (0.028)	0.486*** (0.040)
Fixed effects	No	Yes	No	Yes
Log-likelihood	–	–315.5	–1182.8	–266.7

\*90%, \*\*95% and \*\*\*99% confidence levels. Standard errors are robust.

As in the accessibility model, the Rho estimate confirms the existence of strong and positive spatial dependence. Table 7 report the direct, indirect and total effects for the absorption model. An additional 1% expenditures in R&D in a typical city increases patenting in that city by 0.035% produces an average spillover impact of 0.034% on neighbouring cities. Turning to human capital, both direct and indirect impacts become insignificant in the fixed effects specification. Interestingly, when interacted with the spatial lag of R&D spending, the coefficient on human capital remains significant at the 10% level, with a direct impact of 0.021%.

Table 7: Average marginal effects of the absorption model

	Direct effect		Indirect effect		Total effect	
<i>Inputs</i>						
R&D spending	0.035*	(0.015)	0.034**	(0.014)	0.070**	(0.026)
Human capital	0.024	(0.019)	-0.012	(0.014)	-0.012	(0.011)
<i>Absorptive capacity</i>						
W RD $\times$ RD	0.023	(0.021)	0.012	(0.011)	0.035	(0.030)
W RD $\times$ HC	0.021*	(0.009)	0.013	(0.010)	0.034*	(0.014)
<i>Controls</i>						
Population	0.213*	(0.092)	1.046*	(0.456)	1.259**	(0.497)
Tech. diversity	1.084***	(0.133)	2.607***	(0.755)	3.691***	(0.805)

\*90%, \*\*95% and \*\*\*99% confidence levels. Standard errors are robust.

Overall, there is rather weak evidence of absorptive capacity. Nonetheless, the results confirm the existence of a complementarity between internal and external inputs to innovation, and suggest that certain level of human capital helps to take advantage of neighbours' discoveries. Contrary to expectation, there is no comparable evidence for the R&D spending variable. Finally, the controls have the expected sign and significance.

## 6 Conclusion

Empirical studies on the geography of innovation have established that skilled workers' mobility and collaboration networks shape the diffusion of knowledge across firms and regions. At the same time, the literature on absorptive capacity insisted on the importance of local research capabilities to take advantage of knowledge developed elsewhere. This paper investigates both phenomena in an integrated framework by assuming that mobility and networks provide access to knowledge, but the proportion of accessible knowledge effectively used for innovation depends on absorptive capacity. Such complementarities in regional research efforts are effectively captured using a spatial Durbin model in which the connectivity structure

stems from mobility and collaboration patterns.

This paper contributes to the empirical literature in four ways. First, the analysis is carried out at the level of urban areas, a meaningful unit of analysis with regards to arbitrarily defined regions commonly used in the literature. Second, it proposes a refinement of the typical weight matrices based on purely geographical criteria by using information on the mobility of inventors and their collaborative ties. The model is estimated iteratively using different forms of connectivity to select the matrix associated with the model that fits the data most closely. Results confirm that skilled mobility, and to a lesser extent networks, significantly affect neighbouring cities' innovation processes. Besides, contiguity alone does not reflect the nature of dependence, but serves as a proxy for more meaningful forms of proximity based on social ties. Third, this paper estimates a spatial knowledge production function on a panel of 488 European urban areas over 1998–2009. Maximum likelihood estimates suggest innovation at the urban level is strongly affected by the research effort of their neighbours. Specifically, spending in R&D contributes to local innovation, but also significantly increase patenting in neighbouring cities. By contrast, the aggregate impact of human capital is not significant, because the positive effect on local innovation is offset by a negative spillover effect on neighbours. This is interpreted as a competition effect whereby an increase in human capital in a city draws skilled workers away from neighbouring cities, causing it to grow at the expense of peripheral areas. Fourth, this paper provides an estimate of absorptive capacity, measured as the complementarity between internal and external resources. There is rather weak evidence of this phenomenon but results suggests nonetheless that a certain level of human capital helps to take advantage of others' discoveries.

These findings have implications for the convergence debate. While greater accessibility encourages convergence, the notion of absorptive capacity implies a self-reinforcing effect leading to divergence. Models that study growth and geography in an integrated framework recognize the importance of both workers' mobility and knowledge externalities in determining the location of innovation (Baldwin and Forslid, 2000). On the one hand, if a region becomes relatively more attractive, mobile workers will move to this region, causing it to grow at the expense

of peripheral areas in a circular-causation mechanism. On the other hand, the strength of agglomeration depends negatively on the range of knowledge externalities. In this setting, the aggregate impact of skilled mobility is ambiguous because it favours the core-periphery equilibrium, while its role in the diffusion of knowledge give rise to dispersion. The theoretical literature is unclear about which effect prevails, partly because it does not account for the actual mechanisms through which knowledge diffuses in space. This work represents a step in this direction, as it provides evidence of both complementarity and competition effects among neighbouring cities innovation processes.

Perhaps, a more fine-grained study taking into account regional specificities in innovation would provide a better understanding on the relative importance of these two opposing effects. More generally, the impact on the distribution of innovation critically depends on the nature of mobility. For instance, in the presence of long term mobility, the agglomeration force should be stronger than what theory predicts. By contrast, the increasing development of short-term, circular patterns of mobility should give rise to dispersion. From a methodological perspective, spatial models offer a strong potential to investigate complementarities in research because they model parsimoniously complex relationship between observational units across space and time. However, specifying the weight matrix using non-spatial notions of proximity raises endogeneity concerns. Further theoretical work in this direction would offer a great potential for empirical analysis (Qu and Lee, 2015). In the same spirit, it would be interesting to implement a dynamic panel with a time-varying weight matrix that allow the connectivity structure to change over time (Lee and Yu, 2012). This would allow for a more detailed and dynamic analysis of the importance of mobility and networks for the diffusion of knowledge.



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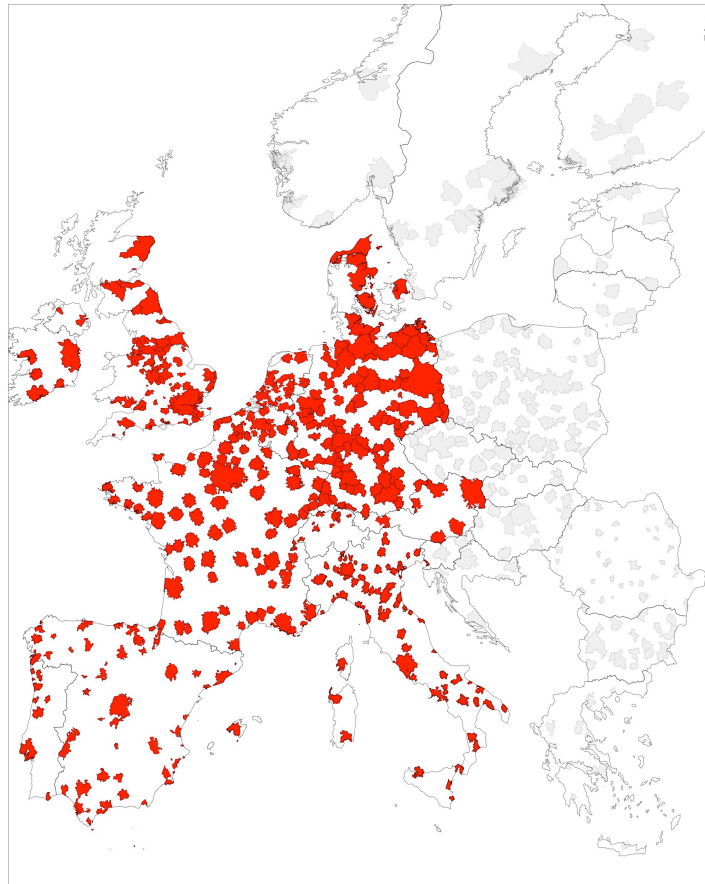
# Appendix

## A1 Functional Urban Areas

Each FUA is composed of a densely populated city core and a commuting zone

- Core: (1) All grid cells with a density of more than 1 500 inhabitants per sq km are selected. (2) The contiguous high-density cells are then clustered, gaps are filled and only the clusters with a minimum population of 50 000 inhabitants are kept as core. (3) All the municipalities with at least half their population inside the urban centre are selected as candidates to become part of the city. (4) The city is defined ensuring that there is a link to the political level, that at least 50% of city the population lives in an urban centre and that at least 75% of the population of the urban centre lives in a city.
- Commuting zone: (1) All municipalities with at least 15% of their employed residents working in a city are identified. (2) Municipalities surrounded by a single functional area are included and non-contiguous municipalities are dropped. (3) If 15% of employed persons living in one city work in another city, these cities are treated as a single city.

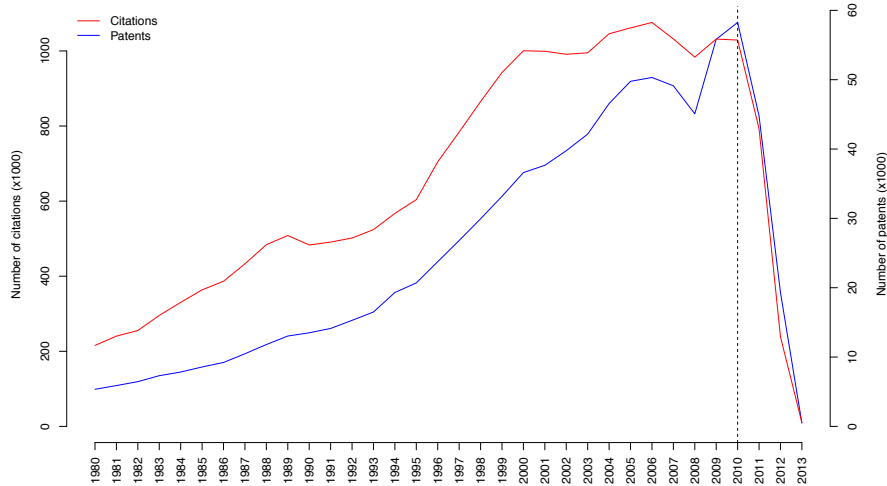
Figure A1: Functional Urban Areas



FUA in red are used in the econometric analysis.

## A2 Innovation

Figure A2: Patents and citations over time



Source: CRIOS

## A3 Disambiguation

The Massacrator routine uses a three-step procedure: cleaning and parsing, matching, and filtering. Specifically, (1) cleaning and parsing involve purging names and surnames strings of typographical errors and converting them to a standard character set. Strings may be parsed into several substrings, whenever appropriate. (2) Then inventors whose names match, either exactly or closely are selecting as likely candidates. (3) During the filtering stage, the selected pairs are filtered using additional information present in the patent documents. The disambiguation is a trade-off between precision and recall.

Table A1: Calibrations of Massacrator

Variables	C1	HR	C3	C4
<i>Network</i>				
Coinventor	1	1	1	1
Three degrees	1	1	1	1
<i>Geographical</i>				
City	0	0	0	0
Province	1	1	0	0
Region	1	1	0	0
State	0	0	0	0
Street	0	0	0	0
<i>Applicant</i>				
Applicant	1	1	1	1
Small applicant	1	1	1	1
Group	0	0	0	0
<i>Technology</i>				
IPC4	1	1	1	1
IPC6	1	1	1	1
IPC12	1	1	1	1
<i>Citations</i>				
Citations	0	0	0	0
ASE	0	0	0	0
<i>Other</i>				
Rare surnames	0	0	0	0
Three years	0	0	0	0
N criteria to be met	2	3	2	3

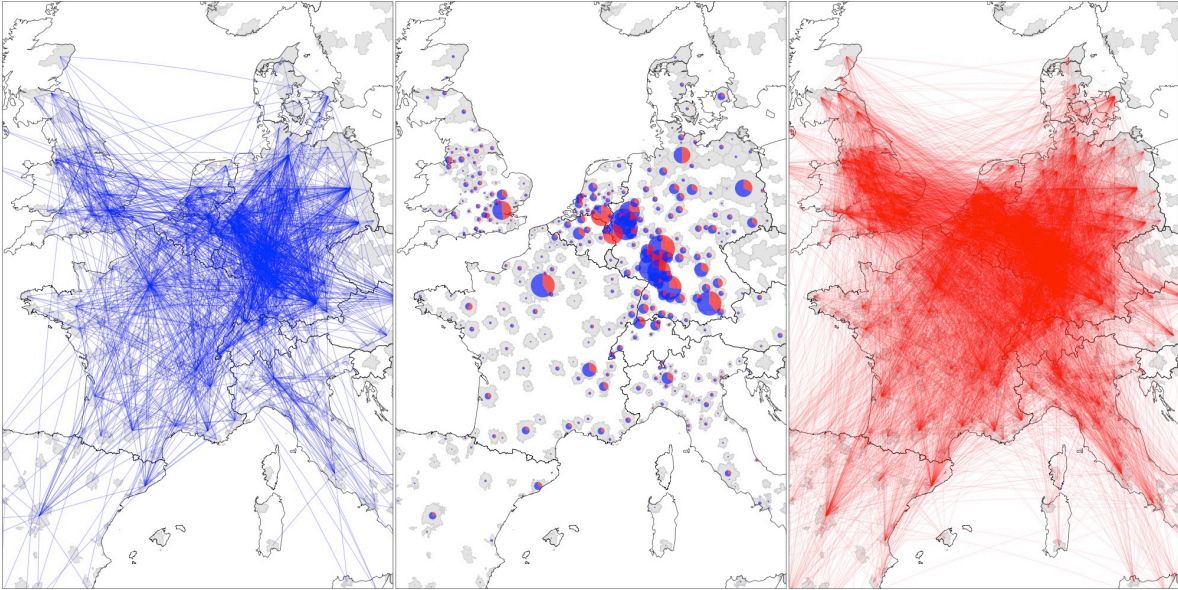
Calibrating Massacrator requires choosing (1) the number of filtering variables and (2) the number of criteria to be met in order for the pair to be considered as a match. For exploratory purposes, four calibrations based on the high-recall calibration of Massacrator (HR) are tested. C1 tests the sensitivity of disambiguation results to the number of criteria to be met. C2 and C3 test the sensitivity of the disambiguation to the removal of geographical criteria. C1 and C3 perform best, both by the number of movers and the number of moves. Results suggest



that disambiguation is much more sensitive to the number of criteria to be met, rather than the inclusion of geographical criteria. The preferred measure of mobility is C1, and C2 is used for robustness checks.

### A4 Connectivity

Figure A3: Connectivity structure



Left panel: Mobility flows, 1998-2009. Right panel: Collaboration networks, 1998-2009. Middle panel: Relative connectivity of cities with regards to their level of mobility flows (blue), both inward and outward, and their number of collaborations (red).

Table A2: Correlation between weight matrices

	$W_M$	$W_N$	$W_D$
$W_M$	1	0.395	0.086
$W_N$	0.395	1	0.161
$W_D$	0.086	0.161	1

### A5 Technology

Table A3: Technological classes and subclasses

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- A – Electrical engineering, Electronics
  - 1 Electrical engineering
  - 2 Audiovisual technology
  - 3 Telecommunications
  - 4 Information technology
  - 5 Semiconductors
- B – Instruments
  - 6 Optics
  - 7 Technologies for Control/Measures/Analysis
  - 8 Medical engineering
  - 9 Nuclear technology
- C – Chemicals, Materials
  - 10 Organic chemistry
  - 11 Macromolecular chemistry
  - 12 Basic chemistry
  - 13 Surface technology
  - 14 Materials, Metallurgy
- D – Pharmaceuticals, Biotechnology
  - 15 Biotechnologies
  - 16 Pharmaceuticals; Cosmetics
  - 17 Agricultural and food products
- E – Industrial processes
  - 18 Technical processes (chemical, physical, mechanical)
  - 19 Handling; Printing
  - 20 Materials processing, textile, glass, paper
  - 21 Environmental technologies
  - 22 Agricultural and food apparatuses
- F – Mechanical engineering Machines, Transport
  - 23 Machine tools
  - 24 Engines, Pumps, Turbines
  - 25 Thermal processes
  - 26 Mechanical elements
  - 27 Transport technology
  - 28 Space technology; Weapons
- G – Consumer goods, Civil engineering
  - 29 Consumer goods

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 Source: ISI, OST, INPI

A simple count of patent classes is not satisfactory as multidisciplinary patents would be over-represented. Building on these considerations, sectors within patents need to be weighted according to some relevant criterion. Three aggregations are performed. A1 retain only first sector. Conversely, A2 gives equal weight to all sectors. Finally, A3 weights sectors according to their relative frequency. The preferred aggregation is A3 and the other two are used for robustness checks.

Table A4: Aggregation of patent classes

Patent	Sector	Rank	A1	A2	A3
A	1	F	1	1/2	1/3
A	2	-	0	1/4	1/3
A	2	-	0	1/4	1/3
B	1	F	1	1	1